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Future evolution of the car stock in Belgium:

CASMO, the new satellite of PLANET

January 2019

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Future evolution of the car stock in Belgium: CASMO, the new satellite of PLANET

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Abstract - The new Belgian CAr Stock MOdel, which is linked to the national transport demand model PLANET, is structured as follows: (a) The total desired car stock in each future year is a function of the country's population and GDP per capita. (b) The probability that a car is scrapped is modelled as a function of its age and accumulated mileage. The desired car stock is then confronted with the remaining car stock to determine total car purchases. (c) Total sales are allocated to individual emission classes, using the parameter values of a Stated Preference discrete choice model. The model is then calibrated in order to reflect the current market and policy context in Belgium (d) The results are mapped into an inventory that is aggregated according to the EURO emission class. (e) In order to represent that the non-price barriers to electrified cars will decrease over time, we have implemented an alternative approach where the perceived acquisition costs decrease over time. Alternatively, this approach can be used to explore what would be the required decrease in subjective costs to reach a given future market share.

Abstract - Le nouveau modèle pour le parc de voitures belge CASMO (CAr Stock MOdel) – lié au modèle national de projection de la demande de transport PLANET – se structure de la manière suivante : (a) Le nombre total de voitures souhaité pour toute année future est une fonction de la population nationale et du PIB par tête. (b) La probabilité de mise à la casse de chaque voiture est modélisée comme fonction de son âge et de son kilométrage accumulé. Le nombre de voitures souhaité est alors comparé au nombre de voitures restant dans le parc pour déterminer le nombre total d'achats de voitures. (c) Les achats totaux de voitures sont attribués aux différentes classes d'émissions au moyen des paramètres d'un modèle de choix discret, estimé sur la base d'une enquête de type « préférences déclarées ». Ensuite, le modèle est calibré pour refléter les conditions de marché et le contexte politique belges. (d) Les résultats sont intégrés dans un nouveau parc de voitures, agrégé selon les classes d'émissions EURO. (e) Pour tenir compte de la diminution progressive des barrières non financières à l'achat de voitures électrifiées, nous mettons en œuvre une approche alternative dans laquelle le coût d'acquisition perçu décroît dans le temps. Cette approche peut également être exploitée pour déterminer les baisses requises de coût subjectif pour atteindre une certaine part de marché.

Abstract - Het nieuwe wagenparkmodel voor België, het CAr Stock MOdel (CASMO), dat gekoppeld is aan het nationaal langetermijnmodel voor transport, PLANET, is als volgt gestructureerd: (a) Het gewenste wagenpark wordt berekend als een functie van de bevolking en het bbp per capita. (b) De waarschijnlijkheid dat een auto uit omloop wordt genomen wordt berekend als functie van de leeftijd van de auto en van de totale kilometerstand. Het gewenste wagenpark wordt dan vergeleken met het overblijvend wagenpark, en dat bepaalt de totale aankopen van nieuwe auto's in een gegeven jaar. (c) Voor de opsplitsing van de totale verkopen per emissie-klasse, gebruiken we parameters van een discrete keuzemodel dat geschat werd aan de hand van een "uitgedrukte voorkeur" onderzoek. We kalibreren het model om de realiteit van de Belgische markt in onze referentieperiode weer te geven. (d) De output van het model wordt geïntegreerd in een nieuw wagenpark, dat wordt geaggregeerd in functie van de emissieklasse van de auto's. (e) Er zijn meerdere elementen die nu een barrière vormen voor een groter marktaandeel voor elektrische en hybride auto's; deze zullen in de toekomst echter waarschijnlijk grotendeels verdwijnen. Om rekening te houden met deze veranderingen hebben we een alternatieve benadering geïmplementeerd waarbij de gepercipieerde aankoopkosten dalen doorheen de tijd. Deze benadering kan ook gebruikt worden om te verkennen hoe ver de subjectieve kosten zouden moeten dalen om een gegeven marktaandeel te bereiken.

Jel Classification - R00, R20, R40, C25, Q50
Keywords - car stock modelling, discrete choice, alternative fuels, electric mobility, survival analysis and scrappage decisions, stated preferences

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Executive summary

Externalities of road transport such as greenhouse gas emissions and local pollution do not only depend on transport activity levels, but also on the composition of the vehicle stock. Indeed, emission factors and fuel consumption depend on the age structure of the vehicle stock, the shares of different powertrains and the distribution of the vehicles' weights. Therefore, in order to assess the environmental impact of road transport, long-term transport demand models need to be linked with vehicle stock models.

In such linked models, the interaction will go in both ways. On the one hand, the modal choices in the transport demand model are affected by the costs of car use, which also depend on the composition of the car stock. On the other hand, the activity levels predicted by the transport demand models influence the average costs of cars, and thus also the demand for specific car types.

In the present paper, we focus on the new implementation of the Belgian CAr Stock MOdel (CASMO), which is linked to the national transport demand model, PLANET.

Ideally, modelling the size and the composition of the car stock requires a fully dynamic model of the car market. Due to data constraints, this is currently not feasible for the Belgian context. Modelling the evolution of the Belgian car stock thus requires a pragmatic approach, with several ad hoc decisions.

Our approach to the car stock model can be summarized as follows:

- The total desired car stock is determined as a function of the country's population and GDP per capita. Car ownership in Belgium is projected to grow from 5.76 million cars in 2018 to 7.04 million cars in 2040 – this is an increase with 22% and corresponds to 0.57 cars per capita by 2040. For comparison, over the same period, GDP is assumed to grow with 37% – this is consistent with a car stock that is approaching its saturation point.
- In order to produce the emissions of the car fleet, cars are classified according to their emission factors, which depend on their age, fuel and size. The emission factors use a tank-to-wheel approach.
- For each vintage in each car class we estimate the probability that a car is scrapped in the current year, as a function of its age and accumulated mileage (survival model with a loglogistic survival function). This determines the remaining car stock.
- The desired car stock is then confronted with the remaining car stock to determine total car purchases in a given year.
- For the allocation of the total sales to the respective emission classes, we use the parameter values of a Stated Preference discrete choice model estimated in The Netherlands. A direct application of the model to the Belgian market results in a poor predictive value, probably due to a combination of the following factors:
  - A still very low familiarity of users with electrified (electric and hybrid) cars. A detailed analysis has shown that, in the current market context, the main barrier to the adoption of electrified cars is no longer their total cost of ownership, at least for realistic values of the expected economic lifetime. Other elements appear to be crucial, some of which are easily quantifiable (such

as the expected autonomy of an electric car, the availability of a charging infrastructure or the diversity of the car models on offer), others less (such as consumers' conservatism and range anxiety).

  - Company cars are an important component of the car stock, but the data do not allow to account for this in the demand model. Fleet managers do not just face different cost structures as private consumers – their choices are also governed by other criteria.
  - The "dieselgate" scandal and the policy measures that have been taken in response to it, have led to a very sharp decrease in the market share of diesel cars – higher than what we would expect a priori from the changes in car taxation only.

- The Alternative Specific Constants (ASCs) of the model represent the part of an alternative's utility that cannot be captured by the observed variables. Using non-linear least squares, we therefore calibrate the ASCs of the model to reflect the reality of the Belgian market in our reference period.
- We then use the calibrated model for long term projections of the market shares.
- Although the projected evolution of the cost and performance parameters tend to make electrified cars more attractive compared to their conventional counterparts, the projected market share for electric and hybrid cars remains below 2% in 2040. The most important driver behind this low sensitivity of the market shares for alternative powertrains to changes in costs and performance are the high values of the estimated ASCs.

The detailed vehicle type-size inventory is then mapped into a new inventory that is aggregated according to the EURO emission class to which the cars belong. This is fed back to the PLANET model, and, combined with an estimate of annual travel, this results in an assessment of environmental impacts.

Given that the calibration of the ASCs to the Belgian market leads to a much-improved match in the period used for the estimation but continues to drive the results until well in the future, we address whether this assumption of unvarying ASC is reasonable.

For instance, in the case of electric and hybrid cars, it could be argued that the low familiarity of consumers with these technologies leads to outdated perceptions regarding their total cost of ownership and range. Indeed, the spectacular improvements in terms of autonomy and costs of electric cars are a recent, and largely unanticipated, phenomenon. Outdated perceptions are likely to be corrected through actual experience and word-of-mouth effects (or "neighbour" effects). Such word-of-mouth effects are typically characterised by positive feedback loops.

Other elements are also likely to improve over time such as: the low density (or the perception of a low density) of the recharging infrastructure, especially of fast-chargers; the lack of diversity in the models that are available; long delays in the delivery of orders…

In order to represent those changes, we have implemented an alternative approach where the perceived acquisition costs decrease over time according to a logistic function. This reflects the typical dynamics of adopting new technologies: first imperceptibly, until a take-off point is reached, after which adoption will increase rapidly, until it converges to a new plateau when all learning effects have levelled out.

Assuming inflection point for hybrid cars around 2020 and for electric cars around 2030, we obtain much higher market shares. We have also found that, under this assumption, the market shares are much more sensitive to changes in the cost parameters. This approach with evolving subjective costs can be used, either to enlighten a debate between different experts, or to better understand the assumptions underlying existing alternative economic models.

Our work has also identified several data needs. In particular, the survival model would be more accurate if there were reliable and representative data on the accumulated mileages of individual cars and on the dates when they are retired from circulation in Belgium.

Synthèse

Les externalités du transport routier telles que les émissions de gaz à effet de serre ou de polluants locaux, dépendent non seulement du volume des flux de transport, mais également de la composition du parc de voitures. En effet, les facteurs d'émission et la consommation de carburants dépendent de la structure par âge du parc de voitures, des parts dans celui-ci des différents types de motorisations, et de la distribution de la masse des voitures. Pour évaluer les impacts environnementaux du transport routier, les modèles de projection à long terme de la demande de transport doivent donc être couplés à des modèles décrivant l'évolution du parc de voitures.

Les interactions entre modèles couplés de la sorte vont dans les deux directions. D'une part, les choix modaux au sein du modèle de demande dépendent du coût total d'usage de la voiture, qui lui-même dépend de la composition du parc de voitures. D'autre part, la demande de transport en voiture projetée influence le coût moyen des voitures, et donc la demande pour des types spécifiques de voiture.

Le présent Working Paper se focalise sur la mise en œuvre d'un nouveau modèle de parc de voitures pour la Belgique, CASMO (Car Stock Model), qui est conçu pour être couplé au modèle de projection de la demande de transport PLANET.

Dans l'idéal, la modélisation de la taille et de la composition du parc de voitures nécessiterait un modèle dynamique complet, tenant compte de toutes les décisions des agents ayant une influence sur ce parc. Du fait de l'indisponibilité d'une partie des données nécessaires à un tel exercice aujourd'hui en Belgique, la modélisation du parc de voitures belge requiert une approche pragmatique impliquant des hypothèses ad hoc.

Notre approche de modélisation peut se résumer de la sorte :

– La taille totale du parc de voiture désiré est déterminée à l'aide d'une fonction de la population du pays et du PIB par habitant. Le nombre de voiture en Belgique devrait évoluer de 5,76 millions en 2018 à 7,04 millions en 2040, soit une croissance de 22 %. Ceci correspond à un taux de possession de 0,57 voiture par habitant en 2040. À titre de comparaison, le PIB belge devrait croitre de 37 % sur la même période. Ces éléments sont cohérents avec l'idée d'un parc de voitures s'approchant de son volume de saturation.

– Pour pouvoir évaluer les émissions totales du parc de voitures, celui-ci est segmenté en fonction de facteurs d'émissions dépendants de l'âge, du carburant, et de la taille des voitures.

– Pour chaque cohorte de voitures, dans chaque classe d'émission, nous estimons la probabilité qu'une voiture soit mise à la casse pour l'année en cours comme fonction de son âge et de son kilométrage accumulé, à l'aide d'un modèle de survie loglogistique. Ceci détermine le parc de voitures restant en service.

– Le parc de voitures désiré est alors comparé au parc restant en service, pour déterminer le total des achats de voitures nécessaires une année donnée.

- L'allocation des achats totaux de voitures entre les différentes classes d'émissions se fait à l'aide d'un modèle de choix discret estimé pour les Pays-Bas au départ d'une enquête de type "Préférences Déclarées". L'application directe de ce modèle présente une capacité prédictive assez faible pour le marché Belge, probablement du fait des facteurs suivants :
  - Les voitures électrifiés (voitures électriques et hybrides) sont encore peu familières pour les utilisateurs belges. Une analyse détaillée démontre que, dans le contexte actuel, le principal frein à l'adoption de ces technologies n'est plus le coût total d'usage du véhicule électrifié – en tout cas lorsque l'on considère des durées de vie économiques réalistes. D'autres éléments jouent un rôle déterminant, certains étant aisément quantifiables (comme l'autonomie attendue d'une voiture électrique, la disponibilité d'infrastructures de recharge, ou la diversité des modèles électriques offerts) et d'autres moins (comme le conservatisme des utilisateurs, ou leur « range anxiety »).
  - Les voitures de société constituent une composante importante et spécifique du parc de voitures, mais les données ne permettent pas de les distinguer dans les modèles économiques utilisés. Les gestionnaires de flotte de voitures fondent en effet leur choix sur un ensemble de critères différents des utilisateurs privés, et sont confrontés à des structures de coût différentes.
  - Le "dieselgate" et les mesures politiques prises en réponse à son retentissement important ont induit une forte baisse de la part de marché des voitures diesel. Cette baisse dépasse ce qui était prévisible a priori du fait de la seule modification de la fiscalité automobile.
- Les Constantes Spécifiques aux Alternatives représentent la part de l'utilité d'une alternative qui ne peut être captée par les variables explicatives observées. Nous procédons dès lors à leur recalibration pour refléter au mieux l'état du marché automobile belge sur notre période de référence, ce au moyen d'une équation aux moindres carrés non-linéaires.
- Le modèle de choix discret recalibré est utilisé pour les projections à long terme des parts de marché.
- L'évolution projetée des coûts et des prestations des voitures électrifiés rendent ceux-ci de plus en plus attractifs en comparaison des voitures conventionnels. Malgré cela, la part de marché projetée pour ces voitures en 2040 reste sous les 2 %. Cette faible sensibilité des parts de marché des motorisations alternatives aux évolutions des coûts et des performances trouve sa cause essentielle dans les valeurs élevées des constantes spécifiques aux alternatives estimées pour la Belgique

Les résultats de la modélisation des achats sont ensuite intégrés dans une nouvelle version du parc de voitures, agrégé selon les classes d'émissions EURO. Cette nouvelle version du parc permet une mise à jour des coûts moyens du transport en voiture au sein du modèle PLANET, qui en retour fournit une projection du nombre de kilomètres parcourus annuellement en voiture. La combinaison de la composition du parc et des distances parcourues rend possible l'estimation des impacts environnementaux de l'usage de la voiture.

La calibration des constantes spécifiques aux alternatives sur les données belges produit un ajustement de bien meilleure qualité pour la période observée. Ces valeurs calibrées ont cependant une influence très importante sur les parts de marché modélisées pour l'ensemble de la projection, jusqu'en 2040. Il est ainsi légitime de remettre en question l'hypothèse de constantes spécifiques inchangées sur toute la période.

Ainsi, dans le cas des voitures électriques, on peut raisonnablement penser que la manque d'expérience de ce type de technologie implique chez les consommateurs des perceptions dépassées en matière de coût total et d'autonomie. En effet, les améliorations spectaculaires des prestations et des coûts de ces voitures sont un phénomène récent et, dans une large mesure, non anticipé. De telles perceptions dépassées ont de fortes chances d'être revues sous l'effet de l'expérience accumulée et du bouche-à-oreille. Les effets de bouche-à-oreille sont en général caractérisés par des phénomènes de renforcement positif.

D'autres aspects liés à cette défiance sont amenés à se résorber avec le temps, tels que : la faible densité (ou la perception d'une faible densité) de l'infrastructure de recharge, particulièrement des chargeurs rapides ; le manque de diversité des modèles électrifiés disponibles ; les délais de livraison importants pour ce type de voitures…

Pour tenir compte de ces changements, nous mettons en œuvre une approche alternative dans laquelle les coûts d'acquisition perçus décroissent dans le temps selon une fonction logistique. Ceci reflète la dynamique typique dans les processus d'adoption de nouvelles technologies : le phénomène commence de manière imperceptible, jusqu'à ce qu'un point critique soit atteint. Après celui-ci, le taux d'adoption augmente rapidement, jusqu'à sa convergence vers un nouveau plateau lorsque les effets d'apprentissage disparaissent.

En supposant que le point d'inflexion de ce processus d'apprentissage se situe aux alentours de 2020 pour les voitures hybrides, et de 2030 pour les voitures électriques, nous obtenons des parts de marché bien plus élevées en 2040. Nous observons également que, sous ces hypothèses d'évolution des coûts subjectifs, les parts de marché sont beaucoup plus sensibles à des changements dans les paramètres de coûts. Cette approche peut être utilisée soit pour éclairer un débat entre différents experts, soit pour mieux comprendre les hypothèses sous-tendant différentes alternatives de modélisation économique.

Ce travail nous a permis également d'identifier plusieurs manques dans les données disponibles. En particulier, le modèle de survie gagnerait en précision si des kilométrages individuels ainsi que des dates de mise au rebut fiables étaient disponibles pour les voitures en Belgique.

Synthese

Externe kosten van wegtransport zoals de uitstoot van broeikasgassen en lokale vervuiling hangen niet alleen af van de transportactiviteit, maar ook van de samenstelling van het wagenpark. Inderdaad, de emissiefactoren en het brandstofverbruik hangen af van de leeftijdsstructuur van de vloot, van de aandelen van de verschillende aandrijftechnologieën en van het gewicht van de voertuigen. Modellen van de evolutie van de transportvraag op lange termijn dienen daarom gekoppeld te worden met modellen van het wagenpark indien men ze wenst te gebruiken voor het schatten van de milieu impact van wegtransport.

In dergelijke gekoppelde modellen gaat de interactie in beide richtingen. Enerzijds worden de modale keuzes in het transportvraagmodel beïnvloed door de kosten van autogebruik, en deze hangen af van de samenstelling van het wagenpark. Anderzijds beïnvloedt de transportvraag de gemiddelde kost van auto's, en dus ook de vraag naar specifieke types auto's.

In deze paper gaan we dieper in op het nieuwe wagenparkmodel voor België, het *CAr Stock MOdel* (CASMO), dat gekoppeld is aan het nationaal langetermijnmodel voor transport, PLANET.

Ideaal gesproken zouden we moeten beschikken over een geïntegreerd model van alle beslissingen die de grootte en de samenstelling van het wagenpark bepalen. Met de gegevens die momenteel beschikbaar zijn, is dit echter niet mogelijk voor België. Het modelleren van de evolutie van het wagenpark in België vereist dus een pragmatische aanpak met een paar ad hoc aannames.

Onze benadering kan als volgt worden samengevat:

– Het gewenste wagenpark wordt berekend als een functie van de bevolking en het bbp per capita. We projecteren een toename van het aantal auto's in België van 5,76 miljoen in 2018 tot 7,04 miljoen in 2040 – dit is een toename met 22 % en komt overeen met 0,57 auto's per capita in 2040. Ter vergelijking: we veronderstellen dat het bbp over dezelfde periode groeit met 37 %. Dit komt dus overeen met een wagenpark dat zijn verzadigingspunt nadert.

– Om de uitstoot van het wagenpark te berekenen, worden auto's geklasseerd in functie van hun emissiefactoren, die afhangen van hun leeftijd, brandstof en grootte. Deze emissiefactoren volgen een tank-tot-wiel benadering.

– Voor elke jaargang en voor elke emissieklasse berekenen we de waarschijnlijkheid dat een auto uit omloop wordt genomen in het lopende jaar, in functie van de leeftijd van de auto en van de totale kilometerstand (aan de hand van een loglogistieke overlevingsfunctie). Dit bepaalt het overblijvend wagenpark.

– Het gewenste wagenpark wordt dan vergeleken met het overblijvend wagenpark, en dat bepaalt de totale aankopen van nieuwe auto's in een gegeven jaar.

– Voor de opsplitsing van de totale verkopen in functie van de respectievelijke emissie-klasse, gebruiken we parameters van een discrete keuzemodel dat geschat werd aan de hand van een "uitgedrukte voorkeur" onderzoek in Nederland. Een rechtstreekse toepassing van dit model in een Belgische context bleek een lage voorspellende waarde te hebben, waarschijnlijk door een combinatie van volgende factoren:

  - Gebruikers zijn nog altijd weinig vertrouwd met elektrische en hybride auto's. Een gedetailleerde analyse heeft aangetoond dat, in de huidige context, de totale eigendomskost van deze auto's niet langer de grootste hinderpaal vormt voor een groter marktaandeel (tenminste niet voor realistische waarden van hun verwachte economische levensduur). Andere elementen zijn cruciaal, waarvan sommigen gemakkelijk kunnen worden gekwantificeerd (zoals de autonomie van een elektrische auto, de beschikbaarheid van een laadinfrastructuur of de diversiteit van het aanbod), terwijl dat bij anderen niet zo evident is (zoals het conservatisme van de gebruikers en hun "range anxiety").
  - Bedrijfswagens hebben een belangrijk aandeel in het wagenpark, maar omwille van beperkingen in de gegevens waarover we beschikken, kunnen we dit niet weergeven in het vraagmodel. Vlootmanagers zullen echter andere keuzes maken dan privé consumenten, niet alleen omdat de kosten voor hen verschillen, maar ook omdat ze waarschijnlijk andere criteria laten meespelen.
  - Als een gevolg van het "dieselgate" schandaal en de beleidsmaatregelen die genomen zijn als reactie daarop, heeft er een zeer scherpe daling plaatsgevonden in het marktaandeel van dieselauto's – meer dan wat we zouden verwacht hebben op basis van de veranderingen in het fiscaal regime alleen.

- De Alternatief-Specifieke Constanten (ASCs) meten het deel van het nut van een bepaalde type auto dat niet kan worden gemeten aan de hand van waargenomen variabelen. We hebben daarom gebruik gemaakt van de niet-lineaire methode van de kleinste kwadraten om de ASCs van het model te herkalibreren zodat ze de realiteit van de Belgische markt in onze referentieperiode weergeven.
- We hebben daarna voor de projecties op lange termijn van de marktaandelen gebruik gemaakt van de nieuw gekalibreerde versie van het model.
- Door de verwachte evolutie van de kost- en prestatieparameters van de elektrische en hybride auto's worden ze doorheen de tijd steeds aantrekkelijker in vergelijking met de "conventionele" tegenhangers. Nochtans blijft het geprojecteerd marktaandeel voor elektrische en hybride auto's in 2040 onder de 2 %. De belangrijkste factor die verklaart waarom de marktaandelen weinig reageren op veranderingen in de kosten en prestaties zijn de hoge waardes van de geschatte ASCs.

De output van het model wordt dan geïntegreerd in een nieuw wagenpark, dat wordt geaggregeerd in functie van de EURO-emissieklasse van de auto's. Dit wordt dan teruggekoppeld naar het PLANET-model, en, in combinatie van een schatting van de afstanden die jaarlijks worden afgelegd, leidt dit tot een schatting van de milieu-impact.

Het herkalibreren van de ASCs in functie van de Belgische marktgegevens leidt enerzijds tot een veel betere overeenstemming met de situatie in de periode die geobserveerd wordt voor het schatten van het model. Anderzijds heeft dit een buitensporig grote invloed op de modelresultaten in de verre toekomst. We dienen ons bijgevolg de vraag te stellen of het wel redelijk is om er van uit te gaan dat deze ASCs in de toekomst ongewijzigd zullen blijven.

Bijvoorbeeld, in het geval van elektrische en hybride auto's, zou men kunnen betogen dat het gebrek aan gebruikservaring met deze technologieën leidt tot voorbijgestreefde percepties met betrekking tot hun totale eigendomskosten en autonomie. De spectaculaire verbetering van de autonomie en de kosten van elektrische voertuigen zijn bijvoorbeeld een recent, en grotendeels onverwacht, fenomeen. Het is echter aannemelijk dat voorbijgestreefde percepties worden bijgestuurd als het gevolg van concrete gebruikservaringen en door mond-aan-mond getuigenissen. Dergelijke effecten worden meestal gekenmerkt door positieve feedback loops.

Ook andere elementen zullen doorheen de tijd waarschijnlijk verbeteren: de lage dichtheid van het aanbod aan oplaadinfrastructuur (of de perceptie dat er een lage dichtheid is), zeker van snelladers; het gebrek aan diversiteit in het aanbod; de vertragingen in de leveringen van de auto's…

Om rekening te kunnen houden met deze veranderingen hebben we een alternatieve benadering geïmplementeerd waarbij de gepercipieerde aankoopkosten dalen doorheen de tijd. We gaan ervan uit dat deze daling een logistische functie volgt. Deze geeft inderdaad weer dat de marktaandelen van nieuwe technologieën eerst onmerkbaar traag toenemen, tot wanneer een keerpunt wordt bereikt waarna het marktaandeel zeer snel toeneemt, waarna het convergeert naar een nieuw plateau nadat alle leereffecten zijn uitgespeeld.

Indien we ervan uitgaan dat dit keerpunt voor hybride auto's wordt bereikt rond 2020, en voor elektrische auto's rond 2030, dan zien we dat dit inderdaad leidt tot veel hogere marktaandelen voor deze aandrijftechnologieën. We hebben ook vastgesteld dat, onder deze aannames, de marktaandelen veel gevoeliger zijn voor veranderingen in de kostenparameters.

Deze benadering met variabele subjectieve kosten kan gebruikt worden om het debat tussen verschillende experts te verhelderen, of om meer inzicht te verwerven in de hypothesen die aan de basis liggen van bestaande alternatieve economische modellen.

Ons werk heeft ook geleid tot de identificatie van lacunes in de data. Het overlevingsmodel zou bijvoorbeeld veel accurater zijn indien we zouden kunnen beschikken over betrouwbare en representatieve data met betrekking tot de totale kilometerstand van individuele auto's, alsook van de datum waarop ze in Belgium uit omloop worden genomen.

1. Introduction

Externalities of road transport such as greenhouse gas emissions and local pollution do not only depend on transport activity levels, but also on the composition of the vehicle stock. Indeed, emission factors and fuel consumption depend on the age structure of the vehicle stock, the shares of different powertrains and the distribution of the vehicles' weights. Therefore, in order to assess the environmental impact of road transport, long-term transport demand models[1] need to be linked with vehicle stock models.

In such linked models, the interaction will go in both ways. On the one hand, the modal choices in the transport demand model are affected by the costs of car use, which also depend on the composition of the car stock. On the other hand, the activity levels predicted by the transport demand models influence the average costs of cars, and thus also the demand for specific car types.

In Franckx (2017), we had addressed the key methodological issues raised by car stock modelling, in particular in the light of emerging technologies and business models. We refer to this paper for a detailed literature study of car stock modelling.

In the present paper, we focus on the new implementation of the Belgian CAr Stock MOdel (CASMO), which is linked to the PLANET model.

At the household level, the size and the composition of a car stock are the result of numerous interrelated variables, such as the annual distances that the household expects to travel; the substitutes to private car travel that are available to the household; and the cost and performance parameters of the cars that are available on the market.

The decision on how many cars to hold, when to replace existing cars and what type of cars to buy are further complicated by other factors.

Firstly, a household's expected annual mileage and the availability of alternative modes are not fully exogenous, but follow from decisions made by the household, such as its place of residence, employment and schools on the one hand and the size of the household on the other hand.

Secondly, some car types are characterised by high acquisition costs and relatively low operating costs, while it is the other way around for other car types. The expected annual mileage, and the typical profile of individual trips, will thus affect the optimal car type for a given household. Until recently, this trade-off was the decisive factor in the choice between a diesel and a gasoline car, but, with electric cars, new criteria (such as the vehicle's range and the availability of a recharging infrastructure) become relevant.

Thirdly, if operating costs change unexpectedly during a vehicle's lifetime (for instance, due to fluctuating fuel prices or to changes in the tax regime), a household's effective travel may deviate from its planned travel when it first purchased the vehicle.

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1 Such as the Belgian transport demand model PLANET - see Desmet et al. 2008 and Mayeres et al. 2010.

Fourthly, the decision to scrap a vehicle depends on parameters such as the expected future costs of keeping the vehicle (for instance, due to increased maintenance costs), the current price of new cars and the current car's expected value on the second-hand market. In the past, one could assume that these elements were mainly affected by a vehicle's type and age. However, in shared mobility modes, annual usage is much higher than for privately owned and used cars and accumulated mileage can also be expected to affect the scrappage decision. If shared mobility gains significant market shares in the coming decades, this could significantly affect the composition of the car stock.

Ideally, modelling the size and the composition of the car stock thus requires a fully dynamic model of the car market. There are some recent examples of papers that go a long way in this direction – see for instance Gillingham et al. (2015) and Yamamoto et al. (2004).

However, due to data constraints, this is currently not feasible for the Belgian context. Modelling the evolution of the Belgian car stock thus requires a pragmatic approach, with several ad hoc decisions. In what follows, we describe the new approach we have taken and we illustrate the methodology with some results. We also discuss some limitations of this new approach and the potential for future improvement.

The paper is structured as follows. The structure of the model is summarized in Section 2, followed by a detailed description of the data we have used in Section 3. Section 4 describes the three components model in detail: the demand model (Section 4.1), the survival model (Section 4.2) and the allocation model (Section 4.3). The resulting long-term projections are presented in Section 5. Section 6 discusses possible improvements to the central model and Section 7 concludes.

2. General structure of the model

The approach to the car stock model can be summarized as follows:

– The total desired car stock is determined by a country's population and GDP per capita. The relation between these variables is based on findings from the international literature.

– For each vintage in each car class[2] , we estimate the probability that a car is scrapped in the current year, as a function of its age and accumulated mileage (survival model). This determines the remaining car stock.

– The desired car stock is then confronted with the remaining car stock to determine total car purchases in a given year.

– A calibrated multinomial logit model (MNL) then splits these new purchases according to the different car classes.

The detailed vehicle type-size inventory is then mapped into a new inventory that is aggregated according to the EURO emission class to which the cars belong. This is fed back to the PLANET model, and, combined with an estimate of annual mileage, this results in an assessment of environmental impacts.

Before proceeding with a more detailed explanation of each step, we give an overview of our main data sources.

[2] Cars are grouped according to their COPERT emission class, which is determined by fuel and size. COPERT is a computer simulation programme used for the calculation of air pollutant emissions from road transport, whose technical development has been financed by the European Environment Agency (EEA), in the framework of the activities of the European Topic Centre on Air and Climate Change. It is used as an input in official annual national inventories (see Emissia 2018).

3. Data requirements and hypotheses

3.1. The COPERT classification

One of the key outputs of the PLANET model is an assessment of the environmental impacts of transport demand. It covers the following pollutants: NO_x, $PM_{2.5}$, CO_2, non-methane volatile organic components (NMVOC) and SO_2.

In order to produce the emissions of the car fleet, cars are classified according to their emission factors, which depend on their age, fuel and size. The emission factors for cars follow the COPERT methodology and use a tank-to-wheel approach.

The car stock model distinguishes the following fuel classes: gasoline, diesel, CNG, LPG, hybrid (both gasoline and diesel), plug-in hybrid (both gasoline and diesel) and electric cars.

In order to be able to apply the COPERT methodology, we have split gasoline, diesel and hybrid cars according to the following criteria:

– Cylinder capacity less than 1400 cc: “small”;

– Cylinder capacity between 1400 and 2000 cc: “medium”;

– Cylinder capacity larger than 2000 cc: “big”.

We have ignored the COPERT class “mini” for gasoline cars, as the number of cars in this size class is negligibly small compared to the existing car stock.

For LPG, CNG and electric cars, there is only one COPERT class. We have however also split electric cars in categories “small”, “medium” and “big” according to the capacity of their batteries. For given dimensions of the car, the battery capacity is a proxy for the autonomy of the car, or, for a given autonomy, for the dimensions of the car. We have taken 20 kWh and 80 kWh as respective thresholds for the “electric car size classes” – while this is a bit arbitrary, it corresponds pretty well to the classification we would obtain based on the car’s physical dimensions. We have also verified that these “size classes”" are relatively homogeneous in terms of driving range.

From the Belgian national vehicle registry, we obtain each car’s age and we can thus apply vintage specific emission factors.

3.2. Data on the composition of the car stock

All data on vehicle registrations have been obtained from the Belgian national vehicle registry, the DIV[3]. The records contain, inter alia, information on the fuel used by the car and its cylinder capacity, which have been used to determine its COPERT class. Note that, while the records identify a car with its chassis number, the DIV only records the time during which a car was linked to a Belgian license plate. This

[3] Direction pour l’Immatriculation des Véhicules/ Dienst voor Inschrijvingen van Voertuigen.

implies that we cannot distinguish between a second-hand car that was imported and a new car that is brought into circulation. Similarly, we cannot see whether a car was scrapped or exported. Some cars also vanish temporarily from the database, because they have been sold on the second-hand market, and there is a transition period between the former owner handing in his license plate, and the new owner requesting a new one.

With these caveats in mind, we have made the following assumptions:

– For the survival model (see Section 4.2), we have taken 2016 as last year for our data set and assumed that all cars that had been taken out of the database and not registered again before the end of 2017, have effectively been scrapped.
– For the discrete choice model (see Section 4.3), we have assumed that all newly registered cars are effectively new cars.

Although the DIV data identify the cars that are owned by leasing companies, they cannot differentiate between privately owned cars and cars owned by a company (other than a leasing company). This is an important limitation, as the decision criteria used by company fleet managers are likely to differ from those used by households. We will come back to this issue in the interpretation of the results.

3.3. Behavioural data

The household data used in the discrete choice model are based on the Belgian national mobility behaviour survey BELDAM. As explained in Laine and Van Steenbergen (2017), BELDAM is a sampled cross-sectional survey, carried out in 2010, and covers the population of Belgian residents. The sample consists of some 8,500 households that represent more than 15,800 individuals aged six or more. This survey is sufficiently large and correctly weighted to be considered as representative of the Belgian population.

The first questionnaire in the survey addresses general characteristics such as household income, the educational and professional status of each household member and many other useful control variables. It also provides detailed information on the number of vehicles owned by the household and their characteristics. It includes aggregate use data in the form of kilometres driven per year.

The second questionnaire is individual, and includes each person in the household aged six or more, for whom a number of items regarding regular mobility behaviour (such as commuting behaviour) and a trip log for a randomly selected day during the survey period are reported.

3.4. Data on car costs and autonomy

In short, the sources for the car related data (such as their cost and autonomy) are:

– All assumptions on tax rates are based on an annual publication by the Federal Public Service Finance, the "Tax survey".

- For each COPERT class, the purchase cost has been calculated as the average purchase cost of the 20 best sold models[4] in the class (weighted according to the share of each model in the sales). The cost information was obtained from the "Moniteur Automobile" for gasoline, diesel and electric cars. Because of the lack of publicly available data on CNG, LPG and hybrid cars, we have compared the purchase cost of a limited number of hybrid cars[5] with their gasoline or diesel "equivalent" and applied the average ratio to all hybrid cars of the same size class.
- For electric vehicles, the range in the base year was estimated per size class as the weighted average range of the ranges per size class (weighted according to the share of each model in the sales). These data were obtained mostly from Wikipedia[6], where we have used the lower bounds to the estimated ranges[7].
- The annual maintenance costs are based on Letmathe and Suares (2017). Insurance costs have been obtained from the National Bank of Belgium[8]. Annual control costs have been estimated using the annual report of GOCA, the professional association of Belgian car inspection centres.
- We have used the projections of fuel prices and electricity prices in the long-term energy outlook for Belgium (Gusbin and Devogelaer 2017).

The expected evolution of the autonomy of electric vehicles and of the purchase costs of cars is based on Cambridge Econometrics (2018), which has validated its assumptions in an extensive stakeholder consultation.

For the classification of the cars according to size class, we have used the cylinder capacity reported by the DIV for cars with combustion engine. For electric cars, we have used data on the battery capacity, which were available on Wikipedia.

3.5. Historical mileages: data and assumptions

The annual report "Kilometers afgelegd door Belgische voertuigen" published by the Federal Public Service Mobility and Transport (FOD Mobiliteit en Vervoer, 2017) contains estimates of the mileage and the car stock for 5 fuel types (gasoline, diesel, LPG, CNG and electric) and for 20 age classes. There is no information in this publication to differentiate according to size classes, but for gasoline, diesel and LPG, we have used old (2013) FOD data of the mileage according to size classes.

Data on annual mileages per age class are needed for two purposes: (a) for the survival model (see Section 4.2), as the accumulated mileage per age and size class affects the probability that a vehicle will be scrapped (b) for emission modelling, as the emission factors depend on a car's age-class.

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4 To the extent that data were available on those models.
5 For instance, the Toyota Yaris and Mitsubishi Outlander.
6 Given that the manufacturers have a very strong incentive to remove any factually incorrect information on their product, we assume that the information provided on Wikipedia is sufficiently reliable for our purposes.
7 This is usually the EPA Federal Test Procedure, which is more conservative (and arguably realistic) than the New European Driving Cycle, which is also often reported.
8 Statistics published as part of the supervisory review process of insurance and reinsurance undertakings.

As we do not always have observations for all age classes (and never for cars older than 20 years), we have estimated the mileage per age class as a quadratic function of age, with the additional constraint that the mileage is bounded away from zero and is non-increasing over the relevant interval. The precise parametrisations differ from fuel to fuel. Given that the oldest cars for which observations are available are 20 years old, out-of-range forecasts are unlikely to be accurate. Moreover, very old cars are likely to be registered as "old timers", which can only be used for very specific purposes and are unlikely to be affected by policy parameters. We therefore ignore all cars that are at least 25 years old.

In order to fill in data gaps in the base year 2015, we have proceeded as follows.

For gasoline and diesel, we have differentiated the age-specific mileages according to size class, assuming that these mileages had evolved proportionally to the observations for 2013. Formally, let $D_{f,a,c,y}$be the annual distance driven for fuel type f (gasoline or diesel), age $a \in A = \{1, \dots, 25\}$ and size class $c \in C = \{s, m, l\}$ in year y, and let $S_{f,a,c,y}$ be the corresponding number of cars. Let $D_{f,a,y}$ be the annual distance driven for fuel type f and age a in year y (averaged over the size classes). As explained above, statistics on $D_{f,a,2015}$, $S_{f,a,c,2013}$ and $D_{f,a,c,2013}$ are available.

Then, for instance, for "medium" cars, we assume:

$$D_{f,a,m,2015} = D_{f,a,2015} * \frac{D_{f,a,m,2013}}{\overline{D_{f,a,2013}}} \text{ where } \overline{D_{f,a,2013}} = \frac{\sum^{c \in C} S_{f,a,c,2013} \cdot D_{f,a,c,2013}}{\sum^{c \in C} S_{f,a,c,2013}}$$

For all other fuel types, it has been assumed that the mileages are the same for all size classes. For hybrid cars, it has been assumed that mileage per age class is the same as for gasoline or diesel cars (depending on the fossil fuel used by the hybrid car).

Moreover, for the purposes of our discrete choice model (see Section 4.3), we need an average "annual mileage" across all age classes to translate the variable costs (which are usually expressed in EURO per km) in costs per month.

For CNG and electric cars, we assume that the annual mileage is the same for each size class, and we take simply the weighted average across all age classes per fuel.

For gasoline, diesel and LPG, we assume that the annual mileage for each size class is the weighted average across the age classes for this size class in 2013, updated to 2015, proportionally to the evolution in the weighted average across all size and age classes for 2015. Formally, using analogous notation as above, we obtain for "medium" cars:

$$D_{f,m,2015} = \overline{D_{f,2015}} * \frac{\overline{D_{f,m,2013}}}{\overline{\overline{D_{f,2013}}}}.$$

The base year data for the annual mileage for hybrid cars are set equal to those of gasoline or diesel cars.

For the future evolution of the annual mileages per age class, fuel type and size class, we have assumed that they grow proportionally with the total demand for passenger cars transport as projected by the modal and time choice module in the PLANET model.

4. Model description

In this section, we describe the three components of our car stock model: (a) the demand model, determining the desired car stock (b) the survival model, determining whether or not a car is scrapped in a given year (c) the allocation model, determining the composition of new sales.

4.1. The demand model

In a first step, we determine how many cars are held, on the aggregate, in a given year. We assume that the total desired car stock per capita follows a Gompertz curve:

$$V_t = V^*. e^{\alpha e^{\beta . y_t}}$$

Where V_t is the desired number of cars per capita in year t, V^* is the saturation level of vehicle ownership expressed as number of cars per capita, α and β are parameters (to be estimated) and y_t is GDP per capita in year t. This specification represents a car stock that increases with income levels, but where growth levels off when a saturation point is reached.[9]

Wu et al. (2014) provide estimates for these parameters for the US, Japan, the OECD as a whole and Europe, with $\alpha = -3.06792$ and $\beta = -0.00013$ for Europe. They assume a saturation level of 0.5 cars per capita. Dargay et al. (2007) have estimated a saturation level of 647 cars per 1000 people for Belgium.

We have initially applied the saturation levels of Dargay et al. (2007) and the parameter estimates of Wu et al. (2014) to Belgium for the period 2008-2016. As illustrated in Graph 1, the estimated car stock is much higher than the actual car stock.

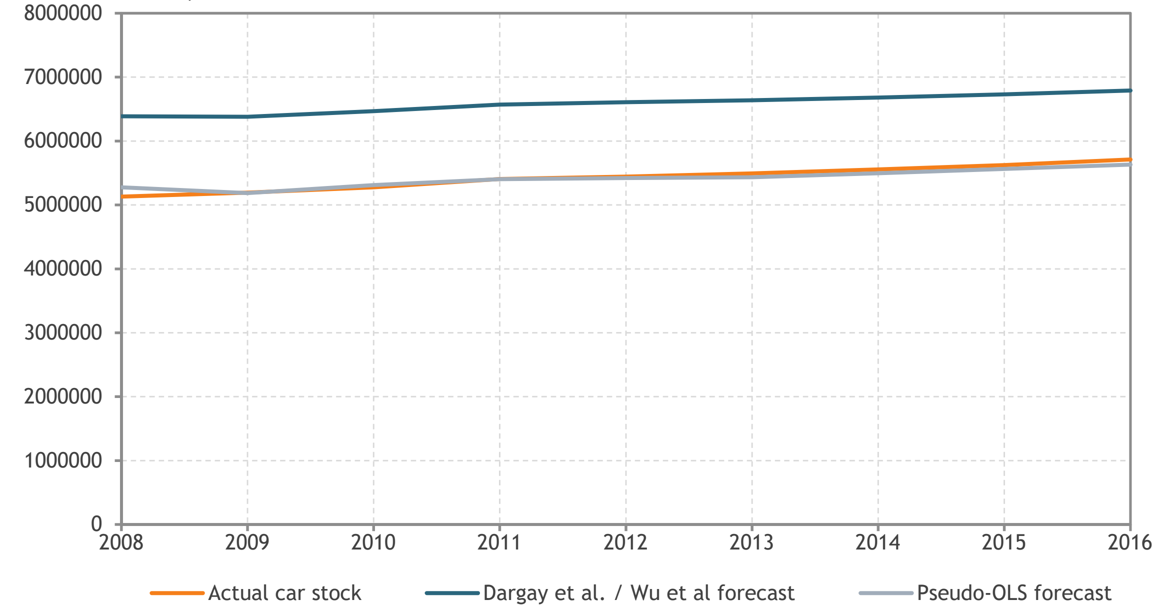
This is what we would have expected: the share of the Belgian population aged 18 or more is projected to remain around 80% in the coming 50 years (Federaal Planbureau and Statbel 2018). A saturation level of 647 cars per 1000 people would imply a car ownership rate of over 80% for the share of the population that is old enough for a driver's license, which seems a lot.

Therefore, we have used an alternative approach, where we have maintained the β value of Wu et al. (2014), but estimated V^* and α with Ordinary Least Squares (OLS). In a Gompertz function, the α translates the graph to the left or to the right. Intuitively, α determines at what point in time the function "takes off", while the β is the growth rate, and determines the speed of the transition to the saturation point. Thus, we assume here that the estimated growth rate for Europe is representative for Belgium, but that the take-off point and the saturation point are idiosyncratic and need to be estimated.

While R^2 = 0.87, with such a sample size, formal statistical tests do not make much sense, but graphical analysis shows that with $\alpha = -8.3851$ and $V^* = 0.61$, we obtain a decent match with the observed car stock. We therefore use this specification for the projections of the future car stock.

[9] One limitation of this approach is that it cannot represent transitions to new mobility paradigms that are centered around "use" rather than ownership.

Graph 1 Forecasted versus actual car stock
Number of cars



Source: DIV and CASMO

4.2. The survival model

In this step, we estimate how many cars are retired from use each year. We estimate a separate survival function per COPERT class – this survival function describes how the probability of being retired from use in Belgium evolves with age. The outcomes per COPERT class and vintage are aggregated to determine the total number of cars that are retired from the car stock.

Note that other variables than a car's age, such as its accumulated mileage, can influence the probability of retirement. As the annual mileage per car changes from year to year, the probability of retirement for a given age will also evolve over time. Therefore, we express the probability of retirement not just as a function of a car's age, but also of its first year of use (its vintage).

To be concrete, for the implementation of this approach, two concepts are key: the survival function $S(t)_{f,s,v}$ and the scrappage rate $h(t)_{f,s,v}$.

$S(t)_{f,s,v}$ gives the probability that a car of vintage v, fuel f and size s is still in use after t years. The scrappage rate $h(t)_{f,s,v} = \frac{S(t-1)_{f,s,v} - S(t)_{f,s,v}}{S(t-1)_{f,s,v}}$ gives the conditional probability that a car of a given COPERT class and vintage will be scrapped after t years, given that it has survived $t-1$ years. It is applied to the surviving stock.

As $h(t)_{f,s,v}$ can be obtained directly from $S(t)_{f,s,v}$, we focus here on the survival function. Two functional specifications have been estimated for the survival function: the loglogistic and the Weibull. In the current version of the model, we have implemented the loglogistic specification (see Cleves et al. (2016), p. 275):

$$S(t)_{f,s,v} = (1 + (e^{-\beta_f - \beta_{size} - \beta_{Km} * AccuKm_{v+t,f,s}} * t)^{1/\gamma_f})^{-1}$$

The β and γ parameters need to be estimated where β_f is a fuel-specific constant, β_{size} is a size-specific dummy variable, γ_f is the fuel-specific shape parameter of the loglogistic function and β_{Km} is the parameter associated with $AccuKM_{v+t,f,s}$, the average accumulated km driven by a car of this fuel and size class and with age $v + t$.

In the current version of the model, three different data sets have been used to estimate this statistical relationship. All data sets have been obtained from the DIV.

The first data set contains observations on accumulated mileages, which the DIV obtained from the professional association of car inspection centres, GOCA. However, as only cars that are older than 4 years are subject to the inspections by GOCA members, the sample was heavily biased towards older cars and contained no information on scrapping of cars that are not subject to GOCA inspections. Therefore, we have decided not to implement this specification yet, and we have set the parameter value for the impact of AccuMileage, β_{Km}, equal to zero. However, obtaining access to data sets with the accumulated mileages for a representative sample of cars is high on our priority list for future actions.

The second data set contains no information on accumulated mileage, and was limited to vehicle scrapping since 2012 – this is the first date for which observations on hybrid vehicles allow us to differentiate between plug-in and charge-sustaining hybrids. For hybrid vehicles and other alternative fuels, these data were used to estimate $S(t)_{f,s,v}$.

Third, for diesel and gasoline engines, we have used all DIV data that have been made available to us, going back to 2002.

Table 1 gives the estimates of β_{γ}, β_{size} and γ for each COPERT class. For the sake of conciseness, the detailed results for individual parameters (such as the confidence intervals) have been omitted here, but they can be obtained from the author on simple request. Note that most values of β_{size} have been set equal to zero by the STATA econometric software to deal with multicollinearity.

Table 1 Estimated parameters of the survival function

Car type	β_{fuel}	β_{small}	β_{medium}	β_{big}	γ_f
Gas	8.5632	0.0000	0.0000	0.000	0.3690
Diesel	8.2104	0.0000	0.0000	0.000	0.4727
LPG	8.7256	0.0000	0.0000	0.000	0.2764
CNG	7.5391	0.0000	0.0000	0.000	0.5683
GH_cs	8.2690	0.4171	0.0000	-0.078	0.5453
GH_phev	8.2394	-0.4393	0.3313	0.000	0.4767
DH_cs	7.6805	0.0000	-0.1582	0.000	0.4093
DH_phev	7.5394	6.2008	0.0000	0.000	0.5693
electric	7.6908	0.0000	0.0000	0.000	0.4667

Source: CASMO

4.3. The allocation model

In this stage, we allocate total car sales in a given year to the respective COPERT classes. As discussed in Franckx (2017), for the purpose of long term projections, the use of models based on observed market behaviour (Revealed Preference) studies is not advised in markets with new or emerging technologies who currently have very low market shares. Moreover, to the best of our knowledge, there are no Revealed Preference studies of the Belgian car market that we could use to estimate the market shares of the different COPERT classes in total new car sales.

We have therefore used the parameter values of a Stated Preference model estimated in The Netherlands. In what follows, we describe succinctly the key features of this model. We discuss why a direct application of the model to the Belgian market results in a very poor predictive value. As discussed in the literature, we thus need to calibrate the model parameters to reflect the reality of the Belgian market in our reference period. We briefly describe the key characteristics of this market, and then discuss the outcomes of the calibration method we used.

4.3.1. The Hoen-Koetse model

For our allocation model, we have used the parameter values of the discrete choice model of Hoen and Koetse (2014). We have chosen this study because (a) it can be applied to *all* the alternative fuels that are included in the PLANET model[10] (b) it is a relatively recent study, undertaken in a country (The Netherlands) that is comparable to Belgium.

Hoen and Koetse have used a stated choice experiment to estimate two discrete choice models of alternative fuel vehicle preferences: a mixed logit (ML) model (not including interaction terms with household characteristics) and a multinomial logit (MNL) model (including interaction terms with household characteristics).

In order to make maximal use of the available data (and in particular the household data reported in BELDAM), we will discuss in detail the model results based on the parameters estimates of the multinomial logit model (Table 9 in Hoen and Koetse). However, in order to test the robustness of the results, we will also summarize the results of model simulations based on the mixed logit model (Table 7 in Hoen and Koetse) – see Section 5.5.

[10] Lebeau et al. (2012) have estimated the market potential for electrified vehicles in Flanders. However, the estimation approach used (hierarchical Bayes) cannot readily be integrated into our modelling framework.

Table 2 Coefficients of the MNL model

Description	Coefficient
Alternative specific constants	
ASC for hybrid cars	-0.8587
ASC for electric cars	-3.0912
ASC for plug-in hybrid cars	-1.7162
Coefficients without interaction effets	
Driving range electric cars	0.0018
Monthly costs	-0.0031
Purchase cost	-0.0672
Interaction effets with “commuting at least 5 times per week”	
HybridHighCommute	-0.1929
ElectricHighCommute	-0.1012
PlugInHybridHighCommute	-0.1958
Interaction effets with “annual distance driven”	
Electric_7500_15000	-0.4636
Electric_15000_25000	-0.8562
Electric_25000_35000	-0.9324
Electric_35000	-1.4541
Interaction between “driving range EV” and “annual distance driven”	
ElecRange_7500_15000	0.0016
ElecRange_15000_25000	0.0025
ElecRange_25000_35000	0.0023
ElecRange_35000	0.0037
Interaction effect with “current car is a diesel”	
HybridCurrDiesel	0.191
electricCurrDiesel	-0.2147
PlugInHybridCurrDiesel	-0.1068
Interaction effect with “current car is a LPG”	
HybridCurrLPG	-0.3153
electricCurrLPG	-0.0115
PlugInHybridCurrLPG	-0.3339
Interaction effect with “respondent was female”	
MonthCostFemCoef	-0.0018
PurchCostFemCoef	-0.00135
Interaction effect with “annual distance driven is less than 7500 km”	
SmallMileageCoef	-8e-04
PurchCstSmallMlgCf	0.0098
Interaction effect between “driving range electric” and “charging potential at home”	0.2397

Source: Hoen and Koetse, 2014, Table 9

The most important limitation of this model is that a household’s choices are assumed to be independent of its income level. It does include a wide range of other socio-economic variables, though. Actually, some of the features used in the MNL model are not available in BELDAM and could not be used. Table 2 reports the coefficients that we have effectively used.

Compared to the previous version of the car stock module in the PLANET model (Mayeres et al. 2010), an important change is that this model does not have a nesting structure. However, Hoen and Koetse explain in the paper that they have estimated variants with a nesting structure, but that these do not appear to add a lot compared to the MNL specification.

In order to apply the model to Belgian data, note that the Hoen-Koetse discrete choice model distinguishes between “acquisition costs” and “variable costs”. In Belgium, the “acquisition costs” are composed of the actual purchase price (including VAT) and the licence tax. The “variable costs” are composed of the fuel costs (including excise duties), the annual circulation tax and the insurance, maintenance and inspection costs, all including indirect taxes such as the VAT. In the discrete choice model, these “variable costs” are expressed as costs per month. As fuel costs depend on the distance driven, the application of the model thus requires data on the annual distance driven per COPERT class.

4.3.2. Calibration of the SP model to Belgian data

It is also well known (see for instance Axsen et al. 2009) that stated preference models of alternative fuels tend to result in overly optimistic estimates of the alternative powertrains. Axsen et al. (2009) have argued that the joint use of Stated Preference (SP) and Revealed Preference (RP) data can combine their specific strengths. Indeed, in the deterministic terms of the random utility function, the attribute coefficients represent the trade-offs between the attributes (for instance, the cost per km of fuel consumption versus the autonomy of the model) while the alternative specific constant terms (ASC) represent utility that is not captured by the attributes. The ASC can then be used for calibrating RP models to fit observed market shares – data that are readily available from the DIV.

Table 3 Market shares in Belgium versus those predicted by Hoen-Koetse model before calibration to Belgian market shares
Percentages

COPERT	Observed	Forecast
CNG	0.4592	9.9511
LPG	0.0405	0.6959
dies_small	0.6428	17.8772
dies_medium	41.3733	6.1825
dies_big	3.8045	1.4692
gas_small	37.6881	21.3168
gas_medium	10.0790	12.0928
gas_big	0.8530	0.4937
gashybr_cs_small	0.0005	9.4279
gashybr_cs_medium	1.7696	5.5565
gashybr_cs_big	0.5044	0.2835
dieshybr_cs_small	0.0000	4.1480
dieshybr_cs_medium	0.0103	1.3101
dieshybr_cs_big	0.0232	0.2184
gashybr_phev_small	0.1501	3.3780
gashybr_phev_medium	1.6740	1.8623
gashybr_phev_big	0.3003	0.0878
dieshybr_phev_small	0.0001	2.2870
dieshybr_phev_medium	0.0002	0.5178
dieshybr_phev_big	0.1277	0.1069
electric_small	0.0315	0.4694
electric_medium	0.2448	0.2508
electric_big	0.2229	0.0164

Source: DIV and CASMO

Table 3 confirms that, with the ASC taken from Hoen and Koetse, the predictions of the market shares in 2017 are wide off the mark. The following observations are noteworthy:

– The forecasted shares for CNG are much larger than the actual shares, probably because the estimated parameters in the Hoen-Koetse model do not adequately reflect some disadvantages of CNG cars (lower performance, reduced storage space, reduced range compared to gasoline etc) – note that Hoen and Koetse had not explicitly included CNG in their choice set.

– According to the Hoen-Koetse model, "small" diesel cars should be more popular than "medium" diesel cars – in the Belgian reality, "medium" cars completely dominate the diesel market, probably reflecting the importance of the company cars in this segment.[11]

[11] Indeed, the fiscal treatment of the private use of company cars distorts the market for passenger cars, but our data do not allow to deal with this in a satisfactory way. The problem is not just that the financial incentives facing fleet managers of companies differ from those faced by private households: their behavioural response to prices are also likely to be different (arguably more rational) - see for instance Brand et al. 2017.

- The Hoen-Koetse model underestimates the share of "small" gasoline car by about 50%.
- The most striking observation, though, are the higher shares predicted for electrified (electric and hybrid) cars: for charge-sustaining gasoline hybrids, 15.27%; for plug-in gasoline hybrids, 5.33%; for charge-sustaining diesel hybrids, 5.68%; for plug-in diesel hybrids, 2.91%, and for electric cars, 0.74%. This probably reflects that, in the perception of the Belgian consumers, there are some intrinsic disadvantages to electrified cars that are not captured in the Hoen-Koetse model. We also need to keep in mind that, for the cost data on hybrid cars, we had to rely on extrapolations from very small data sets. It is not clear to what extent the cost data we have found are representative, but is clear that everything written here about hybrid cars should be interpreted with caution.

These findings confirm the need to calibrate the ASC to the Belgian market outcomes.

A first possible approach is to find ASC such that the predicted market shares for each powertrain are the observed market shares in the base year of the model (Train 2009, p 33). The procedure can be summarized as follows:

- For each household in the BELDAM survey, and for each COPERT class, we calculate the probability that the household will choose a vehicle in this COPERT class, given the characteristics of the household, and the average costs and range of vehicles in each COPERT class.
- We calculate the weighted averages of these probabilities (where the weights are the weights of each household in the BELDAM survey).
- These simulated probabilities P are compared with the observed shares S, and the alternative constants are modified according to the following formula:

$$ASC_{New} = ASC_{Old} + \log\frac{S}{P}$$

With our data, this procedure converges within 5 steps. However, in line with the literature (see Jensen et al. 2017), we found that our estimates of the ASC were highly sensitive to the year (and the corresponding market share) used for calibration. Actually, market shares in the period 2012-17 were very volatile, and we will now briefly digress on the causes for this volatility before proceeding with an alternative calibration method.

4.3.3. Evolution of market shares and costs in Belgium between 2012 and 2017

Between 2012 and 2017, important changes have taken place in the policy environment, and these have clearly affected observed choices in this period.

Indeed, as a result of the "Dieselgate" scandal that erupted in September 2015, governments in Europe have started taking measures to reduce the attractiveness of diesel cars.

On the one hand, these measures include changes in the Belgian fiscal regime governing these cars. Between 2015 and 2018, excise duties on diesel have increased from 0.43 to 0.59 EURO per litre, while those on gasoline just increased from 0.61 to 0.63 EURO per litre. Moreover, the calculation methods for the licence tax and the annual circulation tax were modified. Such measures directly affect the costs of cars and are adequately captured by discrete choice models of vehicle choice.

On the other hand, (mostly local) governments throughout Europe have announced "diesel bans" and Low Emission Zones (see for instance Hockenos 2018). These measures also affect the value of diesel cars: even if the measures will only enter into force in the future, they reduce the second-hand value of diesel cars, and this also reduces the value of diesel cars on the market for new cars.

It can indeed be verified (see the Annex for the details) that, as the result of changes in the annual circulation tax, in the "big" segment, the average variable costs of diesel cars have increased, and those of gasoline cars have decreased since 2015. For the other size classes and for electric, there are no noteworthy changes.

In the same period, the average licence taxes have increased more for gasoline and electric cars than for electric cars. However, compared to total acquisition costs, these changes are very small.

As the result of these changes, there has been an important decrease in the market shares of diesel cars, especially in the "medium" segment, in parallel with an important uptake in the share of "small" gasoline cars. Although these trends were already visible before 2015, there is a clear acceleration as from 2015 on.

These changes in market shares are higher than what we would expect *a priori* from the changes in the circulation tax only, and probably reflect a broader concern amongst car buyers that the general policy climate has become less favourable to diesel.

The market shares of electric cars remain very small (around 0.5 per cent over all size classes), even if we can observe some growth in the medium and the big segments – in the "big electric" segment, this is too a large extent a "Tesla effect".

In 2017, the last year used for the calibration, the total acquisition cost of electric and hybrid cars was still higher than for gasoline and diesel cars. In the size segment "big", the acquisition costs are about twice as high as for diesel cars. The differences are slightly less pronounced for the "medium" and "small" cars but remain non-negligible.

If we zoom in on the cost differences between the "conventional" fuels, we see that in the "small" segment, the differences between diesel and gasoline cars have become very small. In the "medium" segment, diesel cars are more expensive, while the opposite is true for the "big" segment – a more detailed analysis of the data has shown that this largely attributable to the big share of premium cars in the "big gasoline" segment.

The picture is different when we look at the variable costs: in all size classes, electric cars, plug-in hybrids and gasoline hybrids have lower variable costs than gasoline and diesel cars. Diesel cars now have higher variable costs than gasoline cars. As discussed before, this reflects important changes in the tax policy vis-à-vis diesel. Diesel hybrids generally have rather high variable costs, even when compared to gasoline and diesel cars.

4.3.4. Results of the calibration

Given the unstable context between 2012 and 2017, we have not proceeded with an exact calibration to replicate market shares in one single year but have instead estimated the ASC with non-linear least squares, as implemented by Jensen et al. (2017).

In this approach, we again take the coefficients estimated by Hoen and Koetse (2014) for our discrete choice model, except for the ASC. In order to estimate the ASC, we take the observed market shares of each COPERT class in the years for which we have observations for all COPERT classes (2012 to 2017) and calculate the ASC that minimize the sum of the squares of the differences between the observed and the estimated market shares. In other words, the ASC are chosen to minimize the differences between predicted behaviour (using the parameters of the micro-econometric model) and observed behaviour at the aggregate level.

Because the ASC appear both in the numerator and the denominator of the logit function, non-linear least squares are necessary.

In the estimation procedure, we have to take into account the following constraints:

- In each year, the market shares sum to one. As a result, for each observation year, we need to fix one of the ASC.
- For some COPERT classes, the observed market shares are zero, and the ASC must thus be infinitely large (or take a value that is sufficiently large to ensure that the predicted market shares are indeed zero).

The non-linear least-squares model (NLLS) has been estimated with the nlsLM function from the minpack.lm library in the R programming language. This function requires the user to provide initial values for the parameters that need to be estimated. We have used the values resulting from the exact calibration in 2017. Note that the procedure is extremely sensitive to the choice of these initial values, and that different values can lead to non-convergence of the algorithm (or to the convergence towards a minimum rather than a maximum).

Table 4 NLLS estimates of the ASC

term	estimate	std.error	statistic	p.value
dies_medium	2.36	0.33	7.21	0.00
dies_big	1.63	0.35	4.72	0.00
gas_small	0.47	0.33	1.42	0.16
gas_medium	-0.21	0.34	-0.61	0.54
gas_big	0.39	0.82	0.48	0.63
gashybr_cs_medium	-1.38	0.53	-2.63	0.01
gashybr_cs_big	0.34	1.43	0.24	0.81
dieshybr_cs_big	-0.76	4.83	-0.16	0.88
gashybr_phev_small	-3.19	3.63	-0.88	0.38
gashybr_phev_medium	-0.98	0.82	-1.19	0.24
gashybr_phev_big	0.92	2.20	0.42	0.68
dieshybr_phev_big	-0.05	4.60	-0.01	0.99
electric_small	-2.20	10.40	-0.21	0.83
electric_medium	-0.21	2.74	-0.08	0.94
electric_big	2.66	2.63	1.01	0.31
DieselGate	-0.34	0.04	-9.42	0.00

Source: CASMO

Some preliminary estimates showed that, despite the important changes in the market shares of medium diesel and small gasoline cars after 2015, our estimates failed to capture these changes and perpetuated the market behaviour observed in 2012-15. We have therefore added a dummy "DieselGate" to the expected utility of diesel cars purchased from 2015 on. As can be seen in Table 4, the coefficient for this dummy is statistically significant and has the expected sign: all other things being equal, the utility of diesel cars decreases from 2015 on, probably reflecting the negative climate (and changing policy environment) as a result of the Dieselgate scandal. Table 4 also shows that, for most COPERT classes, the ASC are not statistically significant from zero. (We have omitted the values of the 6 ASC that we had fixed exogenously).

5. Results

In this section, we summarize the key outputs of the model: the evolution of the total car stock and the market shares of the different COPERT classes. We relate these results to the underlying assumptions regarding the evolution of the cost and range parameters. Where possible, we compare our results with those of other models. We also discuss how the projected market shares of the different COPERT classes evolve if we use the Mixed Logit model estimated by Hoen and Koetse rather than the Multinomial Logit.

5.1. Evolution of the car stock

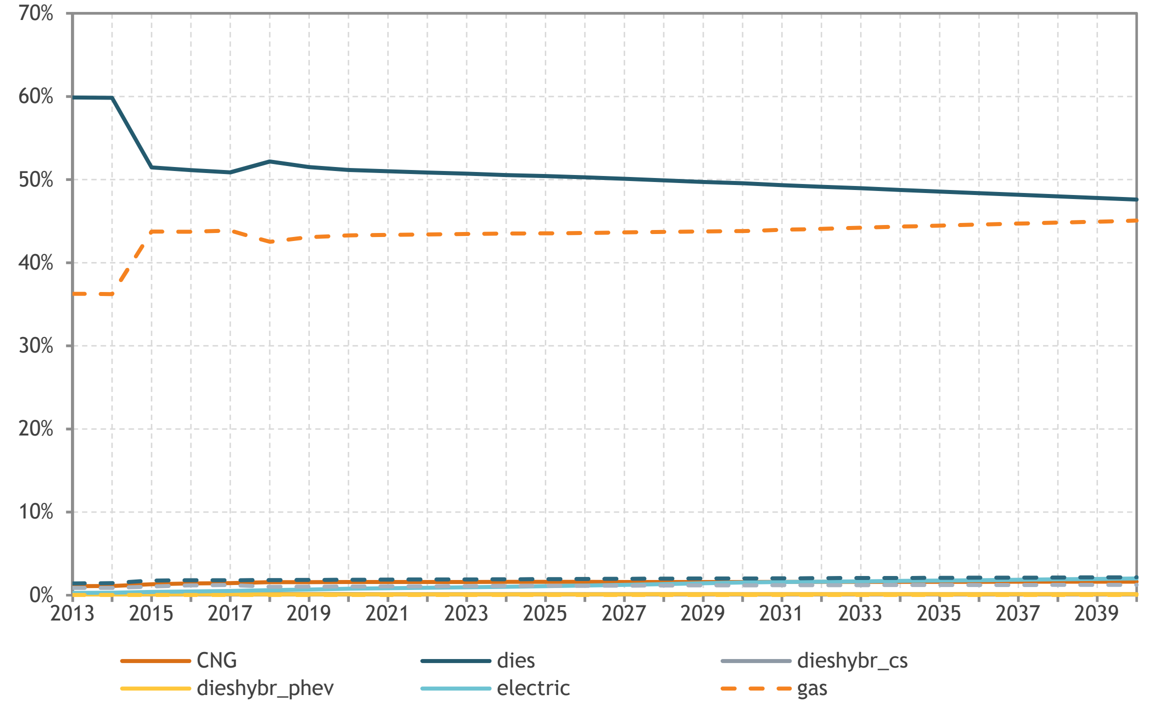
Car ownership in Belgium is projected to grow from 5.76 million cars in 2018 to 7.04 million cars in 2040 – this is an increase with 22.18% and corresponds to 0.57 cars per capita by 2040. For comparison, over the same period, GDP is assumed to grow with 37.21% – this is consistent with a car stock that is approaching its saturation point.

5.2. Evolution of the market shares

Graph 2 represents the evolution of the market shares of new cars. We observe a very sharp increase in the shares of gasoline cars around 2015, largely at the expense of diesel cars. As discussed before, this largely reflects the behavioural responses to the policy changes induced by Dieselgate. Also keep in mind that these changes are *observed* changes, not modelled ones. From 2020 on, the increase in the share of gasoline cars and the decrease in the share of diesel cars are projected to continue, albeit at a much slower pace.

The shares of the "alternative" fuels remain very low, even though there is a steady increase in the share of electric vehicles.

Graph 2 **Evolution of the market shares of new cars**
Percentages

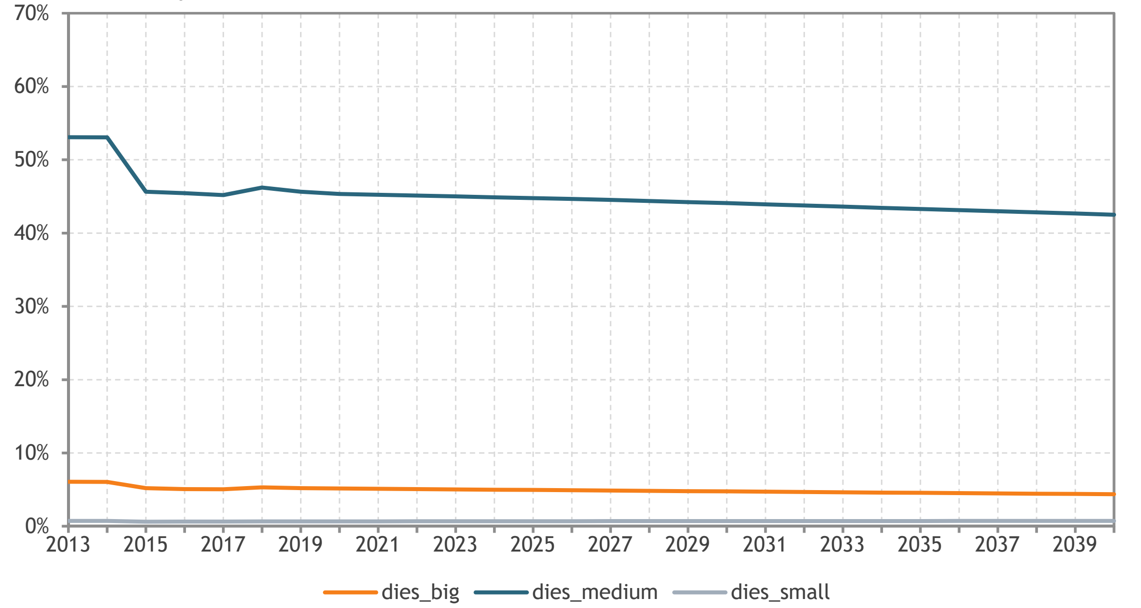


Source: CASMO

We will now also have a look at the evolution per size class for diesel, gasoline and electric cars. This type of disaggregation wouldn't be very informative for the other fuels, given their very small shares.

Graph 3 shows that the decrease in the market share for diesel can be almost entirely attributed to the size segment "medium", which was the most popular before "Dieselgate" broke out.

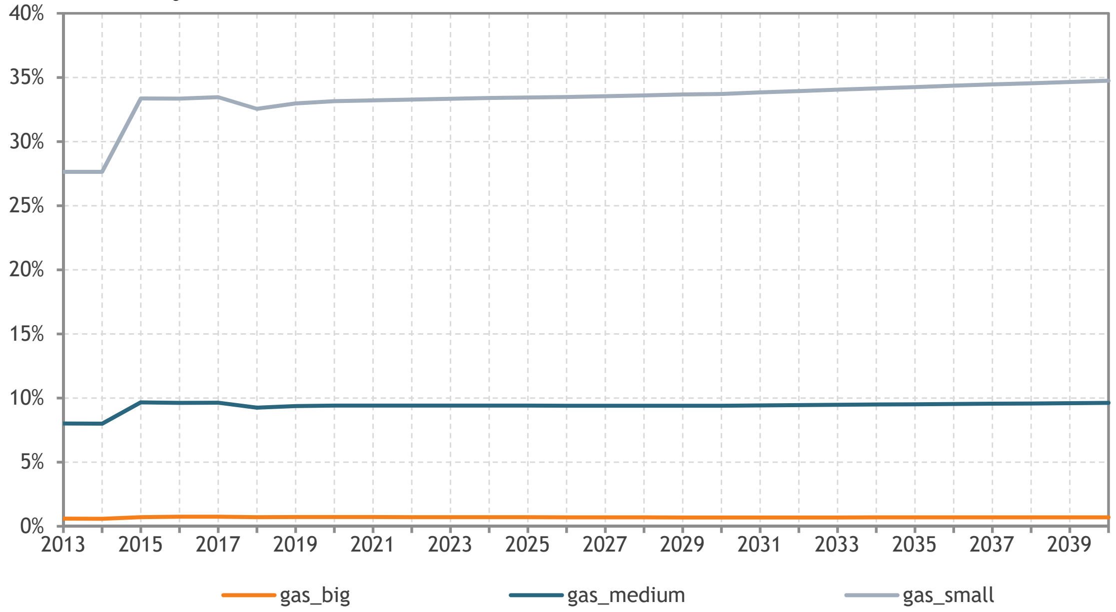
Graph 3 **Evolution of the market shares of new diesel cars**
Percentages



Source: CASMO

Graph 4 shows that the projected increase in the market share for gasoline cars is mainly driven by the size segment "small" and, to a lesser extent, by the size segment "medium". The size segment "big" remains at a very low level – as discussed before, this is mainly a segment for premium cars.

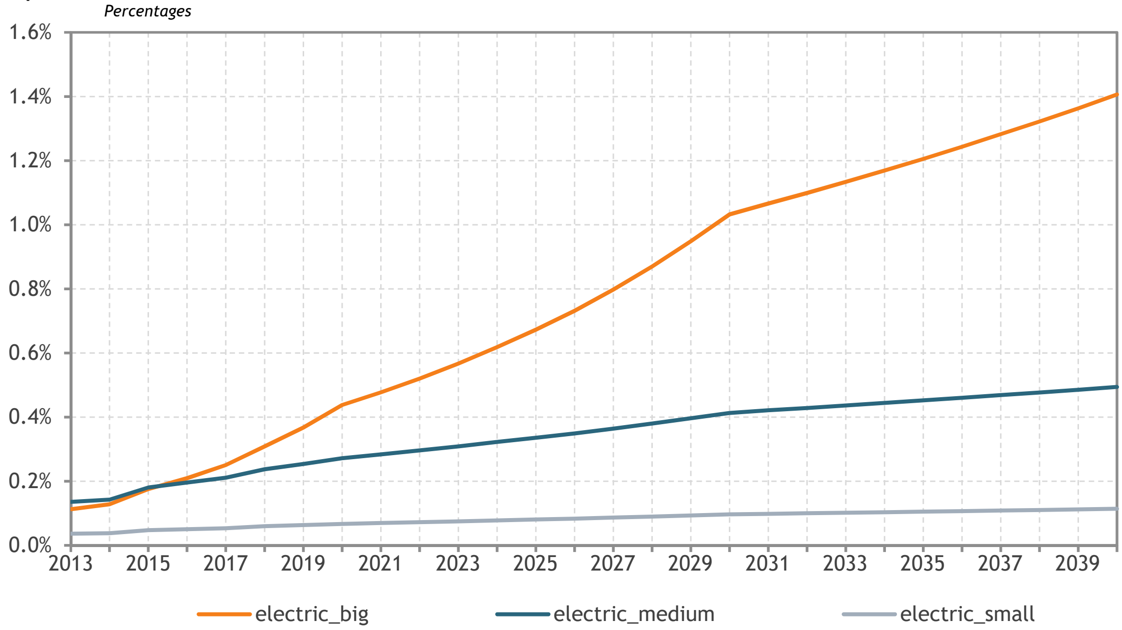
Graph 4 **Evolution of the market shares of new gasoline cars**
Percentages



Source: CASMO

Finally, Graph 5 shows that the projected increase for electric cars is driven by both the "medium" and the "big" segments, while the share of "small" electric cars remains very small indeed. Total market shares for electric cars are not projected to exceed 2% in 2040.

Graph 5 **Evolution of the market shares of new electric cars**
Percentages



Source: CASMO

5.3. Evolution of costs and range

It is important to understand the drivers behind this very slow uptake of electric vehicles. In the discrete choice model, the following three variables determine the utility of electric vehicles: the purchase cost, the monthly operating cost and the range of the electric vehicles.[12]

The monthly costs are assumed to grow steadily during the projection period: by 7% between 2018 and 2040 for "big" electric cars, for instance (see the Annex for the details). It can be verified that this is mainly driven by changes in the price of electricity.

The model also assumes a steady decline for the purchase costs of electric vehicles (by -8% between 2018 and 2040 for "big" electric cars) combined with an increase in the autonomy of electric vehicles (by 62% between 2018 and 2040 for "big" electric cars).

We can now compare this with the evolution of the costs for diesel and gasoline cars.

The model assumes an important increase in the monthly costs of diesel cars (around 26% for "big" cars by 2040), combined with an essentially constant purchase cost. Since the increase in the circulation tax in 2015, this increase in monthly costs is essentially driven by the increase in the fuel cost per km, which steadily increases between 2018 and 2040, by approximately 62%.

The model also assumes a steady increase in the monthly costs of gasoline cars after an initial decrease: between 2020 and 2040, monthly costs are assumed to increase with 18% for "big" cars, for instance. It can be verified that this is due to (a) the decrease in the circulation tax in 2015 (b) the increase in the fuel cost per km between 2020 and 2040 (by 46%). The purchase cost is also assumed to stay essentially constant.

Summarizing, while the purchase costs are assumed to decline for electric vehicles, they are assumed to remain constant for diesel and gasoline cars. The monthly costs increase for all powertrains, but less quickly for electric cars. Finally, the range of electric cars also improves over time. Thus, all parameters tend to make electric cars more attractive compared to their conventional counterparts. Given these evolutions, one would have expected a higher share for electric cars by 2040. However, between now and 2040, almost all substitutions between fuel types take place between gasoline and diesel cars.

The most important driver behind this low sensitivity of the market shares for alternative powertrains to changes in costs and performance are the high values of the estimated alternative specific constants. Indeed, these constants represent the part of an alternative's utility that cannot be captured by the observed variables (see Section 4.3.2). Given the high values of the ASC, they continue to drive the results until well in the future. We will argue now that this is in line with similar modelling approaches applied in other countries. In Section 6.1 we shall discuss how the results change for different values of the ASC.

[12] These variables also interact with household characteristics. In our projection, these household characteristics are kept constant, but we have verified (detailed results are available on request) that our model outcomes are not very sensitive to changes in those household characteristics.

5.4. Comparison with other models

Comparing these projections with the results of other long-term forecasts and scenarios is not always an easy task.

For instance, Bloomberg New Energy Finance projects, that, by 2030, 28% of new car sales will be electric cars (BNEF, 2018). However, as the underlying methodology is not in the public domain, we cannot assess why these results differ so much from ours. Based on a review of the literature, Berckmans et al. (2017) predict that by, by 2030, "25% of all vehicles sold will be either fully electric or hybrid."

The approach used in the IEA's MoMo model (which are also used in the International Transport Forum's Transport Outlook – see Fulton (2017a,b)) is broadly similar to ours, but the full details are not publicly available, which makes comparisons difficult.

Even when the underlying methodology is transparent, market shares in new vehicle sales are often an intermediate result, and reports emphasize the final outcomes, such as emissions of pollutants and energy consumption – see for instance the survey of how the energy demand and CO_2 emissions from transportation are modelled in five global models in Girod et al. (2013a,b).

We can however compare the projected market shares in 2030 with those of a limited number of alternative recent models that cover countries in the EU, and who do publish their assumptions and intermediate results:

- In the reference scenario for the UK considered by Brand et al. (2017), "average purchase prices for BEV cars were assumed to decrease by 2.8% pa from 2015 to 2020, by 1.6% pa until 2030 and 0.6% pa until 2050. The Reference scenario further assumed gradual improvements in specific fuel consumption and tailpipe CO_2 emissions per distance traveled (…) Fuel consumption and CO_2 improvement rates for future car vintages were assumed 1.5% pa". Under these assumptions, sales of plug-in vehicles remain below 5% of new vehicle sales in 2030 (Figure 6 in Brand et al.), which is only slightly higher than our projections. Under the EV2 scenario, 37% of new cars in 2030 are PHEVs and 8% BEVs, but this requires substantial policy changes.
- The Market Acceptance of Advanced Automotive Technologies (MA3T) is a Multinomial Nested Logit model developed in the US (see Liu and Lin 2017). The model includes transition dynamics (such as manufacturers' learning by doing and economies of scale) and user heterogeneity. The model assumes that, with time, the unobserved attributes of plug-in electric vehicles will become similar to those of conventional ones, and thus that the ASCs will converge as well. It projects the following market shares by 2030: 57% for conventional fuels, 11% for hybrids, 12% for plug-in hybrids and 20% for electric cars. By 2040, the projected market shares are, respectively: 38%, 13%, 17% and 32%.

Thus, the outcomes of Reference scenario for the UK is similar to our model results, while the MA3T is much more optimistic than our model for the prospects of electrified cars. As we shall argue below (Section 6.1), this is mainly driven by the assumed change in the ASC.

5.5. Sensitivity: alternative allocation model

As announced, we now have a brief look at the model predictions based on the Mixed Logit (ML) model estimated by Hoen and Koetse.

In abstract terms, a mixed logit model can be defined as *any* model where the choice probabilities (for decision maker n and alternative i) can be expressed as (see Train 2009, Chapter 6):

$$P_{ni} = \int L_{ni}(\beta).\,f(\beta).\,d\beta$$

where $L_{ni}(\beta) = \frac{e^{V_{ni}(\beta)}}{\sum_{j=1}^{J} e^{V_{nj}(\beta)}}$ (the logit probability evaluated for parameters β), $V_{ni}(\beta)$ is utility as a function of β and $f(\beta)$ is a density function. For linear utility functions, we obtain:

$$P_{ni} = \int \frac{e^{\beta'.x_{ni}}}{\sum_{j=1}^{J} e^{\beta'.x_{nj}}}.\,f(\beta).\,d\beta.$$

As summarized by Train, the "mixed logit probability is a weighted average of the logit formula evaluated at different values of β, with the weights given by density $f(\beta)$".

If the "mixing" distribution is discrete, the mixed logit model reduces to the "latent class model", where the weights correspond to the shares in the population of each "segment" with distinct choice behaviour or preferences. With continuous distributions, the β can be interpreted as coefficients that vary over utility-maximizing decision-makers according to density $f(\beta)$. Moreover "(v)ariations in taste that are related to observed attributes of the decision-maker are captured through specification of the explanatory and/or the mixing distribution."

If one assumes that the density follows a normal distribution, the modelling thus entails the estimation of the means of the β and their co-variance matrix.

Hoen and Koetse have estimated random parameters for the ASC of alternative-fuel cars and for the driving range of electric cars, and fixed parameters for the monthly cost and the purchase cost.
Table 5 gives the means and the standard deviation for the stochastic parameters, and Source: Hoen and Koetse (Table 7)

Table 6 gives the estimates of the fixed parameters (for the purchase of new cars only) – the reader should keep in mind that we only report the coefficients for the variables that we use in our own discrete choice model.

Table 5 Distribution of the stochastic parameters in the ML model

Description	Mean	Standard.deviation
ASC for hybrid cars	-1.3432	1.0439
ASC for electric cars	-4.3908	2.2593
ASC for plug-in hybrid cars	-1.9846	1.2138
Driving range electric cars	0.0063	0.0032

Source: Hoen and Koetse (Table 7)

Table 6 Coefficients of the fixed parameters in the ML model

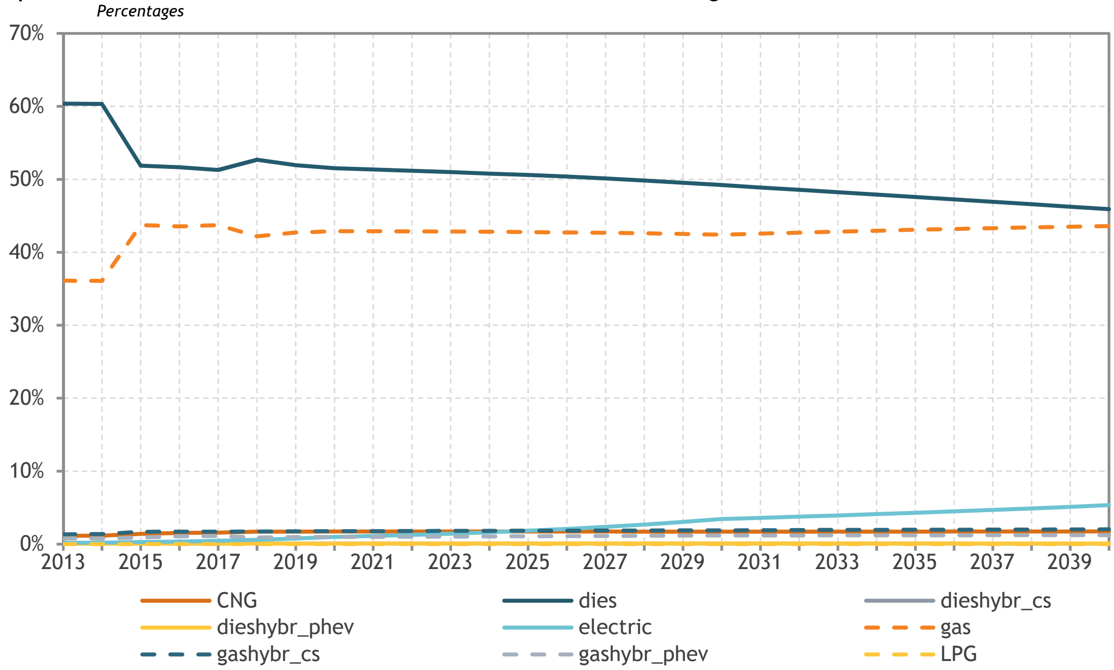
Description	Mean
Monthly costs	-0.0047
Purchase cost	-0.1223

Source: Hoen and Koetse (Table 7)

In order to apply the model to the Belgian context, we have again used NLLS to re-estimate the ASC using Belgian registration data in the time-span 2013-17.

Graph 6 gives the projection of the market shares until 2040, using the re-calibrated Mixed Logit (ML) model. Compared to the Multinomial Logit model (MNL) (see Graph 2), we see that the markets share of BEV grows somewhat more, mostly at the expense of gasoline and diesel cars.

Graph 6 Evolution of the market shares of new cars with the mixed logit model
Percentages



Source: CASMO

It is important to try to understand the driving forces behind these differences.

In the MNL model, the households are explicitly represented through interaction effects between household characteristics with the cars' features (for instance, the interaction between the driving range of electric cars and the commuting behaviour of the households). The coefficients have been estimated with a Dutch sample and applied to a sample of Belgian households (the BELDAM sample), assuming implicitly that the findings from the Dutch context can be applied to the Belgian (and thus that the unobserved and observed characteristics of the households are related in the same way in both samples).

In the ML model, there is no explicit representation of the households' characteristics, even the observable ones: differences between the households are captured through the probability distribution for the coefficients. Thus, if there are systematic differences between the sample used by Hoen and Koetse and the BELDAM sample, the ML model will lead to biased projections for Belgium.

Table 7 Household characteristics in BELDAM vs Hoen and Koetse
Percentages

	BELDAM	Hoen.Koetse
Frequency of car commute at least 5 times per week	38.4	33
Annual mileage current car < 7500	29.3	9
Annual mileage current car 7500-15000	23.8	33
Annual mileage current car 15000-25000	25.3	31
Annual mileage current car 25000-35000	12.5	15
Annual mileage current car > 35000	9.0	11
Share of female respondents	56.2	20

Source: BELDAM and Hoen and Koetse

Arguably the most important difference between both samples is the much higher share of female respondents in BELDAM. However, the coefficients for the interaction effects with this variable are not very high.

More importantly, the share of Belgian respondents who drive very little is much higher than in the SP sample used by Hoen and Koetse, while the share of respondents who drive between 7500 and 25000 km on an annual basis is much lower in BELDAM. Given the interaction term with the dummy "electric" in the MNL, one would expect (all other things being equal) that electric cars would be more attractive in the BELDAM sample than in the sample used by Hoen and Koetse. Also, the frequency of households with very high commuting frequencies is somewhat larger in BELDAM.

However, we have verified that the model outcomes are not very sensitive to changes in the behaviour reported in BELDAM. Therefore, we would not expect this different specification to lead to drastically different results. And indeed, the projections based on the MNL do not differ fundamentally from the projections based on the ML model, at least after re-calibration of the ASC to fit the Belgian market in the years used for estimation.

6. Model improvements

6.1. Decreases in perceived costs

Arguably the most striking result of this paper is that almost all substitutions between fuel types take place between gasoline and diesel cars. Although electric and plug-in cars become increasingly cost-competitive, their shares in total sales remain very small in 2040. This stands in contrast with other results that have drawn a lot of attention such as BNEF (2018) but is roughly consistent with other scenarios that are based on explicit econometric modelling (such as Brand et al. 2017 or Fulton et al. 2017b).

In this section, we will explore how this is driven by the values of the ASC. As already pointed out (see Section 4.3.2), these constants represent the part of an alternative's utility that cannot be captured by the observed variables.

We have seen that the actual market shares of CNG, small diesel, electric and hybrid cars are much smaller than predicted by the Hoen-Koetse model without a calibration of the ASC to the Belgian market. The calibration of the ASC to the Belgian market leads to a much-improved match in the period used for the estimation, but leads to a new issue: given the high values of the *calibrated* ASC, they continue to drive the results until well in the future – this is similar to the experience of Fulton et al. (2017).[13]

We need however to raise the question whether this assumption of unvarying ASC is reasonable.

Indeed, on the one hand, in the case of CNG and diesel, these unobserved variables refer to structural variables that are unlikely to evolve endogenously over time (for instance, the reduced storage place in CNG cars that we have already mentioned).

On the other hand, in the case of electric and hybrid cars, it could be argued that the low familiarity of consumers with these technologies leads to outdated perceptions regarding their total cost of ownership and range. Indeed, the spectacular improvements in terms of autonomy and costs of electric cars are a recent, and largely unanticipated, phenomenon.[14] Outdated perceptions are likely to be corrected through actual experience and word-of-mouth effects (or "neighbour" effects). As discussed in the literature on technology adoption (see for instance Massiani 2013), such word-of-mouth effects are typically characterised by positive feedback loops: as the number of people with positive experiences with

[13] Personal correspondence between Lewis Fulton and the author.

[14] Let us just consider a few examples of how reality has outrun even recent predictions of how the cost of batteries would evolve. In 2013, Wietschel et al. constructed three scenarios for electric vehicle penetration in Germany in 2020. In their most *optimistic* scenario, they assumed that, by 2020, a battery price of 320 EUR/kWh can be reached. Under this scenario, it was expected that sales of electric cars would range between 1 million and 1.4 million in Germany alone. In a recent survey, Nykvist et al. (2019) remind that, in 2013, it was assessed that "BEV could start to become attractive when battery costs reach 300 USD/kWh", and that this cost had already been reached by market leaders in 2014. If we take a fast forward with a few years, UBS (2017) concluded after a detailed engineering study of the Chevy Bolt, that the battery pack of the Bolt had a cost of 209 USD/kWh. This report also referred to a battery pack cost of 190 USD/kWh for the Tesla Model S. Even if we take the exact figures with a grain of salt, these figures are approximately one third *below* the most optimistic scenario of Wietschel et al. Of course, while the UBS study is very thorough, one could argue that the Bolt and the Tesla Model S are not typical. However, the IEA (2018) uses the BatPaC model to show that, with high enough production volumes, unit costs are "expected to lean towards the lower end of the USD 155-360/kWh range. This is because of the larger production volumes associated with the lower cost packs." Finally, in their most recent assessment of progress, Nykvist et al. (2019) conclude that "the shift toward average price BEV with a range of 200 miles can start already at battery pack costs of 200-250 USD/kWh".

new technologies increases, their positive comments will reach an ever-increasing number of people, who, if convinced, will also reach out to new potential consumers etc.

This is consistent with a recent survey of consumer in six EU member states (that represent more than 78% of new car sales in the EU in 2016), where Gómez Vilchez et al. (2017) have shown that the respondents' perceptions of the purchase and operating costs of electric cars has evolved positively since 2012. Given that the three models with the highest market shares in Belgium, the Tesla Model S, the BMW I3 and the Nissan Leaf were introduced in Europe in 2013, 2013 and 2011, respectively, the potential for learning effects should not be dismissed lightly.[15]

In the literature, such effects are typically represented by logistic functions or by a Bass diffusion model. Applications in the adoption of alternative fuel technologies are discussed in Massiani (2013), Massiani and Gohs (2015) and Fulton et al. (2017b).[16]

Most of these applications focus on the growth in the sales of alternative fuel vehicles, but Jensen et al. (2017) propose an integration with discrete choice theory. In this approach, "social learning" effects are represented in the utility function for new powertrains: increases in accumulated sales of alternative powertrains lead to increases in their expected utility.

In the CIMS model (see Axsen et al. 2009), neighbour effects are represented by adding an "intangible cost" function to the life-cycle costs of technologies – this intangible cost of a technology at a given time is a decreasing function of the market share of the technology in the previous simulation period. We have estimated such a "CIMS-like" approach, but the parameters of the "learning" function were not significant, and we have not further pursued this approach.

Moreover, this approach cannot account for other elements that are likely to improve over time such as: the low density (or the perception of a low density) of the recharging infrastructure, especially of fast-chargers ; the lack of diversity in the models that are available[17]; long delays in the delivery of orders… Valeri and Cherchi (2016) have also shown that habitual behaviour affects the preferences for specific types of engine technologies. With the passage of time, the purchasing power of younger cohorts of consumers (who are arguably more open to innovation than older ones) also increases, which could in itself lead to increase in the sales of new technologies.[18]

An alternative approach could be to assume exogenous changes in the ASC that would reflect these changes in the unobservables.

[15] Franke and Krems (2013) and Jensen et al. (2013) have also shown that three months of real-life experience with electric cars leads to changes in the willingness-to-pay for a higher range and in the minimal *required* range.

[16] Another way to represent social learning effects is through agent-based models. See for instance Eppstein et al. (2011) or Kangur et al. (2017).

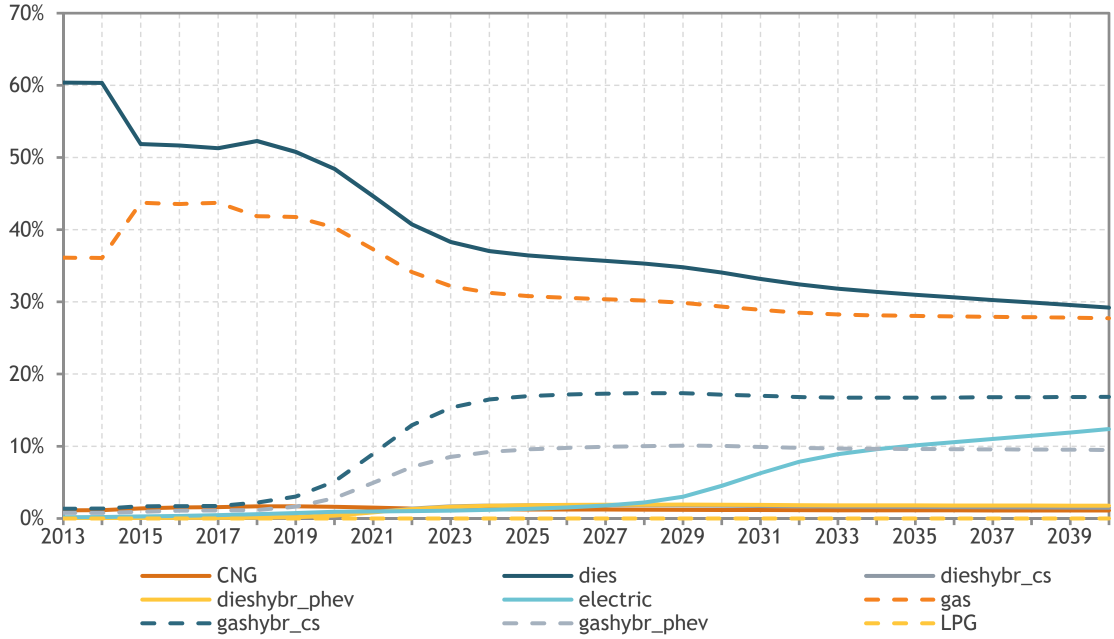
[17] Liu and Lin (2017) and Mulholland et al. (2018) discuss how the density of the charging infrastructure and the availability of diverse models have been incorporated into the MA3T model. Ramea et al. (2018) integrate this behavioural approach in the Energy Systems Optimization Model TIMES. In a survey on the literature on consumer preferences for electric vehicles, Liao et al. (2017) conclude that the lack of diversity "may account for the low sales of EV". Brand et al. (2017) also integrate the variety of supply in their projection model. Here as well, things could evolve very quickly at some point in the future. For instance, Volkswagen has now openly committed to a complete phasing out of combustion engines in its cars (Rauwald and Sachgau, 2018).

[18] Brand et al. (2017) explicitly model different consumer segments but keep their shares constant over time.

For instance, Brand et al. (2017) have "modelled 'consumer learning' and the neighbour effect by assuming that the technology bias encapsulated in the technology preference parameter (ASCi) decreased linearly with increasing sales from 100% of the ASCi value at no sales (essentially the values shown in Figure 5) to 0% when sales reach 25% and above."

Given that our choice model contains 23 choice variables, the changes in the ASC would be hard to interpret. We therefore propose a somewhat different approach: we ask what the market shares of each technology would be, given that the *perceived* purchase cost of cars with alternative powertrains would decrease by a certain amount compared to the *actual* cost in the reference scenario?

Graph 7 Evolution of the market shares of all new car types with decreases in perceived costs
Percentages



Source: CASMO

In order to implement this approach, we have assumed that *perceived* costs decrease according to a simple logistic function. The advantage of this specific approach is that it reflects the typical dynamics of adopting new technologies: first imperceptibly, until a take-off point is reached, after which adoption will increase rapidly, until it converges to a new plateau when all learning effects have levelled out. Formally, the reduction in perceived costs in the current year, $Year$, is:

$$\frac{MaxRedu}{1 + exp(MidPointYr - Year)}$$

where $MaxRedu$ is the reduction in perceived costs to which consumers will eventually converge and $MidPointYr$ is the inflection point in the logistic function (informally, this is the mid-point between 2017 and the year where further changes in the perceived costs become negligibly small).

We can then specify specific inflection points and maximum reductions in perceived costs for different technologies. For instance, Graph 7 represents the evolution of the market shares, assuming the parameter values of Table 8.

Table 8 Parameters of the logistic function

	MaxRedu	MidPointYr
Charge sustaining hybrids	0.45	2020
Plug-in hybrids	0.45	2020
Battery electric	0.15	2030

Source: own assumptions

This evolution of the market shares is indeed what we would expect if the reduction in the perceived costs for hybrid vehicles evolves quickly in the next few years, and then remains stable as from 2025. For electric cars, the evolution corresponds to learning effects that start to take off around 2025, accelerate until 2030, and stabilize around 2035.

Graph 7 also illustrates that, while $MidPointYr$ determines *when* electrified cars will start gaining significant market shares, it is $MaxRedu$ that determines their *eventual* market shares when all non-measured barriers to adoption have been overcome. In other words, we see that, under the $MaxRedu$ we have assumed, fossil fuel cars continue to play a non-negligible role in 2040. This gives an idea of the challenge that lies ahead.

One caveat to keep in mind is that, as long as the reduction in the perceived costs has not taken off, the inflection point and the future plateau cannot be estimated with econometric techniques.

This implies that there are two ways to look at this alternative formulation. One possibility is to use expert opinions on the inflection points and the future plateaus for each technology and to use the model to translate those assessments in future market shares. The model can then be used to enlighten a debate between different experts. A different approach could be to derive inflection points and future plateaus that can "reconstruct" the specific timeline of future market shares projected by published studies. This approach thus leads to a better understanding of the underlying assumptions if those have not been published and makes it easier to assess the plausibility of the results.

6.2. Expected update in the model parameters

The analysis by Hoen and Koetse has been undertaken around 2012. As, in the meanwhile, the trade-offs between cost price and range for electric vehicles could have changed as the result of a higher familiarity of consumers with electric and hybrid cars, an update study has been performed.[19] We intend to update our model as soon the results of the follow-up study are publicly available.

[19] Personal correspondence between Hoen and the author.

7. Conclusion

This paper describes the structure and the key assumptions of the new car stock module of the PLANET model. It also projects the composition of new vehicle sales and the total car stock until 2040.

Arguably the most striking result of this paper is that, in the central scenario, almost all substitutions between fuel types take place between gasoline and diesel cars. Although electric and plug-in cars become increasingly competitive in terms of both fixed and variable costs, their shares in total sales remain very small in 2040. This stands in contrast with other results that have drawn a lot of attention such as BNEF (2018) but is roughly consistent with other scenarios that are based on explicit econometric modelling (such as Brand et al. 2017 or Fulton et al. 2017b).

We have argued that this is mainly due to the high values of the estimated alternative specific constants, which represent the part of an alternative's utility that cannot be captured by the observed explanatory variables (see Section 4.3.2).

However, given the high values of the calibrated ASC, they continue to perpetuate the low market shares of alternative fuels until well in the future. Sensitivity analysis (results are available on request) has also shown that the projected market shares are not very sensitive to changes in the cost parameters.

The picture changes if we allow for an exogenous decrease over time of the "perceived" acquisition costs (for instance as the result of social learning): assuming inflection point for hybrid cars around 2020 and for electric cars around 2030, we obtain much higher market shares. We have also found that, under this assumption, the market shares are much more sensitive to changes in the cost parameters.

We have also discussed how this approach with evolving subjective costs can be used, either to enlighten a debate on the evolution of future costs between different experts, or to better understand the assumptions underlying existing alternative economic models.

Our work has also identified several data needs. In particular, the survival model would be more accurate if there were reliable and representative data on the accumulated mileages of individual cars and on the dates where they are effectively retired from circulation in Belgium.

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Annexes

Annex A: Evolution of market shares and costs between 2012 and 2017

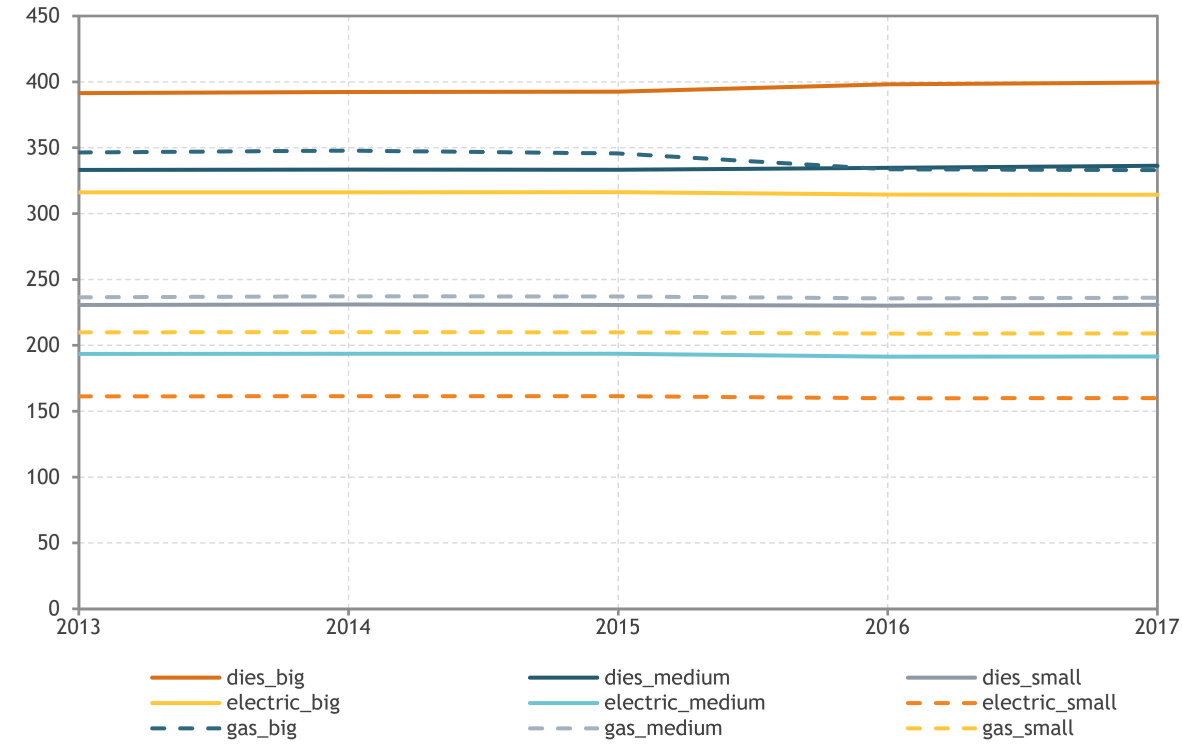
In this annex, we discuss in more detail the Belgian new car market between 2012 and 2017.

We will limit ourselves here to diesel, gasoline and electric cars. Indeed, in the case of hybrid cars, market shares are too small and volatile to say anything meaningful. The market shares for LPG and CNG are also extremely small, and, contrary to electric cars, we have no reasons to expect fundamental changes in the foreseeable future.

Let us first consider the evolution of the costs.

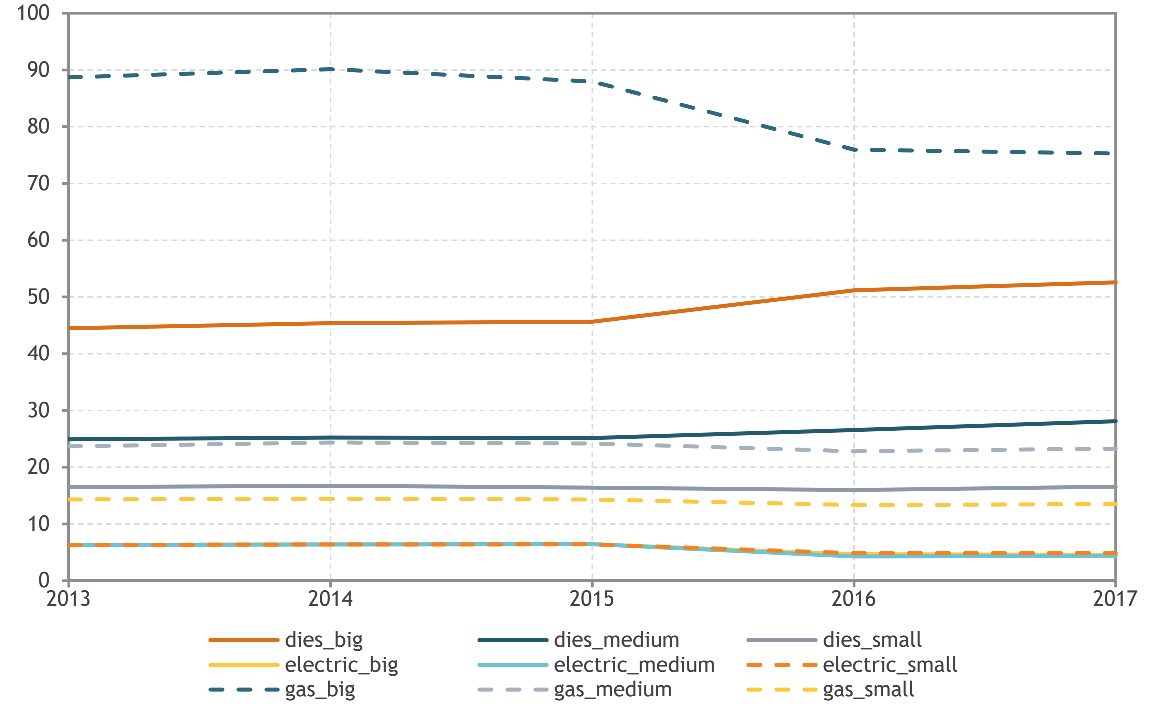
From Graph 8, we see that, in the "big" segment, the average variable costs of diesel cars have slightly increased, and those of gasoline cars have decreased since 2015. For the other size classes and for electric, there are no noteworthy changes. It can be verified that these mainly reflect changes in the annual circulation tax – see Graph 9.

Graph 8 Variable costs in period 2013-17
EURO/month



Source: CASMO

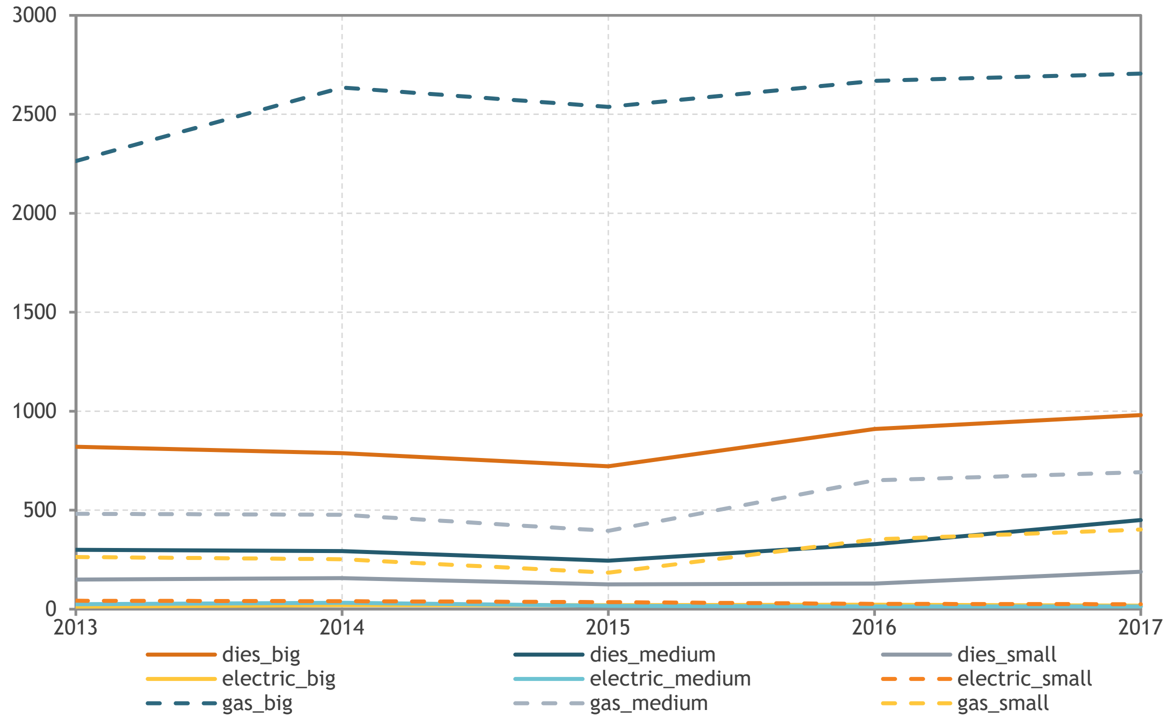
Graph 9 **Annual circulation tax in period 2013-17**
EURO/month



Source: CASMO

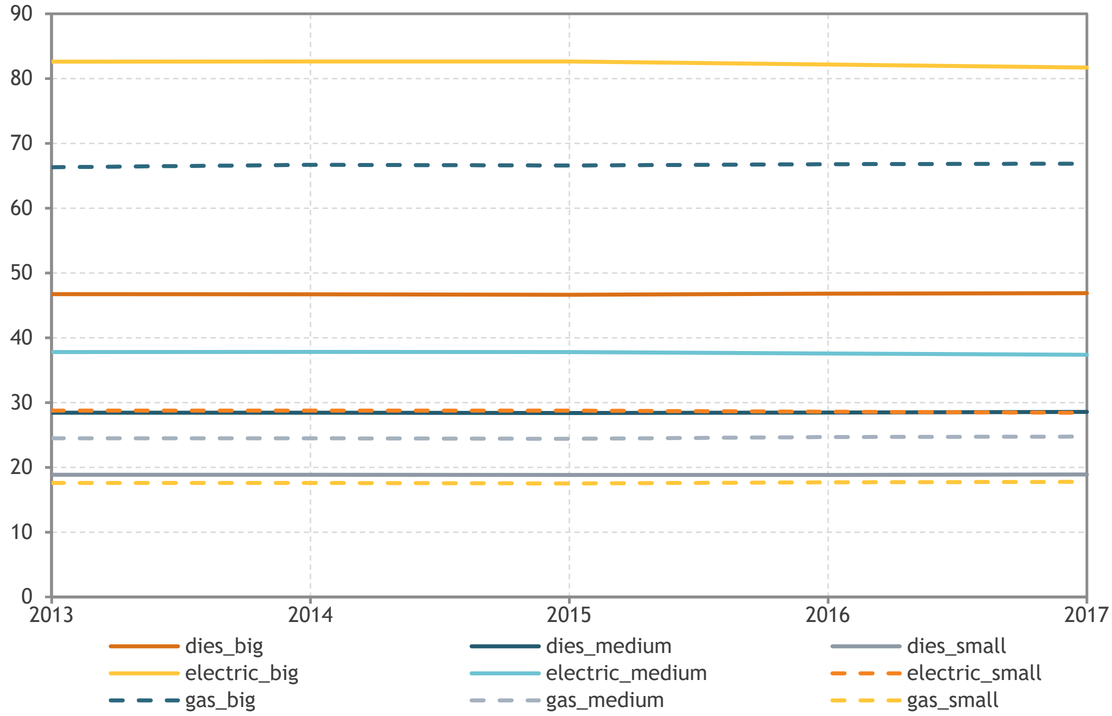
Graph 10 shows that the average licence taxes have increased more for gasoline and electric cars than for electric cars. However, compared to total acquisition costs, these changes are not large enough to result in a meaningful change in these costs – see Graph 11.

Graph 10 **Licence tax in period 2013-17**
EURO



Source: CASMO

Graph 11 Total acquisition costs in period 2013-17
thousand EURO



Source: CASMO

Let us now have a look at the evolution of the market shares of new cars.

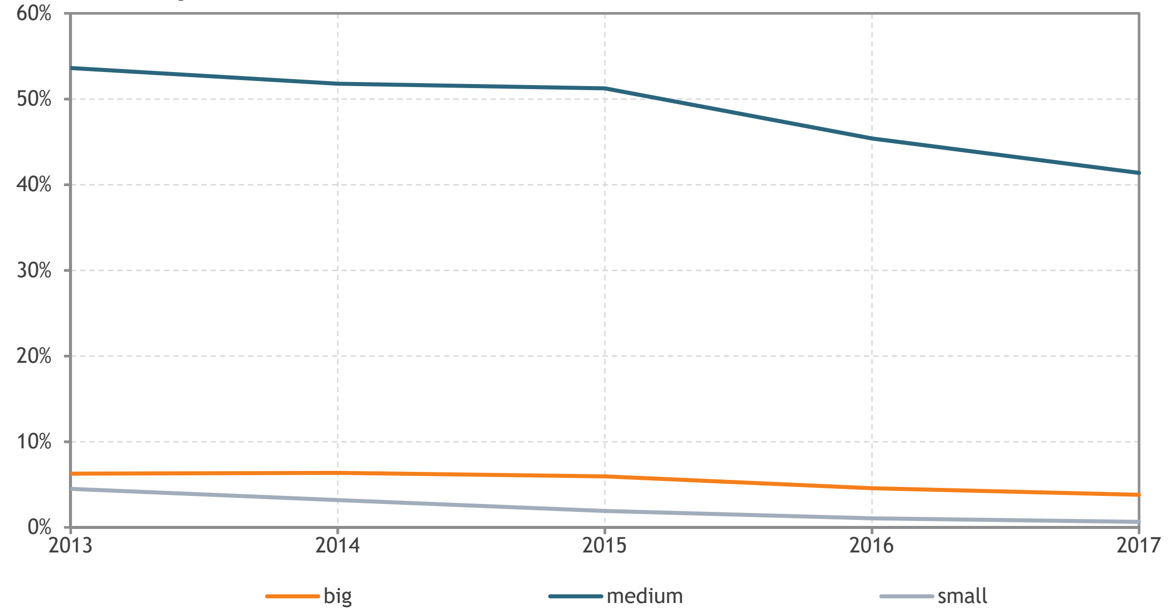
Graph 12 and Graph 13 confirm an important decrease in the market shares of diesel cars, especially in the "medium" segment, in parallel with an important uptake in the share of "small" gasoline cars. Although these trends were already visible before 2015, there is a clear acceleration as from 2015 on.

These are higher than what we would expect *a priori* from the changes in the circulation tax only, and probably reflect a broader concern amongst car buyers that the general policy climate has become less favourable to diesel.

As illustrated in Graph 14, the market shares of electric cars remain very small (around 0.5% over all size classes), even if we can observe some growth in the medium and the big segments. A more detailed analysis of the data[20] in the "big electric" segment has revealed that this is too a large extent a "Tesla effect".

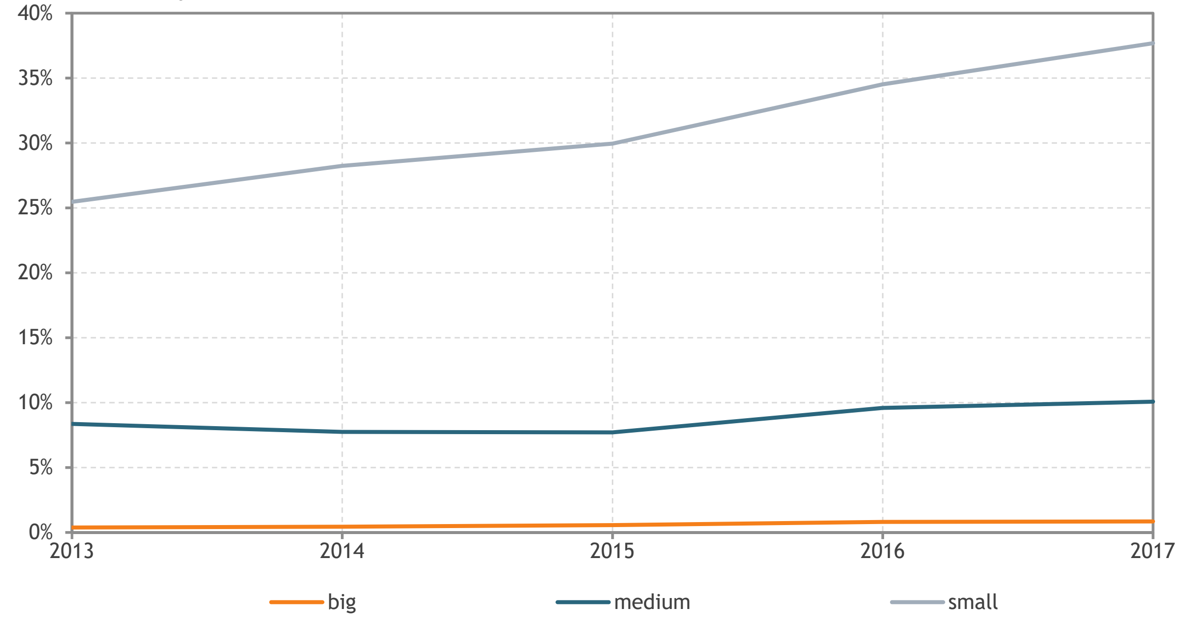
[20] Details are available from the author on request.

Graph 12 Diesel market shares (sales) in period 2013-17
Percentages



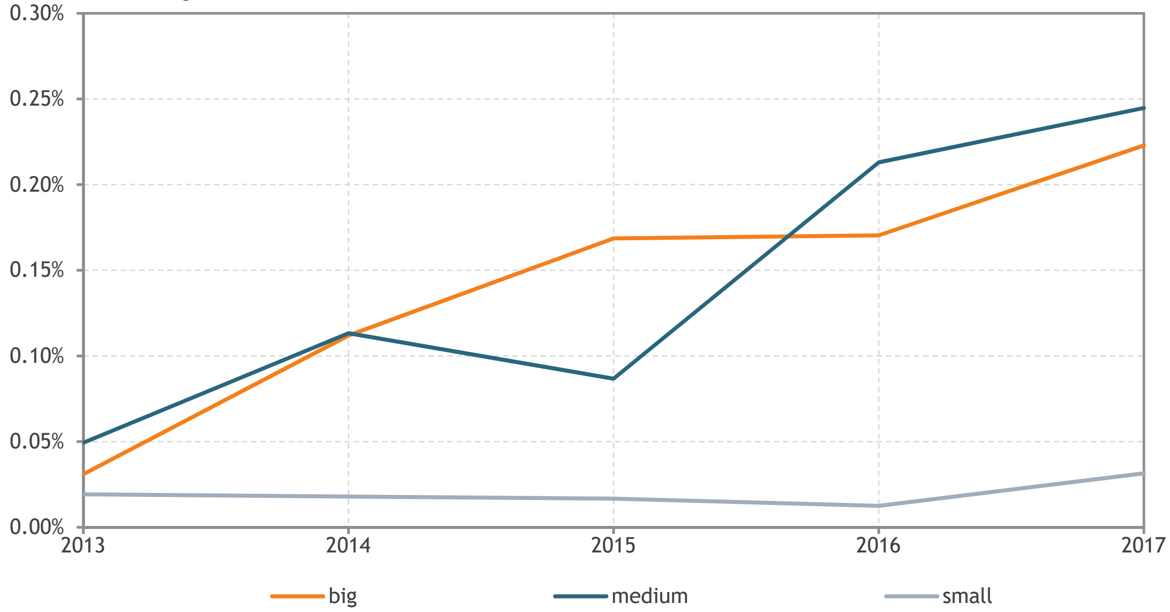
Source: CASMO

Graph 13 Gasoline market shares (sales) in period 2013-17
Percentages



Source: CASMO

Graph 14 Electric cars market shares (sales) in period 2013-17
Percentages



Source: CASMO

Annex B: Costs per COPERT class in 2017

It is also insightful to compare the costs of diesel, gasoline, hybrid and electric cars in 2017.

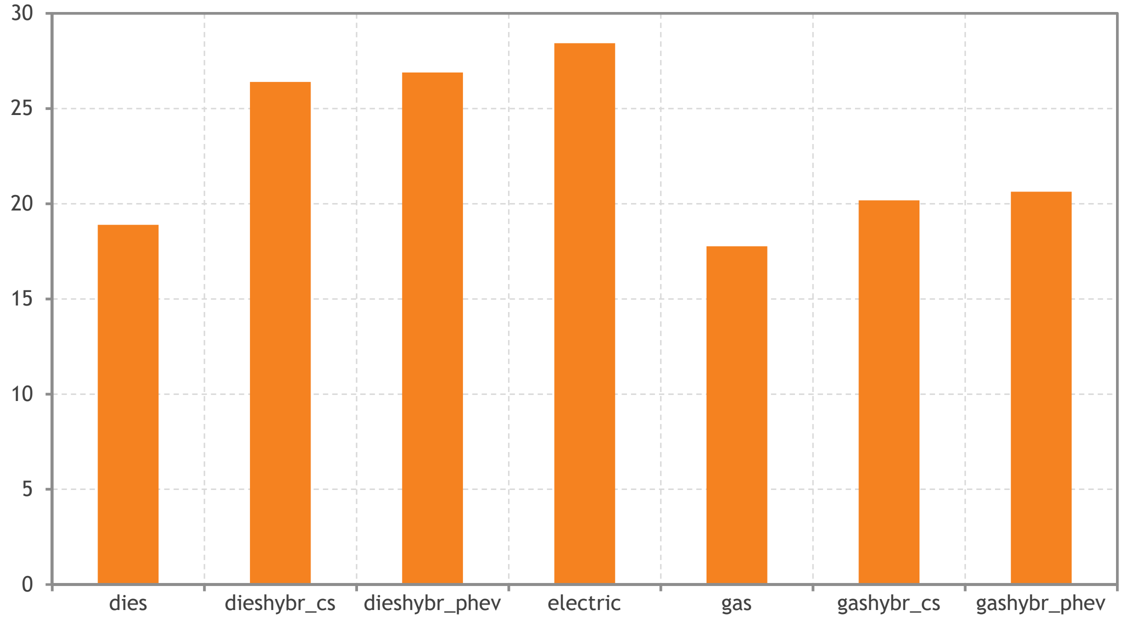
We start with the *acquisition costs*.

Graph 15, Graph 16 and Graph 17 show that, in all size classes, the total acquisition cost of electric and hybrid cars is still higher than for gasoline and diesel cars. In the size segment "big", the acquisition costs are about twice as high as for diesel cars. The differences are slightly less pronounced for the "medium" and "small" cars but remain non-negligible. It should be noted that, in the size class "big", the cost differences between gasoline and hybrid cars is also rather small. In this size class, diesel hybrids and plug-in hybrids even have a slight cost-advantage compared to gasoline cars. However, given that the cost estimates for hybrid cars are based on a much smaller data set than for the other fuel types, we should be very careful in drawing any strong conclusions from this.

In the "small" segment, the differences between diesel and gasoline cars have become very small. In the "medium" segment, diesel cars are more expensive, while the opposite is true for the "big" segment – a more detailed analysis of the data has shown that this largely attributable to the big share of premium cars in the "big gasoline" segment.

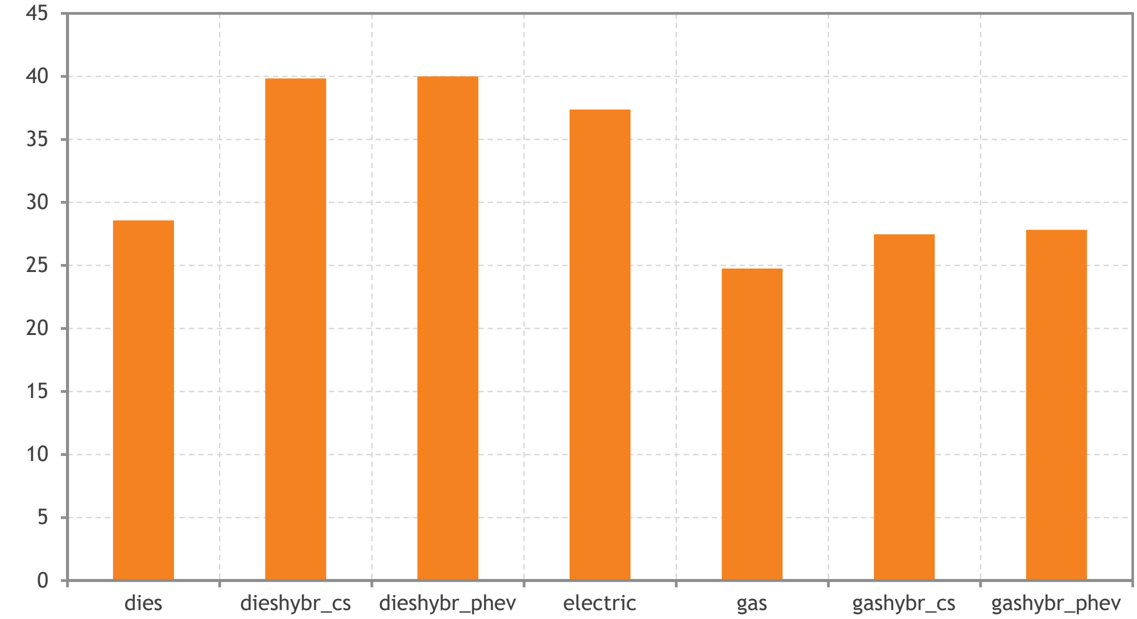
Finally, although the purchase cost of electric cars is higher than for hybrids and plug-in hybrids in the size segments "small" and "big", this is not the case in the size segment "medium", where diesel hybrid and plug-in hybrids are more expensive than electric cars.

Graph 15 Acquisition costs small cars in 2017
1000 EURO



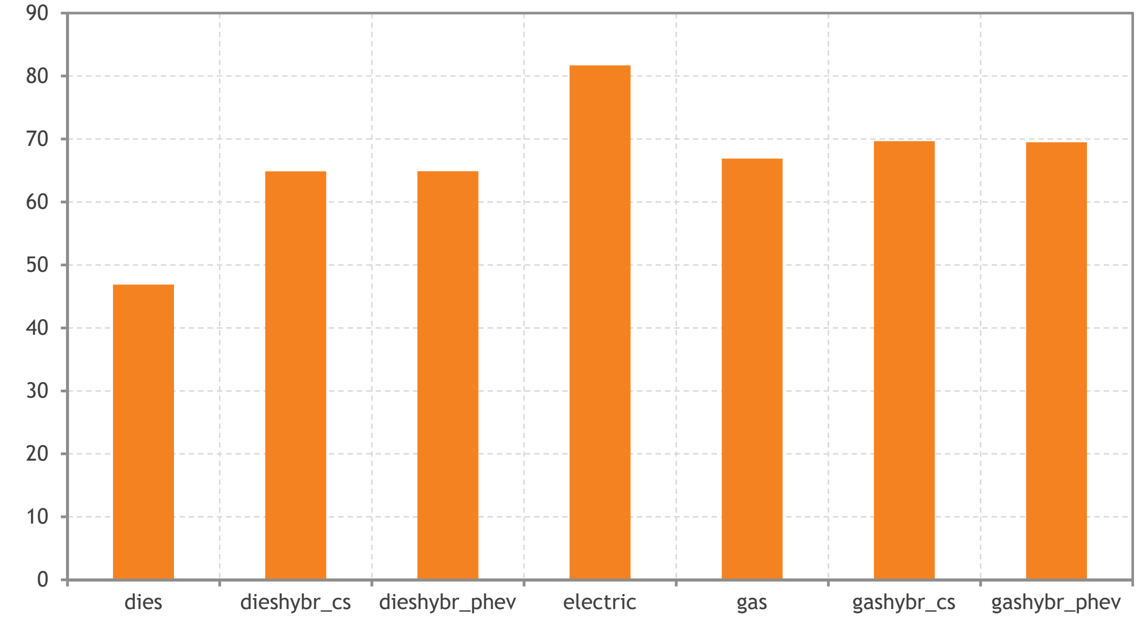
Source: CASMO

Graph 16 Acquisition costs medium-sized cars in 2017
1000 EURO



Source: CASMO

Graph 17 Acquisition costs big cars in 2017
1000 EURO



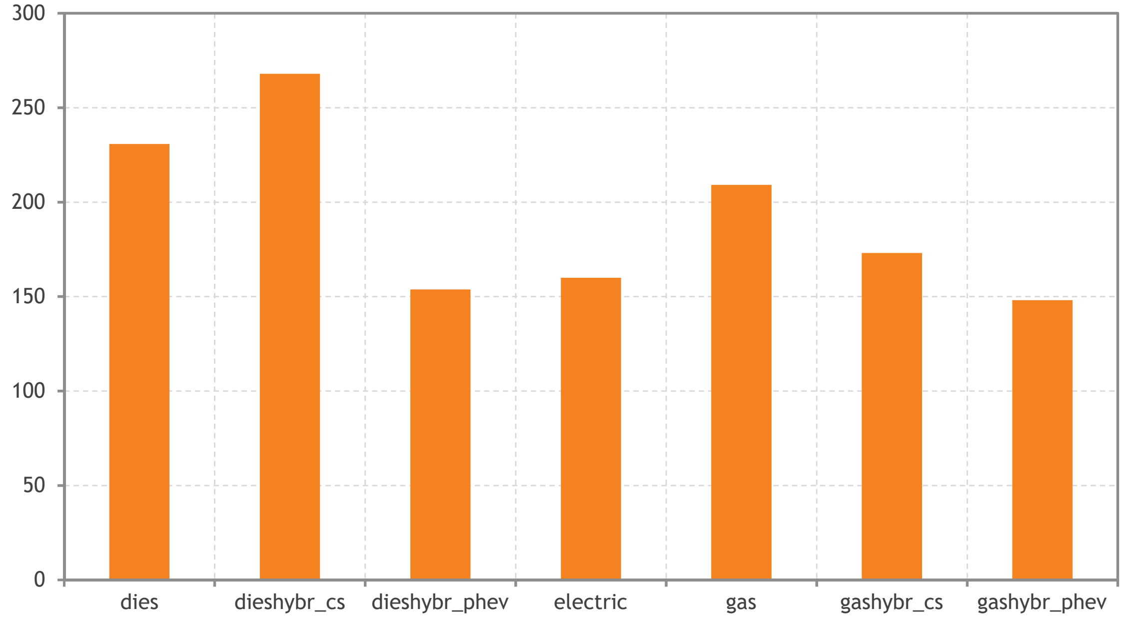
Source: CASMO

Let us now consider the *variable costs*.

Graph 18, Graph 19 and Graph 20 show that, in all size classes, electric cars, plug-in hybrids and gasoline hybrids have lower variable costs than gasoline and diesel cars. Diesel cars now have higher variable costs than gasoline cars. As discussed before, this reflects important changes in the tax policy vis-à-vis diesel. Diesel hybrids generally have rather high variable costs, even when compared to gasoline and diesel cars.

Graph 18 Variable costs small cars in 2017

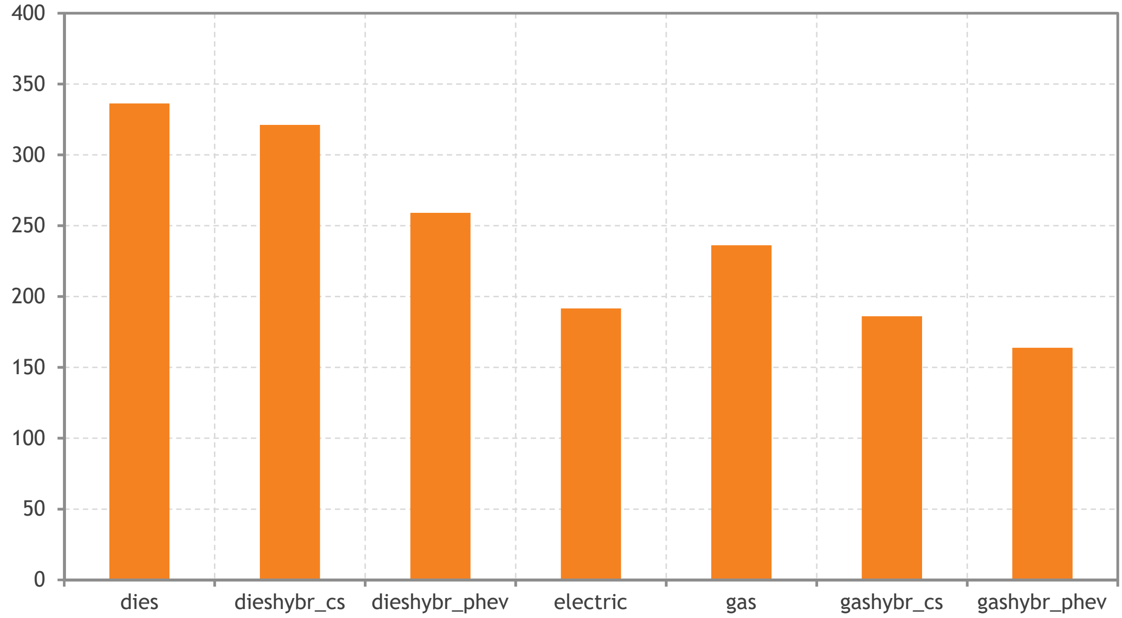
EURO/month



Source: CASMO

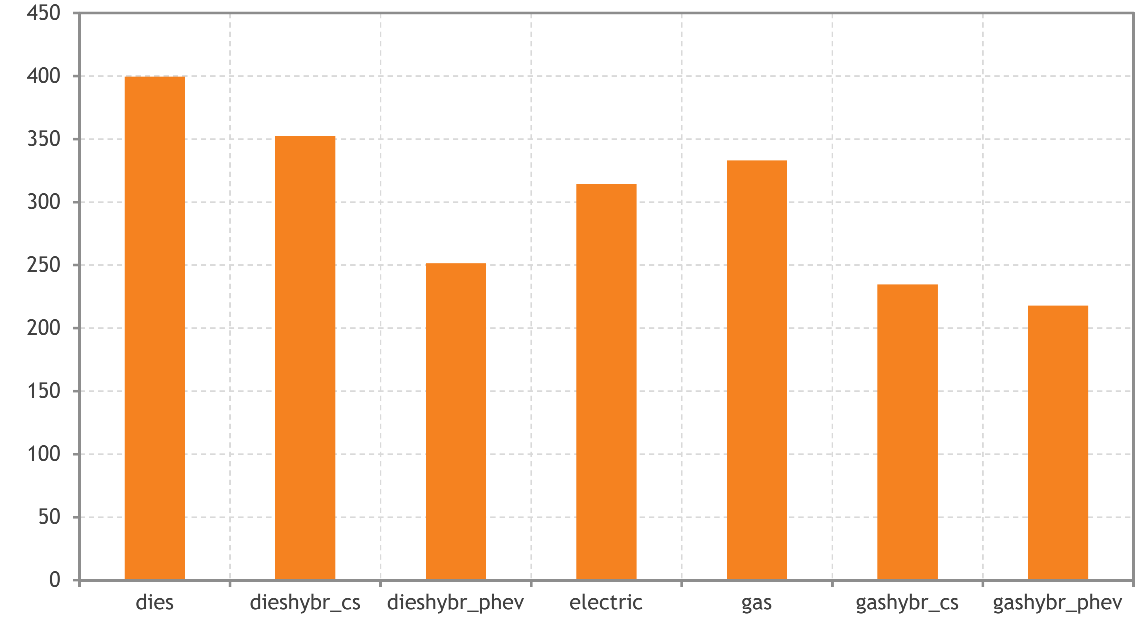
Graph 19 Variable costs medium-sized cars in 2017

EURO/month



Source: CASMO

Graph 20 Variable costs big cars in 2017
EURO/month



Source: CASMO

Given that electric cars and hybrid cars are, as a general rule[21], more expensive than conventional fuels in terms of acquisition costs, but have lower running costs, the natural next question is how they compare to other cars in terms of total cost of ownership (TCO). The Hoen-Koetse model does not refer explicitly to the TCO: the purchase costs and the monthly user cost enter directly the cost function, without reference to the expected lifetime and/or the discount rate. However, we would expect that respondents have (implicitly) an estimate in mind of these variables, given their household characteristics.

We are addressing this in detail in a forthcoming paper, which we briefly summarize here. The key result of this paper is that the time horizon used by the consumer is the key parameter.

Indeed, with an expected lifetime of 15 years and a private discount rate is 1.5%, medium electric cars are close to cost-competitive with gasoline cars. Compared to diesel, the TCO of electric cars is clearly smaller in the "medium" segment, but much higher in the segment "big" – remember that we have already pointed out above that "big" gasoline and electric cars are both mostly in the premium market. Finally, in the category "small", electric and diesel cars are almost on par. For diesel hybrid cars, the overall picture is not clear-cut but gasoline hybrids and plug-in hybrids are always amongst the cheaper car types for each size class.

However, there are several sources of uncertainty regarding the relevant value for the expected lifetime:

– Electric and hybrid cars can be expected to have a different use profile as diesel and gasoline cars. Indeed, because of their high fixed and low variable costs and limited autonomy, most existing electric cars are mostly suited for use profiles who drive a lot on an annual basis but whose individual trips are typically relatively short and who have readily access to overnight charging – think of

[21] Diesel hybrids are an exception: they have both higher acquisition *and* higher monthly costs.

service cars. This should lead to a shorter lifetime in years. However, electric cars are also less subject to maintenance and wear and tear, and this should lead to a longer lifetime. The net effect on their expected lifetime is not yet clear: electric cars have not yet been long enough on the market to yield useful data.

– Very little data exist on the economic lifetime of batteries and their potential applications in a possible second-hand market. Moreover, this is an area where technology is evolving very quickly.

– Greene (2010) has argued that most consumers overvalue the acquisition cost of cars compared to variable costs when buying a car. In line with this, Element Energy Ltd (2013) assume consumers typically consider pay-back periods of four years, which is indeed much smaller than any empirical estimate of a car's economic lifetime.

Further analysis has confirmed that, if consumers have a time horizon of 4 years, diesel, gasoline and hybrid gasoline cars perform best, and have broadly comparable TCOs. With such a very short mental time horizons, electric cars are at a clear competitive disadvantage. However, for the size segments "small" and "medium", hybrid gasoline cars remain relatively competitive from a TCO perspective. Therefore, consumer myopia alone cannot explain the very low market shares for hybrid gasoline cars in Belgium in the reference years.

This confirms our hypothesis that, in the current market context, the main barrier to the adoption of electric cars is not their total cost of ownership. Other elements appear to be crucial, some of which are easily quantifiable (such as the expected autonomy of an electric car or the availability of a charging infrastructure), others less (such as consumers' conservatism and range anxiety).

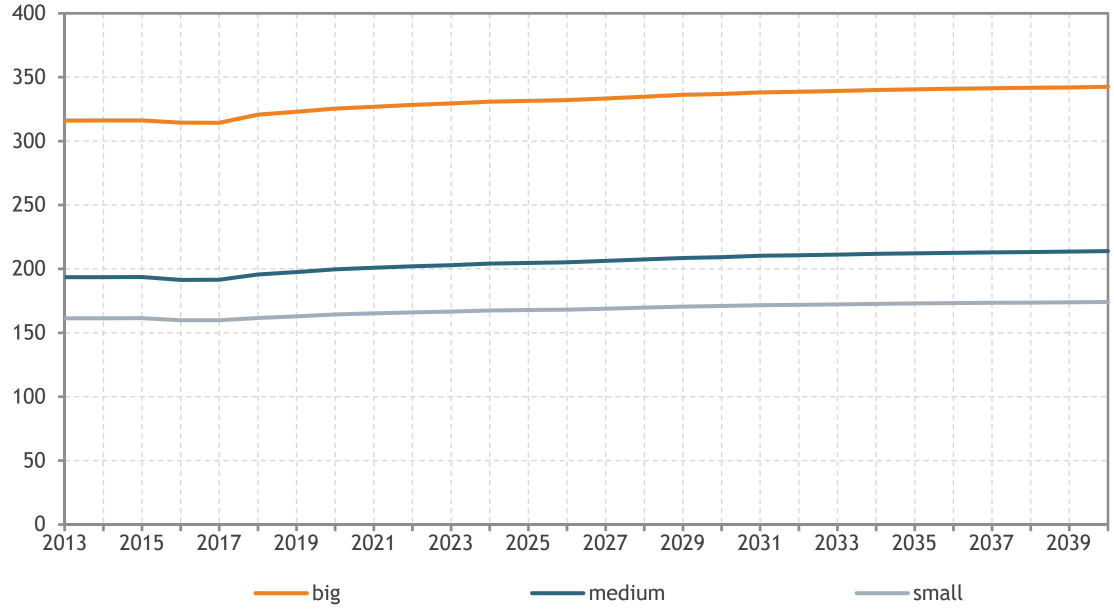
The very low penetration rate of gasoline hybrid and plug-in hybrids is especially puzzling, given their TCO. However, as discussed in Section 3.4, the cost estimates for hybrid cars are more speculative than for the other fuel types and we need to be very careful in our discussion of the potential for this power-train.

Annex C: Evolution of costs and range

Let us first consider the changes over time of the cost parameters and the range for electric cars.

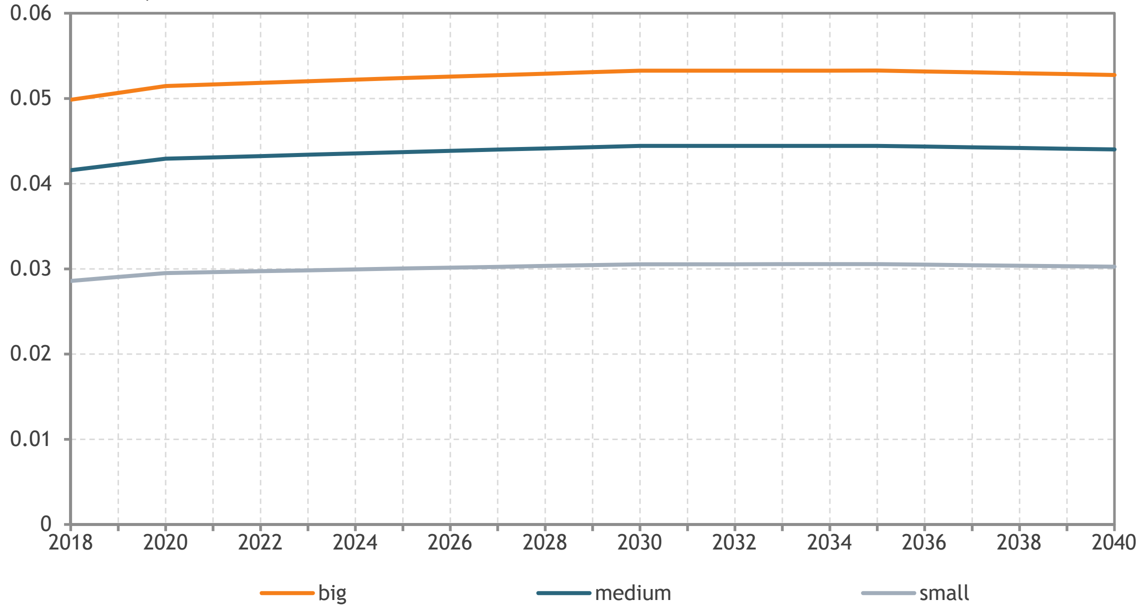
Graph 21 shows that monthly costs for electric cars have fluctuated in the period that was used for the estimation of the model (mainly due changes in the traffic tax) but are assumed to grow steadily during the projection period: by 7% between 2018 and 2040 for "big" electric cars, for instance. It can be verified that this is mainly driven by increases in the fuel costs.

Graph 21 Evolution of the variable costs of electric cars
EURO/month



Source: CASMO

Graph 22 Evolution of the fuel cost of electric cars
EURO per km

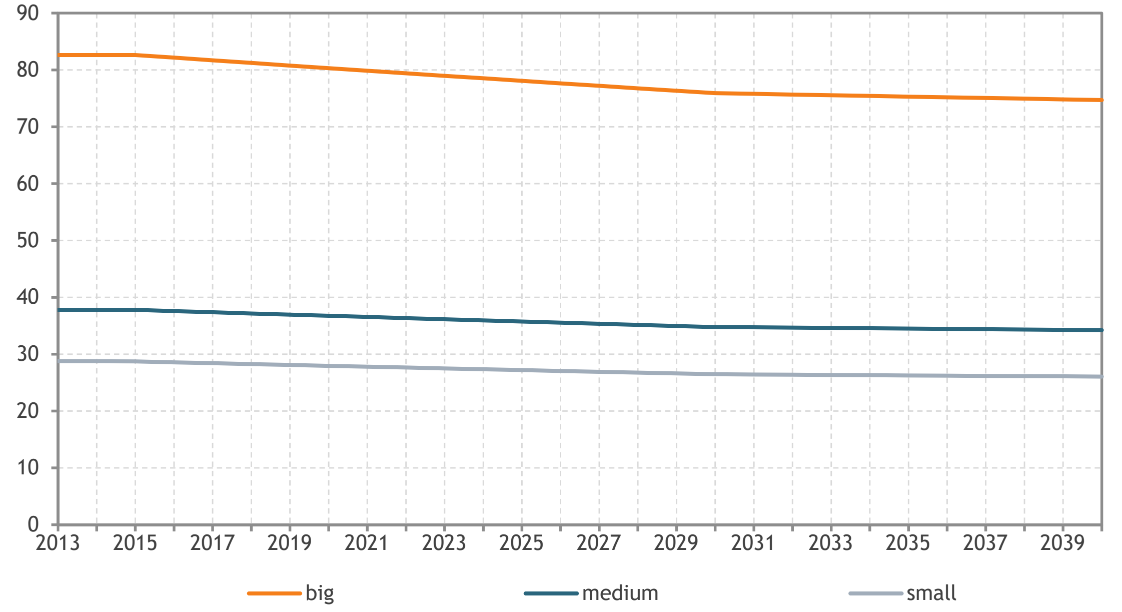


Source: CASMO

We have to keep in mind that the periodic fuel cost reflects not only changes in the cost per km, but also changes in the annual mileage (which grow proportionally for all powertrains). Therefore, we single out the evolution of the fuel costs per km of electric vehicles in Graph 22. This cost increases by a bit more than 3% between 2020 and 2030, and then remains on a plateau until 2035, after which there is a small decrease. Note that the consumption of electricity per km is assumed to remain constant over this period – the evolution of the cost per km is entirely driven by changes in the price of electricity.

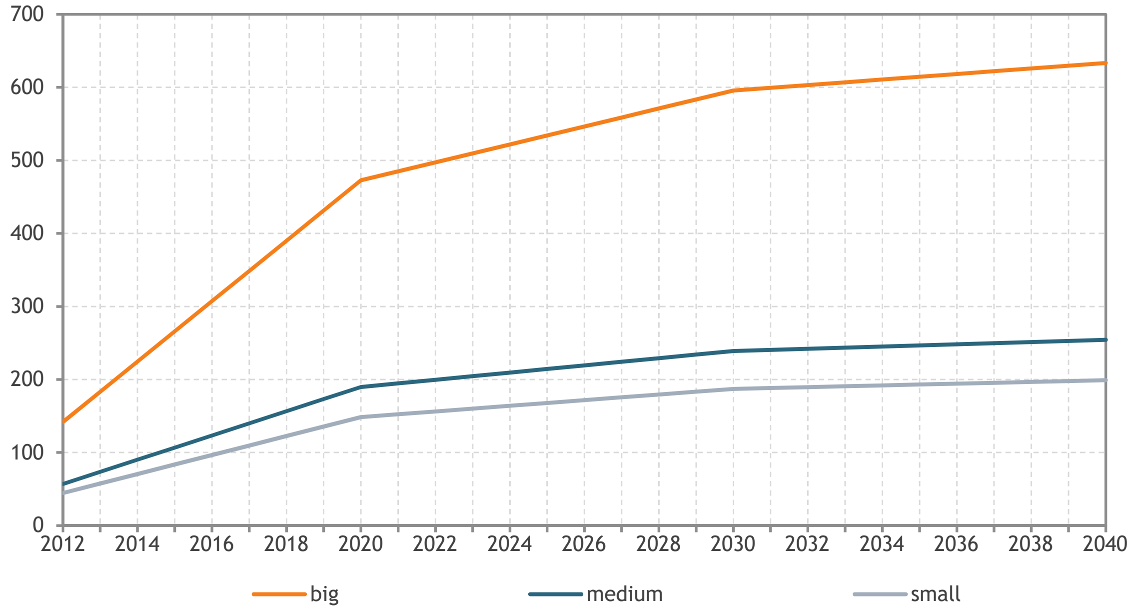
Finally, as shown in Graph 23 and Graph 24, the model assumes a steady decline for the purchase costs of electric vehicles combined with an increase in the autonomy of electric vehicles.

Graph 23 Evolution of the purchase cost of electric cars
1000 EURO



Source: CASMO

Graph 24 Evolution of the autonomy of electric cars
km

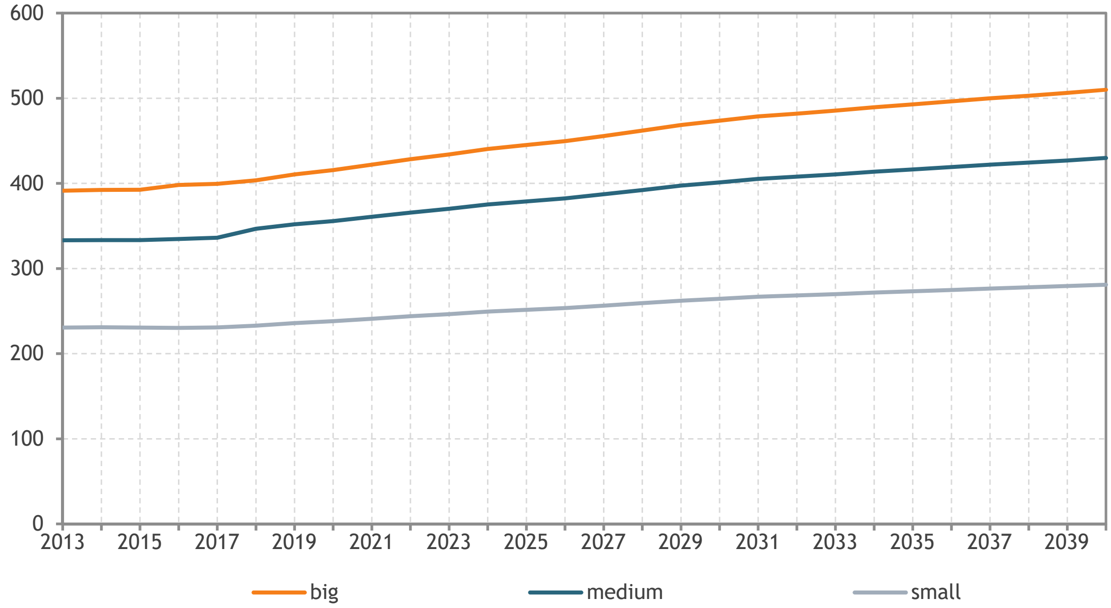


Source: CASMO

We can now compare this with the evolution of the costs for diesel and gasoline cars.

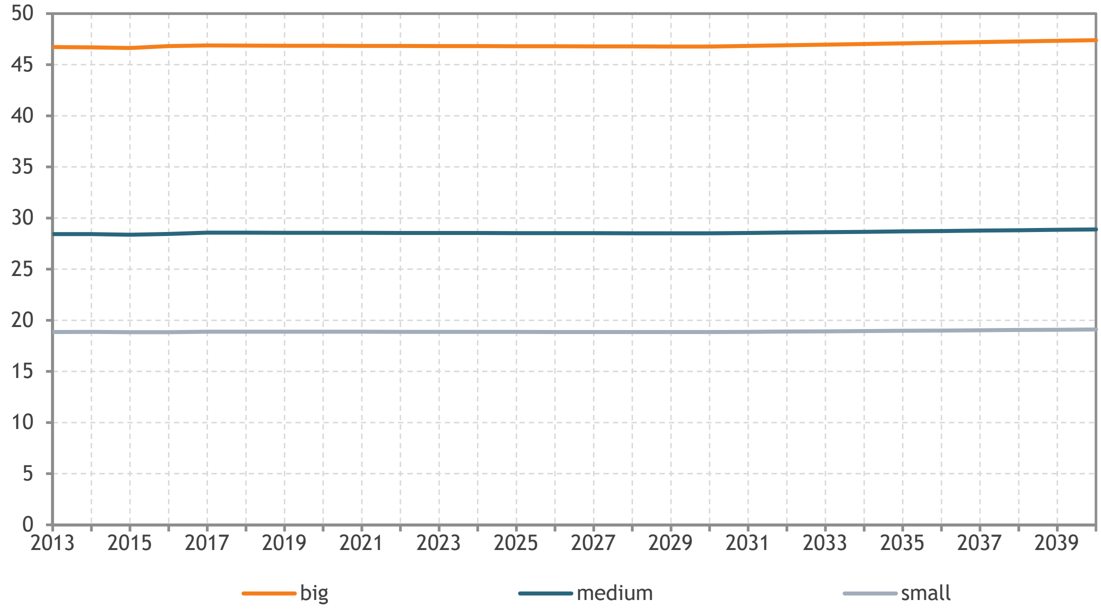
As shown in Graph 25 and Graph 26, the model assumes an important increase in the monthly costs of diesel cars (around 26% for "big" cars by 2040), combined with an essentially constant purchase cost. It can be verified that, after the increase in the circulation tax in 2015, the increase in monthly costs is essentially driven by the increase in the fuel costs. Graph 27 shows that the fuel cost per km steadily increases between 2018 and 2040, by approximately 62%.

Graph 25 Evolution of the variable costs of diesel cars
EURO/month



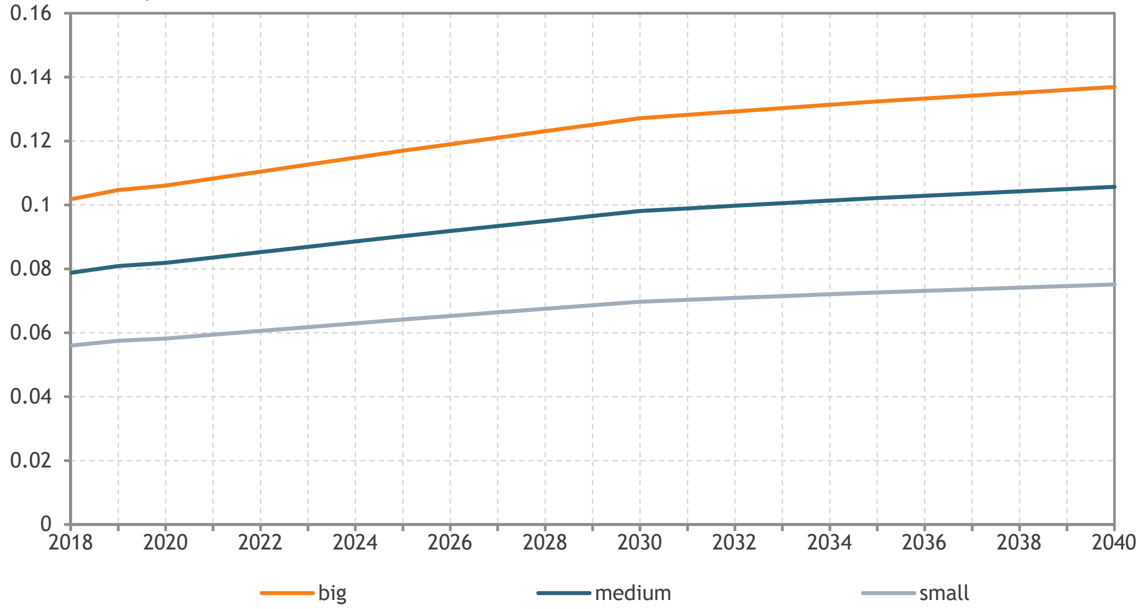
Source: CASMO

Graph 26 Evolution of the purchase costs of diesel cars
1000 EURO



Source: CASMO

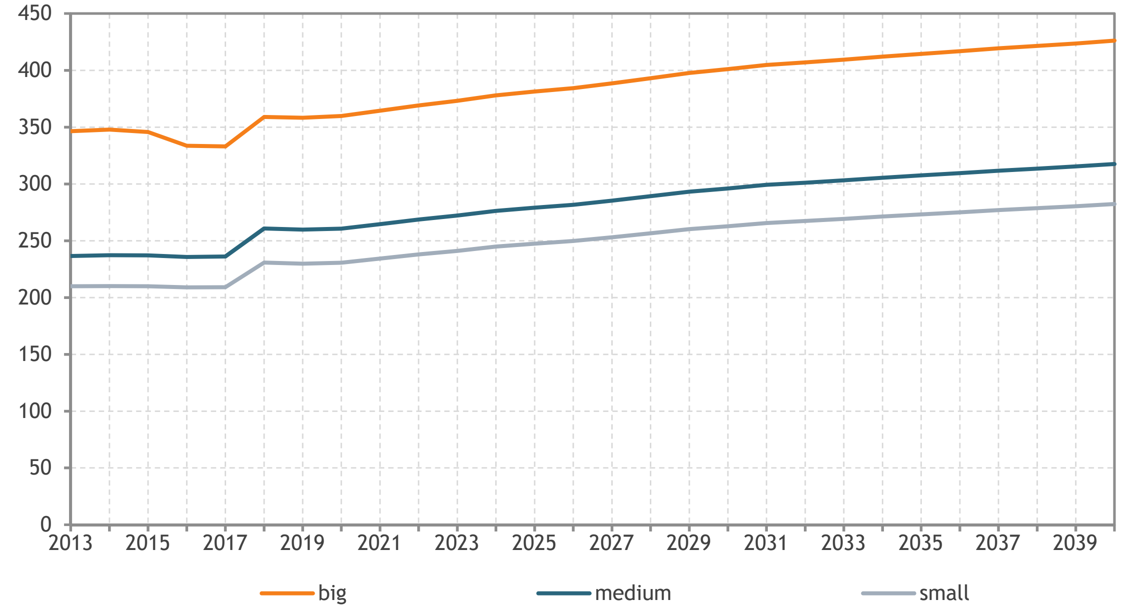
Graph 27 Evolution of the fuel cost of diesel cars
EURO per km



Source: CASMO

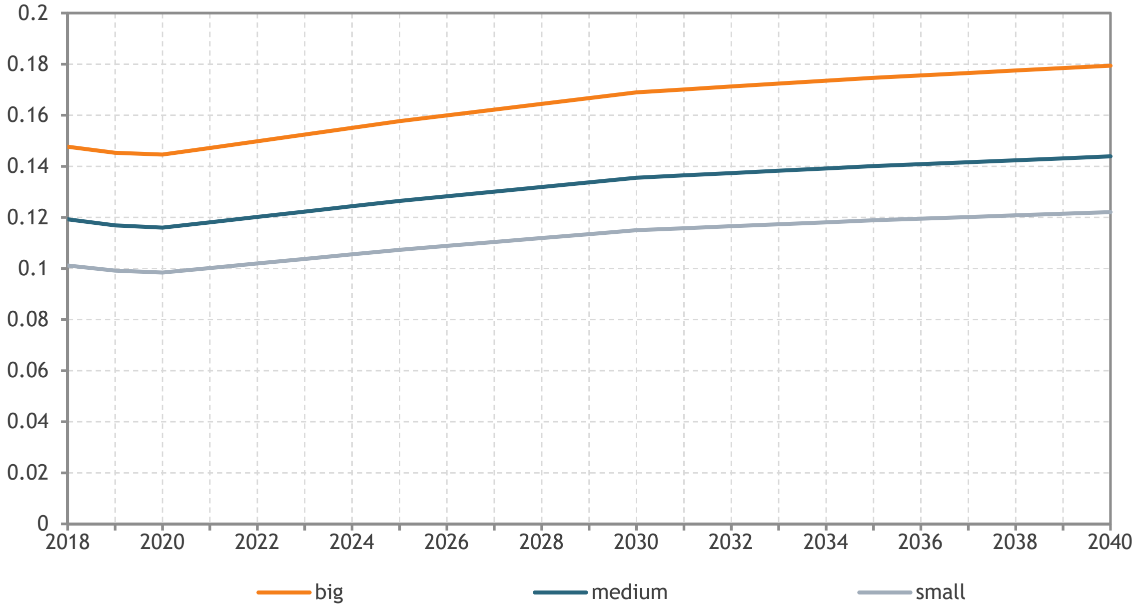
As shown in Graph 28, the model assumes a steady increase in the monthly costs of gasoline cars after an initial decrease: between 2020 and 2040, monthly costs are assumed to increase with 18% for "big" cars, for instance. It can be verified that this is due to (a) the decrease in the circulation tax in 2015, (b) the increase in the fuel costs as from 2020 on. Graph 29 confirms an important increase in the fuel cost per km between 2020 and 2040 (by 46%).

Graph 28 Evolution of the variable costs of gasoline cars
EURO/month



Source: CASMO

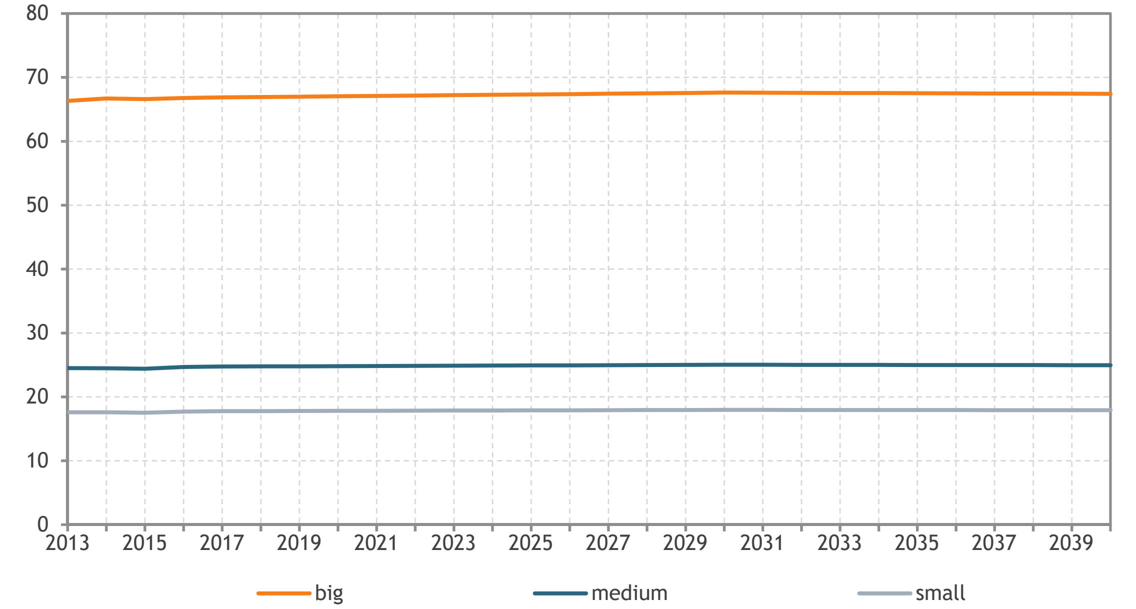
Graph 29 Evolution of the fuel cost of gasoline cars
EURO/km



Source: CASMO

As shown in Graph 30, the purchase cost for gasoline cars is also assumed to stay essentially constant.

Graph 30 Evolution of the purchase costs of gasoline cars
1000 EURO



Source: CASMO