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Modélisation de la demande de transport routier français et de ses impacts environnementaux pour les véhicules particuliers à l'horizon 2050.

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Introduction

Introduction générale

Le monde est encore loin d'atteindre l'objectif de stabilisation du réchauffement climatique à 1,5 °C malgré les engagements pris à Paris en 2015. Le Groupe d'experts intergouvernemental sur l'évolution du climat (GIEC) indique que les concentrations mondiales de gaz à effet de serre (GES) ont déjà atteint des niveaux qui pourraient entraîner une augmentation de la température mondiale de plus de 1,5 °C par rapport aux niveaux préindustriels d'ici à 2100, ce qui nécessiterait d'importantes réductions des émissions. Même en déployant un maximum d'efforts, on prévoit une augmentation de 1,7 °C d'ici à 2100. Pour atteindre l'objectif, les émissions doivent être réduites à 23 gigatonnes (Gt) d'ici 2030 et à zéro net d'ici 2050 (International Energy Agency, 2022). L'Accord de Paris, signé par 197 pays en 2015, vise à limiter cette augmentation à 2°C, idéalement 1,5°C. Les Nations unies précisent que la réalisation de cet objectif nécessite des changements sociétaux sans précédent, une réduction de 45 % des émissions mondiales de dioxyde de carbone (CO2) par rapport aux niveaux de 2010 d'ici à 2030, et des émissions nettes nulles d'ici à 2050 (European Environment Agency, 2022).

Passant d'accords mondiaux à des engagements régionaux, le pacte vert européen propose une réduction de 55 % des émissions de gaz à effet de serre d'ici à 2030 par rapport à 1990, et vise à ce que l'UE devienne neutre sur le plan climatique d'ici à 2050. Cet objectif a été inscrit dans la loi européenne sur le climat et signifie que toutes les émissions de GES restantes doivent être compensées par le captage du carbone. Pour atteindre cette neutralité climatique globale, le secteur des transports devra réduire ses émissions de GES de 90 % d'ici à 2050, comme le prévoit la stratégie pour une mobilité durable et intelligente (Sustainable and Smart Mobility Strategy). La réduction des émissions de carbone du secteur des transports est un élément clé de la réduction durable des émissions mondiales de GES. En Europe, il s'agit du deuxième plus grand émetteur après les industries de l'énergie. Le secteur contribue à environ 24 % des émissions totales de GES, dont 72 % proviennent du transport routier (Commission, 2018). Les émissions de gaz à effet de serre du transport routier dans l'UE ont augmenté de 28 % entre 1990 et 2019, représentant 72 % des émissions totales du transport dans l'UE (European Environment Agency, 2022).

Si l'on analyse les tendances passées, entre 2000 et 2019, les émissions de dioxyde de carbone des voitures particulières dans l'UE ont augmenté de 5,8 %, principalement en raison d'une croissance de 16 % des volumes de transport de passagers et d'une légère augmentation de la part du transport automobile parmi les modes de transport terrestres (European Environment Agency, 2022). Les facteurs qui sous-tendent cette tendance sont l'augmentation de la demande de transport, la croissance des volumes de transport de passagers et l'augmentation de la part du transport automobile parmi les modes de transport terrestres. Ces augmentations ne sont que partiellement compensées par l'amélioration de l'efficacité énergétique et l'utilisation de biocarburants.

Malgré des réductions globales des émissions dans d'autres secteurs, les émissions de dioxyde de carbone dues aux transports devraient être supérieures de 3,5 % en 2030 par rapport à 1990, et ne diminuer que de 22 % d'ici 2050 par rapport aux niveaux de 1990. Pour atteindre l'objectif de neutralité climatique, une réduction de 90 % est nécessaire (European Environment Agency, 2022). Dans cette optique, et afin de se conformer à l'accord de Paris de 2015, la Commission européenne (CE) s'est fixé pour objectif de réduire les émissions de GES provenant des transports de 20 % par rapport aux niveaux de 2008 d'ici à 2030. En outre, dans le cadre de sa feuille de route pour 2050, la CE a également identifié un potentiel de réduction de 60 % des émissions de GES par rapport aux niveaux d'émission de 1990. Ainsi, le transport routier apparaît aux autorités comme l'un des secteurs clés dans la lutte contre le changement climatique et la pollution de l'air. Le secteur est confronté à deux défis : i) un défi global, celui de la réduction de ses émissions de GES, et ii) un défi plus local de santé publique, celui de la réduction de ses émissions de particules fines, de monoxyde de carbone, etc. générées par l'augmentation du nombre de transports motorisés dans les villes. Une réduction de 95 % des émissions dues aux transports d'ici à 2050 nécessite de nouvelles infrastructures de grande envergure et des technologies propres. D'ici 2050, toutes les voitures en circulation devront fonctionner à l'électricité ou à l'aide de piles à combustible, tandis que l'aviation et le transport maritime feront largement appel aux biocarburants et aux carburants synthétiques.

La transition vers les véhicules électriques (VE) est essentielle pour atteindre les objectifs de l'accord de Paris sur le climat (IEA, 2017). Les véhicules électriques produisent moins de gaz à effet de serre et de polluants atmosphériques tout au long de leur cycle de vie que leurs homologues à essence ou diesel. Ils offrent également des avantages en termes de qualité de l'air grâce à des émissions de polluants nulles ou faibles à l'échappement. En Norvège et aux Pays-Bas, les nouvelles voitures particulières ont émis 54 % et 38 % de CO en moins en 2017 qu'en 2001 respectivement, grâce à la combinaison de l'électrification du parc et de la diminution des émissions des nouveaux véhicules à moteur à combustion interne, toutes deux impulsées par des politiques favorisant les véhicules à faibles émissions (European Environment Agency, 2019).

Cependant, les véhicules électriques (VE) présentent plusieurs inconvénients par rapport aux véhicules à moteur à combustion interne (MCI). Tout d'abord, le prix d'achat des VE avant subventions est généralement plus élevé, le prix d'achat moyen d'une nouvelle voiture électrique en 2021 étant supérieur d'environ 10 000 dollars à la moyenne du secteur pour les véhicules à essence.[1] Même si cet écart devrait se réduire grâce aux progrès technologiques, il constitue toujours un obstacle pour de nombreux acheteurs potentiels. Deuxièmement, l'autonomie des VE est généralement plus courte, le VE le plus abordable en 2023 offrant une autonomie estimée à 415 kilomètres, contre environ 700 kilomètres pour un véhicule à moteur à combustion interne typique.[2] Enfin, les temps de charge des VE sont plus longs que les temps de ravitaillement standard des véhicules à moteur à combustion interne, même avec des options de charge rapide (l'utilisation d'une station de charge rapide à courant continu prend généralement entre 20 minutes et 1 heure pour charger un BEV à 80 %)[3], ce qui ajoute des inconvénients pour les utilisateurs et limite potentiellement la praticité des VE pour les voyages de longue distance. Compte tenu des défis auxquels sont confrontés les véhicules électriques, le soutien politique est essentiel pour favoriser leur adoption et leur compétitivité par rapport aux véhicules à moteur à combustion interne. En apportant leur soutien par des politiques favorables, les gouvernements peuvent accélérer la transition vers des transports plus propres, réduire les émissions de gaz à effet de serre et stimuler l'innovation et la

[1] "Electric vs Gas Cars : Is It Cheaper to Drive an EV ?" (Voitures électriques contre voitures à essence : est-ce moins cher de conduire une VE ?) Natural Resources Defense Council (NRDC), https://www.nrdc.org/stories/electric-vs-gas-cars-it-cheaper-drive-ev.

[2] Chevrolet, "Bolt EV : Electric Car,", https://www.chevrolet.com/electric/bolt-ev.

[3] United States Department of Transportation, "Charger Types and Speeds," 2023, https://www.transportation.gov/rural/ev/toolkit/ev-basics/charging-speeds.

croissance dans l'industrie des véhicules électriques.

L'intervention des pouvoirs publics peut se faire tant du côté de l'offre que de la demande, par une combinaison d'incitations et/ou de restrictions. Une distinction classique est faite entre les mesures réglementaires contraignantes (par exemple, les normes d'émission et les limitations de vitesse) et les outils économiques de nature incitative (tels que les taxes, les incitations à l'achat et les pénalités). Ces différents types de politiques ne ciblent pas tous les mêmes types d'usages et les mêmes types d'acteurs dans le secteur des transports, et peuvent également poser des problèmes d'équité. Cependant, elles visent toutes à améliorer l'efficacité énergétique des véhicules de transport et à augmenter la part des carburants renouvelables ou non fossiles dans le secteur des transports. Les pays qui ont adopté des politiques proactives en matière de véhicules électriques ont enregistré des réductions substantielles de leurs émissions. Parmi les défis à relever figurent la mise en place d'infrastructures de recharge suffisantes, la gestion de l'augmentation de la demande d'électricité et la production de batteries à grande échelle (European Environment Agency, 2022). Les chargeurs accessibles au public sont essentiels à l'adoption des VE, en particulier dans les zones urbaines denses où la recharge à domicile est limitée. En 2022, il y avait 2,7 millions de points de charge publics dans le monde, dont plus de 900 000 ont été installés cette année-là - une augmentation de 55 % par rapport à 2021 et conforme à la croissance prépandémique (International Energy Agency, 2023). L'infrastructure de recharge publique se développe, soutenue par des initiatives telles que le règlement de l'Union européenne sur les infrastructures pour carburants alternatifs (AFIR) et le National Electric Vehicle Infrastructure Formula Program (NEVI) des États-Unis (International Energy Agency, 2023). Malgré la croissance du marché des VE, le comportement d'achat des consommateurs et les politiques publiques doivent s'aligner pour promouvoir les véhicules à faible émission de carbone.

La Commission européenne a fixé des objectifs spécifiques pour les transports, en se concentrant sur une réduction de 55 % des émissions de GES d'ici 2030 par rapport aux niveaux de 1990.[4] Les gouvernements ont recours à un ensemble d'incitations réglementaires et économiques pour accroître l'efficacité énergétique et l'utilisation des carburants renouvelables. Parmi les politiques récentes, citons le paquet "Fit for 55", qui exige une réduction de 55 % et 50 % des émissions des nouvelles voitures et

[4] Commission européenne, "2030 Climate Target Plan", Climate Action, https://climate.ec.europa.eu/eu-action/european-green-deal/2030-climate-target-plan_en.

camionnettes d'ici à 2030 (par rapport à 2021) et de 100 % pour les deux d'ici à 2035 (International Energy Agency, 2023). Cela fait partie des ambitions croissantes de l'UE en matière de décarbonisation par l'électrification.

Aux États-Unis, la loi sur la réduction de l'inflation met l'accent sur le renforcement des chaînes d'approvisionnement nationales pour les VE, les batteries de VE et les minéraux de batteries, conformément aux critères d'éligibilité aux crédits d'impôt pour les véhicules propres. Elle prévoit divers incitations fiscales et programmes de financement pour accélérer l'adoption des VE, tels que le crédit d'impôt pour les véhicules propres. Elle a également introduit, du côté de l'offre, des crédits d'impôt pour la production manufacturière avancée, qui fournissent des subventions pour la production nationale de batteries. Toutefois, ces mesures sont subordonnées à l'assemblage du véhicule aux États-Unis. (International Energy Agency, 2023). Le California Air Resources Board a approuvé la règle Advanced Clean Cars II (ACC II) en novembre 2022, qui vise à augmenter progressivement la part des véhicules à zéro émission (ZEV) jusqu'à ce que tous les véhicules vendus à partir de 2035 soient des ZEV ou des PHEV. Plusieurs États américains ont fait de même (International Energy Agency, 2023). Plusieurs pays européens ont renforcé leurs politiques pour accélérer l'adoption des VE : Le Royaume-Uni prévoit de mettre fin à la vente de voitures et de camionnettes à moteur à combustion interne (ICE) d'ici 2030, et de passer à 100 % de ventes de ZEV d'ici 2035. La Grèce n'autorise la vente de ZEV qu'à partir de 2030. D'autres pays comme l'Italie, l'Espagne, le Danemark, la Finlande, l'Autriche, la Croatie et Chypre ont introduit diverses subventions et modifications fiscales. La politique a joué un rôle important dans la croissance des VE. Sur les principaux marchés de VE comme la Chine, l'Europe et les États-Unis, l'adoption précoce a souvent été stimulée par des politiques telles que des incitations à l'achat de véhicules et des incitations directes pour les constructeurs automobiles (International Energy Agency, 2023). Cependant, des pays comme la Norvège, le Royaume-Uni, l'Allemagne, l'Irlande, les Pays-Bas, la Suède et la France ont commencé à réduire les incitations ou les subventions aux VE à mesure que ces derniers devenaient plus abordables et plus répandus (International Energy Agency, 2023).

Malgré un certain développement du marché des véhicules électriques (la part de marché en Europe atteindra 10,5 % en 2020 pour les BEV et les PHEV), une grande partie des BEV n'est pas encore en vue dans le parc automobile. Le faible taux de renouvellement du parc automobile soulève deux questions : i) comprendre le comportement d'achat des consommateurs et ii) concevoir au mieux les politiques publiques pour stimuler et promouvoir la diffusion de véhicules particuliers à faible émission de carbone. Alors que le développement de solutions de transport innovantes et à faible émission de carbone peut se heurter à des difficultés sans le soutien des décideurs publics, l'abondance des politiques publiques soulève la question de savoir comment elles peuvent être coordonnées efficacement pour garantir l'efficience sans devenir une charge trop lourde pour les gouvernements.

Depuis les événements du "Dieselgate" (2015), nous avons assisté à une augmentation des implications de ces acteurs publics et à différentes échelles d'application (urbaine, interurbaine, nationale, internationale). Ces différentes initiatives peuvent avoir des effets contradictoires ou indésirables. Par exemple, le fait que certaines villes commencent à mettre en place des interdictions de circulation pour les vieux véhicules diesel (Paris 2024) pourrait à la fois accélérer le changement du parc et exclure les ménages les plus pauvres de ce processus en faisant chuter le prix de revente de ces véhicules sur le marché de l'occasion. En outre, ces politiques ne sont pas faciles à mettre en œuvre, la ville de Paris avait en 2014 l'objectif d'interdire les voitures diesel d'ici 2017 ; cet objectif a dû être repoussé de quatre ans et a finalement été mis en œuvre en 2021.[5] Cela reflète une réelle difficulté à mettre en œuvre des mesures fortes contre les voitures à moteur à combustion interne dans la politique, même dans des zones très favorables comme la ville de Paris où la pollution et la santé sont une question particulièrement aiguë, compte tenu de la densité d'habitants, et où une alternative vraiment efficace au transport automobile est déjà en place.

Pour être atteints, les objectifs fixés par l'Union européenne en matière de réduction des émissions de gaz à effet de serre ou de traitement des pollutions locales devront combiner l'amélioration de l'efficacité des moteurs à combustion interne avec le développement d'énergies alternatives ou de technologies automobiles alternatives telles que les véhicules hybrides, les carburants alternatifs, les moteurs électriques et les piles à combustible.

L'efficacité des politiques environnementales, telles que les taxes sur le carbone, les zones à faibles émissions et les normes réglementaires, dépend de l'acceptation du public. Un manque de soutien public peut conduire à l'échec de politiques bien intentionnées, même si elles sont économiquement et écologiquement saines. Dans

[5] "La maire de Paris déclare la guerre au diesel", Capital.fr, 7 décembre 2014, [En ligne]. Disponible : https://www.capital.fr/economie-politique/la-maire-de-paris-declare-la-guerre-au-diesel-996759.

plusieurs cas, le rejet du public a entraîné l'abandon ou la modification des politiques, comme la taxe carbone australienne et "l'écotaxe" française. Le cas de l'écotaxe française montre que des ressources considérables peuvent être gaspillées pour planifier, concevoir et mettre en œuvre une politique qui sera ensuite annulée en raison de l'opposition de l'opinion publique. Les coûts irrécupérables associés à ces annulations peuvent grever les budgets gouvernementaux et détourner des ressources d'autres domaines vitaux. En outre, les mouvements sociaux qui s'opposent aux politiques environnementales, tels que les "gilets jaunes" en France, peuvent entraîner des troubles sociaux et un mécontentement plus large à l'égard des autorités gouvernementales. Cela peut éroder la confiance dans la gouvernance et accentuer la polarisation. L'acceptabilité du public n'est pas seulement une question d'efficacité politique, mais aussi un aspect essentiel du maintien de la cohésion sociale et de la confiance dans le gouvernement.

Les raisons sous-jacentes du rejet peuvent varier : manque de compréhension, perception d'une atteinte aux intérêts individuels, polarisation politique ou préoccupations en matière de justice sociale et environnementale. Si elles ne sont pas largement acceptées par le public, les politiques peuvent se heurter à des résistances, à des protestations ou à des contestations juridiques, ce qui nuit à leur mise en œuvre et à leur efficacité. Il est donc essentiel pour les décideurs politiques de s'intéresser au sentiment du public et de favoriser sa compréhension afin de garantir la réalisation des objectifs environnementaux.

Ajout à la recherche

L'élaboration de scénarios à moyen et long terme, ainsi que l'anticipation des percées technologiques, des changements radicaux dans les politiques publiques ou des changements dans le comportement des utilisateurs, restent un exercice difficile. C'est ce que cette recherche cherche à réaliser en s'attachant à i) comprendre les principaux déterminants du comportement d'achat des véhicules privés (voitures particulières), ii) les critères et conditions d'une diffusion plus ou moins rapide des véhicules à faible émission de carbone dans la flotte en circulation, iii) et les politiques publiques d'accompagnement nécessaires. C'est en effet l'analyse conjointe de ce triptyque - offre technologique, demande d'achat et, à l'intersection des deux premiers, la conception optimale du policy-mix qui permettra de modéliser au mieux la demande de transport routier européen et ses conséquences en termes d'émissions polluantes à l'horizon 2040.

Suite au projet européen SCelecTRA, IFPEN a développé un modèle de demande de transport routier : le modèle $DRIVE^{RS}$ pour la modélisation des choix discrets pour les scénarios de flotte de véhicules à faible émission de carbone. Ce modèle de simulation intégré permet d'établir des scénarios d'évolution du parc routier en France et en Europe à l'horizon 2040 en étudiant la dynamique du marché des véhicules particuliers par type de technologie (mode de propulsion). Il permet également d'étudier les effets d'une large gamme d'instruments et de politiques publiques et d'évaluer les impacts environnementaux (CO_2, CH_4, CO, SOx, NOx, particules) de ces politiques dans le domaine des transports (SCelecTRA, 2015).

Le modèle DRIVERS se concentre sur le comportement individuel en ce sens qu'il simule les changements de comportement des consommateurs en réponse à l'évolution des conditions économiques. Il se compose de deux modules. Le premier module consiste en un modèle économétrique de la demande de transport routier (Gastineau, P., Chèze, B., 2018). Ce module fournit des projections de la demande de transport routier jusqu'en 2040, par année et par pays. Elle est exprimée soit en termes de nombre total de véhicules (i.e., stock), sans distinction de type de véhicule ou de technologie, soit en termes de distance parcourue (i.e., mobilité). Le deuxième module consiste en un modèle de choix discret qui permet de ventiler les nouvelles ventes pour chaque année entre les différents types de véhicules existants, c'est-à-dire par type de voiture et par technologie. Les prévisions de ce module reposent sur un calcul du coût total de possession (CTP), qui attribue une désutilité à chaque élément de coût tel que le prix d'achat, les coûts de carburant et les coûts d'entretien. La consommation unitaire d'énergie des différents véhicules et leurs émissions polluantes sont ensuite déduites. Ce type de modélisation de la demande de transport à l'aide de modèles de choix discrets est relativement courant dans la littérature. Le modèle MoMo, par exemple, utilisé par l'AIE dans ses projections de la demande de transport, est basé sur cette méthodologie. La structure du modèle DRIVERS est donc largement basée sur celle du modèle TREMOVE (De Ceuster et al., 2007) développé à l'origine pour la Commission européenne.

En général, le comportement d'achat des véhicules traditionnels (ICE) et leur diffusion dans le parc automobile total sont assez bien décrits par des modèles de choix discrets. Toutefois, ce n'est pas le cas pour les véhicules à faible émission de carbone, en particulier dans le modèle DRIVERS. Il peut être nécessaire de prendre en compte des facteurs autres que les simples comparaisons de coûts pour expliquer les préférences des individus pour les véhicules à faible émission de carbone, et plus généralement pour toute nouvelle technologie. Ces facteurs peuvent inclure les caractéristiques socio-économiques et culturelles de l'individu, telles que sa sensibilisation à l'environnement, son affinité avec les nouvelles technologies ou sa tolérance au risque lié à l'adoption d'une nouvelle technologie.

Au-delà de la compréhension des préférences des individus pour les technologies vertes, il convient d'examiner la question de l'intervention des pouvoirs publics en faveur de ces véhicules à faibles émissions de carbone. En raison notamment des coûts fixes très élevés (pour l'installation des infrastructures de recharge, par exemple), il est très difficile de voir ces technologies émerger sans une politique de soutien pour les aider à se lancer. Comme pour les technologies telles que l'énergie solaire ou éolienne, il faut s'attendre à des réductions de coûts très importantes pour ces technologies au fur et à mesure de leur développement. Une fois qu'une certaine masse critique de production de ces véhicules a été atteinte et que les coûts initiaux des véhicules ressemblent à ceux des véhicules à moteur à combustion interne, l'aide publique peut donc être réduite grâce aux effets de "l'apprentissage par la pratique" et des économies d'échelle sur les coûts de production.

L'apport original de cette thèse réside d'abord dans le développement d'un modèle intégré de la demande de transport routier, afin de formuler des scénarios cohérents de diffusion des différentes technologies automobiles, par pays et au niveau européen, pour les véhicules particuliers. Ces modèles sont très gourmands en données, ce qui explique qu'il y en ait relativement peu qui atteignent l'échelle du modèle DRIVERS.

Ensuite, d'un point de vue théorique, l'originalité de cette thèse par rapport à la littérature consiste à intégrer des idées de l'économie comportementale dans la méthode de modélisation DRIVERS, qui jusqu'à présent repose principalement sur une analyse basée sur le TCO, afin de mieux modéliser le développement et la diffusion dans le parc européen de véhicules à faible émission de carbone. L'objectif est d'"endogénéiser" le comportement d'achat de ces types de véhicules en le faisant dépendre d'un certain nombre de facteurs explicatifs spécifiques à chaque type de véhicule.

Le premier facteur est l'impact des différentes politiques publiques existantes : l'utilisation de subventions, le développement d'infrastructures de recharge, l'augmentation de la fiscalité, voire les interdictions de circulation mises en place par certaines villes pour les véhicules les plus polluants, etc. Le deuxième facteur est la préférence pour les caractéristiques du véhicule en elles-mêmes : prix d'achat, coûts du carburant et de l'entretien, état actuel des infrastructures de recharge. Cependant, la diffusion de ces véhicules dépendra également de caractéristiques telles que le temps de recharge nécessaire, l'autonomie des batteries et leurs coûts, par exemple. Ces caractéristiques peuvent évoluer positivement dans le temps au fur et à mesure que ces technologies se répandent grâce à des effets de réseau, des économies d'échelle ou des effets d'apprentissage. Tous ces éléments doivent être correctement modélisés pour définir la meilleure combinaison de politiques - et sa dynamique temporelle - afin de déclencher le lancement de ces nouvelles technologies et de soutenir leur développement.

Pour encourager le déploiement rapide de ces véhicules, les autorités publiques doivent mettre en œuvre des politiques visant à la fois l'achat de ces nouveaux modes de transport et le développement de leur infrastructure de recharge. Dans le premier cas, les pouvoirs publics agissent principalement sur la demande en créant des incitations, monétaires ou non, pour les consommateurs, rendant ainsi la possession de ces véhicules plus favorable. La demande de ravitaillement en énergie qui en résulte devrait naturellement accélérer le déploiement des points de recharge. Dans le second cas, le gouvernement agit davantage du côté de l'offre en encourageant le déploiement d'infrastructures par le biais de subventions ou de partenariats public-privé coordonnés, ce qui, à son tour, encouragera la demande pour ces véhicules.

Depuis la contribution de Bass (1969), les modèles de diffusion-adoption des nouvelles technologies reposent sur l'hypothèse qu'une population d'acheteurs peut être divisée en deux classes distinctes : les "adoptants" et les "suiveurs". Les premiers sont des technophiles, en ce sens que leur intérêt pour les nouvelles technologies (qu'ils possèdent) l'emporte sur les coûts souvent (plus élevés) associés à leur achat.

Afin de classer la population des acheteurs potentiels, nous devons comprendre que dans le cas des VE, les adoptants prennent plusieurs risques. Tout d'abord, la disponibilité et la suffisance de l'infrastructure de recharge constituent un obstacle important à l'adoption des véhicules électriques à batterie (BEV). L'incertitude quant au niveau futur de l'infrastructure de recharge électrique rapide, combinée à la faible proportion actuelle de stations de recharge, suscite l'appréhension des utilisateurs potentiels. Cette incertitude a un effet négatif sur le taux d'adoption des véhicules. En outre, l'anxiété liée à l'autonomie, ou la crainte de manquer de batterie avant d'atteindre une station de recharge, reste un facteur influent, malgré les progrès technologiques. L'autonomie des BEV est toujours considérée comme un inconvénient par rapport aux véhicules conventionnels.

C'est pourquoi il est important de connaître les préférences en matière de risque pour comprendre et surmonter les obstacles à l'adoption des VE. Les risques associés aux véhicules électriques peuvent être perçus différemment selon les individus, en fonction de facteurs tels que leurs connaissances sur les voitures électriques, leur attitude à l'égard de la technologie, la qualité de l'environnement et leur tolérance personnelle au risque. Reconnaître ces variations dans les préférences en matière de risque peut aider les décideurs politiques et les fabricants à adapter leurs stratégies à des groupes spécifiques, tels que les "adopteurs précoces" ou les personnes "soucieuses de l'environnement" qui peuvent avoir une plus grande confiance dans les BEV. En intégrant l'incertitude et les attitudes à l'égard du risque dans l'analyse, il devient possible de créer des politiques publiques et des incitations plus réalistes et plus efficaces pour surmonter les obstacles et augmenter les taux d'adoption des véhicules électriques. L'intégration du risque et de l'incertitude dans la méthodologie de recherche peut donc fournir des informations plus approfondies sur les facteurs affectant l'adoption des VE et faciliter le développement d'interventions ciblées pour soutenir la transition vers une mobilité propre.

La littérature actuelle manque encore d'enquêtes auprès des consommateurs pour caractériser correctement les catégories d'utilisateurs de véhicules dans le cas des véhicules à faible émission de carbone, et les politiques d'incitation qui en découlent. En menant de telles enquêtes, en utilisant des méthodes de révélation des préférences déclarées, cette thèse apportera une contribution certaine au domaine de l'économie des transports. Plus précisément, elle observera l'hétérogénéité et la distribution des préférences de la demande. Les résultats seront analysés statistiquement en utilisant les méthodes d'estimation micro-économétriques les plus avancées pour traiter les questionnaires d'expériences de choix afin d'étudier le comportement des ménages, leur sensibilité à différents outils politiques (incitations), et l'hétérogénéité de leurs préférences pour les véhicules à faible émission de carbone.

Méthodologie

L'analyse de la transition vers des technologies alternatives pour les véhicules est une entreprise complexe qui nécessite une série de méthodologies. Chacune d'entre elles a ses points forts et ses limites, ce qui les rend adaptées à des domaines d'étude spécifiques, que nous examinerons plus en détail dans quelques instants.

La méthode de l'expérience de choix discret

Les expériences de choix discrets (DCE) présentent aux individus des alternatives exclusives et leur demandent de choisir leur préférence, généralement par le biais d'une enquête. Chaque alternative est décrite par un ensemble d'attributs, et les niveaux de ces attributs varient d'une alternative à l'autre. Ces alternatives peuvent couvrir un éventail de possibilités, allant de produits concurrents à des modes d'action distincts. Dans toutes ces situations, le résultat de la décision ne peut adopter que des valeurs spécifiques et dénombrables. En observant les choix que font les individus parmi différents ensembles d'alternatives, les chercheurs peuvent déduire les préférences sous-jacentes et les compromis que les individus sont prêts à faire entre différents attributs. En observant les choix que font les individus parmi différents ensembles d'alternatives, les chercheurs peuvent déduire les préférences sous-jacentes et les compromis que les individus sont prêts à faire entre différents attributs.

L'un des principaux atouts des DCE est leur capacité à estimer la valeur que les individus accordent à des biens ou à des attributs non marchands. Par exemple, les DCE peuvent être utilisées pour estimer la valeur que les gens accordent à la préservation d'un habitat naturel ou à la réduction de la pollution atmosphérique. En économie des transports, les expériences de choix discrets sont particulièrement utiles pour modéliser et analyser les décisions en matière de transport, qu'il s'agisse du choix d'un mode de transport, d'un itinéraire ou même de la durée d'un voyage, qui consistent intrinsèquement à faire des choix parmi des alternatives discrètes. Par exemple, lorsqu'ils évaluent les options de transport public, les individus peuvent prendre en compte des facteurs tels que la durée du trajet, le coût, la commodité et la fiabilité. En présentant aux individus des scénarios hypothétiques qui font varier ces attributs, les DCE peuvent aider les chercheurs à comprendre les compromis que les navetteurs sont prêts à faire. Au-delà des préférences individuelles, les DCE en économie des transports peuvent également mettre en lumière l'adoption potentielle de nouvelles initiatives en matière de transport ou l'effet de l'investissement dans des infrastructures telles que les stations de recharge.

Les données des DCE sont ensuite analysées à l'aide d'un modèle de choix discret. Selon les travaux de Train (2009), un modèle de choix discret est une approche conceptuelle visant à comprendre et à prédire les décisions prises par des entités, qu'il s'agisse d'individus ou d'entreprises. L'objectif principal est ici de découvrir le mécanisme comportemental à l'origine de ces choix. D'un point de vue causal, les choix ne sont pas faits de manière isolée ; ils sont influencés par différents facteurs. D'une part, nous avons des facteurs observés, qui sont des éléments mesurables tels que le prix ou la réputation d'une marque qui peuvent influencer une décision. D'autre part, il y a les facteurs non observés, qui sont des variables insaisissables telles que les préférences personnelles ou les expériences passées. Ces facteurs observés et non observés interagissent pour façonner le choix de l'agent, appelé processus comportemental, cette fonction fonctionne de manière déterministe. Compte tenu des variables connues et inconnues, elle peut prédire avec précision la décision de l'agent. Par conséquent, une expérience de choix discret vise essentiellement à déterminer comment différents éléments tangibles et intangibles influencent une décision parmi un ensemble d'options (Train, 2009).

Au cœur des modèles de choix discrets se trouve l'hypothèse selon laquelle les individus prennent des décisions pour maximiser leur utilité ou leur satisfaction. Cette hypothèse est souvent examinée à l'aide d'un modèle d'utilité aléatoire (RUM). S'inspirant de l'étude fondamentale sur les applications de transport réalisée par Domencich and McFadden (1975), les chercheurs utilisent généralement des modèles logit ou probit pour déterminer les probabilités de choix de chaque option et pour identifier les différents facteurs qui influencent ces probabilités.

Cependant, l'un des principaux défis à la crédibilité de la méthode des préférences déclarées est la question du biais hypothétique (L'Haridon, 2018). Les gens peuvent prendre des décisions qui s'écartent de leur comportement dans le monde réel parce que la question est posée dans un contexte hypothétique sans engagements ou conséquences économiques réels. Cette question est particulièrement importante dans un contexte politique, où les individus peuvent ne pas être disposés à admettre leurs véritables opinions, ou peuvent prendre des décisions trop vertueuses, lorsqu'ils sont confrontés à un sondage.

La méthode de l'expérience en laboratoire

En économie expérimentale, une expérience en laboratoire est une étude contrôlée menée en laboratoire pour étudier les comportements économiques et les processus de prise de décision. Contrairement aux expériences sur le terrain ou aux études d'observation, les expériences en laboratoire sont menées dans un cadre contrôlé, généralement une salle équipée d'ordinateurs où les participants prennent des décisions qui ont souvent des conséquences monétaires réelles. Ce cadre permet aux chercheurs de manipuler des variables spécifiques et d'observer les effets sur les choix et les comportements des participants (L'Haridon, 2018).

Dans la recherche économique, l'utilisation de jeux dans les expériences en laboratoire est devenue une méthodologie fondamentale pour étudier les interactions stratégiques, la coopération et les processus de prise de décision. Les jeux, tels que le dilemme du prisonnier, le jeu de l'ultimatum et le jeu des biens publics, simulent des scénarios du monde réel dans lesquels les participants doivent prendre des décisions qui ont des implications à la fois pour eux-mêmes et pour les autres. Les expériences en laboratoire permettent d'observer les effets de l'influence sociale au sein d'un groupe. Dans les limites contrôlées d'un laboratoire, les chercheurs peuvent systématiquement introduire et manipuler la dynamique de groupe pour observer comment les processus de prise de décision des individus sont affectés par la présence et les opinions des autres. Par exemple, en plaçant les participants dans des groupes et en leur permettant de discuter ou d'observer les choix des autres, les chercheurs peuvent déterminer si les individus se conforment aux normes du groupe, s'ils succombent à la pression de leurs pairs ou s'ils adoptent un comportement grégaire. Ce processus est crucial, car les décisions prises sous l'influence des pairs peuvent s'écarter considérablement de celles prises isolément.

Selon Roth (1988), les expériences en laboratoire en science économique servent trois objectifs essentiels. Les expériences en laboratoire permettent tout d'abord d'évaluer les modèles théoriques en les soumettant à des tests empiriques. Ce faisant, elles valident ou réfutent l'applicabilité de ces modèles en imitant les comportements et les résultats économiques de la vie réelle. Au-delà de la simple vérification des théories existantes, les expériences plongent de manière proactive dans la réalité pour découvrir de nouveaux faits et de nouvelles observations. Dans ce contexte, les expériences fonctionnent comme des "expositions" et non comme de simples "tests", comme le souligne Sugden (2005). Ces "expositions" de comportements et de résultats réels dans des environnements contrôlés peuvent ensuite être utilisées pour affiner ou même construire de nouveaux modèles théoriques. Enfin, les expériences ne se limitent pas au monde universitaire. En exploitant les enseignements tirés des tests théoriques et des expositions dans le monde réel, les expériences en laboratoire peuvent directement influencer l'élaboration des politiques. Elles jouent le rôle de conseillers précieux, offrant des perspectives fondées sur des preuves qui peuvent guider les décisions politiques vers des résultats plus efficaces et plus efficients. Cela est particulièrement vrai lorsqu'il s'agit d'informer les régulateurs ou d'autres décideurs clés sur les résultats potentiels de politiques publiques nouvelles ou révisées. Le principe sous-jacent consiste à exploiter les expériences en tant que terrains d'essai pour différents environnements décisionnels, qu'il s'agisse de mécanismes de marché, de structures organisationnelles ou de modifications de politiques (L'Haridon, 2018).

Pour garantir la validité interne de l'expérience, il est essentiel d'établir une relation de cause à effet claire entre les changements de la variable indépendante et les changements observés dans la variable dépendante. En s'appuyant sur les recherches de Smith (1982), des incitations monétaires ont été incorporées dans les expériences en laboratoire. Ces incitations sont essentielles pour tirer des conclusions sur les comportements dans l'expérience, qui sont censés être influencés par l'environnement et les institutions mises en place dans le laboratoire. En introduisant ces incitations, l'expérience en laboratoire peut être perçue comme un système microéconomique dans lequel : plus est toujours préférable à moins, les différences de gains rendent les choix significatifs et l'expérience globale offre suffisamment de valeur pour compenser le coût d'opportunité de la participation.

Les incitations monétaires répondent également aux préoccupations relatives à la validité externe, en garantissant que les comportements observés dans le cadre de l'expérience peuvent être généralisés en dehors du laboratoire. En nous appuyant sur le principe du parallélisme, nous soutenons que "les propositions sur le comportement individuel et les performances institutionnelles testées dans les micro-économies de laboratoire sont également applicables aux micro-économies hors laboratoire, à condition que les mêmes conditions ceteris paribus soient remplies" (Smith, 1982).

Résumé

Cette thèse cherche à comprendre les changements de comportement des utilisateurs de véhicules, à anticiper les ruptures technologiques et à définir les meilleures politiques publiques possibles pour soutenir la mobilité durable en les intégrant dans un modèle de choix discret, dans le but de développer des scénarios intégrés et cohérents pour la diffusion de différentes technologies pour les véhicules de tourisme

en France à un niveau agrégé. Notre analyse est divisée en trois parties. Le premier chapitre utilise une expérience de choix discret pour analyser les préférences des utilisateurs pour les nouvelles technologies automobiles. Le deuxième chapitre utilise des méthodes d'économie expérimentale, également appelées "expériences en laboratoire", afin de rechercher les préférences des sujets pour différentes politiques publiques promouvant la mobilité durable, telles que les taxes ou les réglementations sur les achats de voitures. Le troisième chapitre utilise les connaissances économiques et comportementales du premier chapitre et les applique au modèle "DRIVERS", qui cherche à donner des projections sur la composition future du parc automobile français en fonction de différents scénarios de politique publique. Jusqu'à présent, le modèle "DRIVERS" ne s'appuie que sur des facteurs de coût total de possession et des données économiques pour faire des projections sur la taille et la composition du parc automobile.

S'appuyant sur les observations empiriques de ces trois chapitres, la thèse se conclut par une série de recommandations politiques. Les actions politiques devraient englober des conditions qui promeuvent activement les véhicules propres, y compris des investissements substantiels dans les infrastructures de recharge, des subventions ciblées pour les technologies des véhicules électriques et alternatifs, et des campagnes de sensibilisation du public de grande envergure. Ces stratégies sont essentielles pour étendre l'attrait des VE au-delà des adeptes de la première heure et des enthousiastes, en veillant à ce qu'ils deviennent une option attrayante pour un segment plus large de la population. Cela est particulièrement important dans les régions situées en dehors des zones urbaines, où l'accessibilité et l'acceptation des véhicules électriques peuvent être plus difficiles. En favorisant ces conditions, les décideurs politiques peuvent faciliter une transition en douceur vers des transports plus propres, en s'alignant sur les objectifs environnementaux et en faisant des véhicules électriques un choix viable pour un éventail de plus en plus diversifié de consommateurs. Il préconise également la mise en œuvre de politiques tenant compte du contexte. Pour réduire efficacement le nombre de véhicules à moteur à combustion interne dans le parc automobile et, par conséquent, la pollution atmosphérique, il sera essentiel de combiner des incitations tarifaires et des restrictions ciblées sur les véhicules à moteur à combustion interne. Ces restrictions peuvent prendre diverses formes, notamment l'interdiction pure et simple des véhicules dans certaines zones, la mise en place de péages spécifiques pour les véhicules à moteur à combustion interne ou la création de zones à faibles émissions qui limitent ou excluent leur accès. En rendant les véhicules à moteur à combustion interne moins attrayants ou moins pratiques dans certains contextes, ces restrictions peuvent accélérer la transition vers des solutions de transport plus propres. Associées à des mesures incitatives qui rendent ces options plus propres financièrement attrayantes, ces stratégies peuvent constituer une approche globale de la réduction de l'impact environnemental des transports et de la promotion d'un avenir plus durable.

L'ordre et le choix de la mise en œuvre des politiques doivent dépendre des considérations culturelles de la région où elles sont mises en œuvre et, dans le cas des taxes, peuvent nécessiter un essai de politique afin d'en améliorer l'acceptabilité. Ensemble, ces recommandations visent à accélérer le passage à des véhicules alternatifs respectueux de l'environnement, afin d'atteindre les objectifs de réduction des émissions.

En résumé, cette thèse vise à démêler l'écheveau complexe des facteurs qui façonnent la transition vers un secteur des transports à faible émission de carbone en France. Grâce à une exploration multidimensionnelle englobant le comportement des consommateurs, l'acceptabilité des politiques et les améliorations de la modélisation, elle cherche à fournir une compréhension plus nuancée de cette transition. Les enseignements tirés de cette étude devraient constituer une contribution précieuse pour les décideurs politiques qui s'efforcent d'atteindre l'objectif de la mobilité durable.

Chapitre 1

Ce chapitre est issu d'une étude réalisée en collaboration avec Benoît Chèze [6] et Johanna Etner.[7] Ce rapport étudie les obstacles à l'adoption des véhicules électriques en France par le biais d'une étude des préférences déclarées, en utilisant une enquête en ligne menée en janvier 2021. Deux expériences de choix discrets ont été réalisées, portant sur les petits véhicules de taille " urbaine " et les véhicules de taille " familiale " de taille moyenne. L'originalité de l'étude réside dans sa prise en compte de l'incertitude concernant le niveau futur de l'infrastructure de recharge électrique rapide, un obstacle important à l'adoption des véhicules électriques.

Les résultats révèlent que des facteurs tels que le prix d'achat, le coût du carburant, l'autonomie, les émissions de gaz à effet de serre et l'infrastructure de recharge sont les principaux déterminants de l'adoption d'un véhicule, quelle que soit sa taille. Les personnes interrogées privilégient les coûts immédiats, tels que le prix d'achat,

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par rapport à d'autres attributs monétaires, et affichent une préférence non linéaire pour l'autonomie du véhicule. L'incertitude quant à l'infrastructure de recharge future a eu un impact négatif sur les taux d'adoption, en particulier pour les véhicules de taille moyenne.

Les profils psychologiques, y compris les connaissances sur les voitures électriques, les tendances à l'adoption précoce et la conscience environnementale, ont eu une influence significative sur les préférences. La connaissance des véhicules électriques, l'intérêt pour la technologie automobile, la tolérance au risque et la conscience environnementale ont été associés à une plus grande acceptation des technologies des véhicules alternatifs. Ces profils sont souvent liés à des individus plus jeunes, plus riches et plus éduqués.

L'étude se termine par des recommandations politiques, soulignant la nécessité d'augmenter les subventions pour les véhicules électriques, de pénaliser les véhicules émettant le plus de gaz à effet de serre et d'investir dans des infrastructures publiques de recharge rapide. L'incertitude entourant l'infrastructure de recharge est considérée comme un obstacle important, en particulier pour les utilisateurs de véhicules de taille moyenne. Le prix d'achat élevé reste le principal obstacle à l'adoption généralisée des véhicules électriques.

Ce premier chapitre ouvre la voie au reste de la thèse en démontrant l'importance de la dimension comportementale dans l'adoption des véhicules à faible émission de carbone. Dans les chapitres suivants, ces idées seront développées et intégrées dans un modèle de simulation des transports afin d'améliorer sa précision prédictive et sa pertinence politique.

Chapitre 2

Ce chapitre est issu d'une étude réalisée en collaboration avec la doctorante Maria J. Montoya-Villalobos.[8] Elle explore les questions relatives à l'acceptabilité des politiques publiques, en se concentrant particulièrement sur les politiques environnementales visant à réduire les émissions de carbone dans le secteur des transports. Par le biais d'une expérience en laboratoire, l'étude compare deux types d'instruments politiques : les taxes avec redistribution égale et les normes réglementaires. Elle étudie également l'influence des visions culturelles du monde sur l'acceptabilité et

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examine comment les essais politiques peuvent affecter le soutien à ces politiques.

L'expérience simule le marché des transports en présentant aux participants des options correspondant à différents modes de transport, notamment les véhicules électriques, les transports publics et les véhicules traditionnels. Deux interventions politiques, la taxation et les normes réglementaires, sont introduites et soumises à un vote majoritaire pour mesurer l'acceptabilité. L'étude est enrichie par des exemples concrets tels que la ZFE (Zone à faibles émissions) de Paris en 2024 et l'ULEZ (Ultra Low Emission Zone) de Londres.

Les résultats révèlent une image nuancée du soutien politique. Les normes réglementaires sont généralement mieux acceptées que les taxes, 57,8 % des participants se prononçant en faveur de leur mise en œuvre. En outre, le soutien est renforcé par l'expérience d'un essai de politique pour les normes réglementaires, mais pas pour les taxes. L'étude met en évidence le rôle des dimensions culturelles, en particulier des visions du monde hiérarchiques-égalitaires, dans le rejet des politiques fiscales.

Ce chapitre souligne que la culture et le contexte régionaux jouent un rôle important dans la mise en œuvre des politiques publiques. Il souligne l'importance de comprendre les variations culturelles et suggère de faire participer le public par le biais de référendums et d'institutions délibératives afin d'améliorer l'acceptation. Les résultats indiquent également qu'il est difficile de modifier les préférences, même après des efforts pédagogiques, en particulier lorsqu'il existe une forte aversion pour les politiques.

La nouveauté de l'étude réside dans sa conception expérimentale qui élargit les possibilités de choix, en ajoutant de l'hétérogénéité et en proposant des interdictions avec des alternatives disponibles. Cela permet une représentation plus réaliste des scénarios de politique publique, en particulier dans le domaine des transports.

Chapitre 3

Dans le contexte de la transition énergétique européenne et de l'objectif collectif de réduction des émissions de gaz à effet de serre (GES), ce chapitre explore l'intégration de l'économie comportementale dans le modèle de flotte existant DRIVERS (DiscRete choIce modeling for low-carbon VEhicles fleet scenaRioS). Cette approche intégrée vise à fournir une représentation plus nuancée de la dynamique d'achat des véhicules privés en France et en Europe jusqu'en 2040, en mettant particulièrement l'accent sur la transition vers une mobilité à faible émission de carbone.

Le modèle DRIVERS original a été développé pour évaluer diverses politiques et stratégies publiques de décarbonisation des transports, sur la base d'une modélisation des choix discrets. Cependant, ses prévisions pour les véhicules à faible émission de carbone pourraient être plus réalistes si l'on y intégrait les connaissances en économie comportementale du chapitre 1. Ce chapitre présente la méthodologie et le processus d'intégration de ces connaissances comportementales, en modifiant le modèle DRIVERS pour mieux expliquer le lancement et le déploiement des véhicules à faible émission de carbone.

Le modèle modifié projette les stocks de véhicules et les distances parcourues jusqu'en 2050, avec des scénarios distincts pour les véhicules électriques et thermiques. Il calcule également la consommation d'énergie et les émissions dans des conditions de conduite réelles. Les résultats mettent en évidence une propension à augmenter les ventes de véhicules thermiques, avec des émissions totales supérieures à celles prévues par le modèle original. Les résultats du modèle révisé montrent également une sensibilité accrue aux politiques publiques, aux avancées technologiques et aux conditions économiques qui affectent l'accessibilité des véhicules.

Le chapitre examine en outre l'impact profond de l'interdiction des ventes de véhicules thermiques d'ici à 2035, en soulignant le besoin urgent de politiques publiques spécifiques pour combler l'écart entre les émissions prévues des véhicules et les objectifs fixés par l'État français. Les nouvelles prévisions, moins optimistes, soulignent le rôle essentiel de l'accessibilité financière et la nécessité d'interdire les véhicules à moteur à combustion interne dans le cadre de la transition vers des technologies automobiles plus écologiques.

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Introduction

General Introduction

The world is still far from reaching the target of stabilizing global warming to 1.5°C despite the 2015 Paris climate pledges. The Intergovernmental Panel on Climate Change (IPCC) reports that global greenhouse gas (GHG) concentrations have already reached levels that could lead to a global temperature increase beyond 1.5°C above pre-industrial levels by 2100, necessitating significant emission reductions. Even with maximum efforts, it is predicted we will reach a 1.7°C increase by 2100. To reach the target, emissions must be reduced to 23 gigatonnes (Gt) by 2030 and net-zero by 2050 (International Energy Agency, 2022). The Paris Agreement, signed by 197 countries in 2015, aims to limit this increase to 2°C, ideally 1.5°C. The United Nations stipulates that achieving this target requires unprecedented societal changes, a 45% reduction in global carbon dioxide (CO2) emissions compared to 2010 levels by 2030, and net zero emissions by 2050 (European Environment Agency, 2022).

Transitioning from global agreements to regional commitments, the European Green Deal proposes a 55% reduction in GHG emissions by 2030 compared to 1990, and aims for the EU to become climate neutral by 2050. This target has been legally enacted in the European Climate Law, and means that any remaining GHG emissions must be offset by carbon capture. In order to achieve this overall climate neutrality, the transport sector will need to reduce its GHG emissions by 90% by 2050, as outlined in the Sustainable and Smart Mobility Strategy (Commission, 2020). Reducing the transportation sector's carbon emissions is a key element in the sustainable reduction of global GHG emissions. In Europe, it is the second largest emitter after the energy industries. The sector contributes to about 24% of total GHG emissions, of which 72% are from road transport (Commission, 2018). Road transport greenhouse gas emissions in the EU have increased by 28% between 1990 and 2019, making up 72% of the EU's total transport emissions (European Environment Agency, 2022).

Analyzing the past trends, between 2000 and 2019, carbon dioxide emissions from passenger cars in the EU increased by 5.8%, primarily due to a 16% growth in passenger transport volumes and a slightly increasing share of car transport among land-based transport modes (European Environment Agency, 2022). Driving factors behind the trend include increasing demand for transport, growth in passenger transport volumes, and a rising share of car transport among land-based modes. These increases are only partially offset by improved energy efficiency and the use of biofuels.

Despite overall reductions in emissions in other sectors, transport carbon dioxide emissions are forecasted to be 3.5% higher in 2030 than in 1990, and to fall by only 22% by 2050 compared to 1990 levels. To meet the climate neutrality target, a 90% reduction is needed (European Environment Agency, 2022). In view of this, and in order to comply with the 2015 Paris agreement, the European Commission (EC) has set a target of reducing GHG emissions from transport by 20 percent below 2008 levels by 2030. In addition, as part of its road-map towards the year 2050 (EC, 2011), the EC has also identified the potential for a 60% reduction in GHG emissions compared to 1990 emission levels. Thus, road transport appears to the authorities as one of the key sectors in the fight against climate change and air pollution. The sector faces two challenges: i) a global challenge, that of reducing its GHG emissions, and ii) a more local public health challenge, that of reducing its emissions of fine particles, carbon monoxide, etc., generated by the growth of the number of motorized transport in cities. Achieving a 95% reduction in transport emissions by 2050 requires extensive new infrastructure and clean technologies. By 2050, all cars on the road will need to run on electricity or fuel cells while aviation and shipping will largely rely on biofuels and synthetic fuels (International Energy Agency, 2021).

The transition to electric vehicles (EVs) is essential to achieve the Paris climate agreement's objectives (IEA, 2017). Electric vehicles produce less greenhouse gases and air pollutants across their lifecycle compared to their petrol or diesel counterparts. They also offer air quality benefits due to zero or low exhaust emissions of pollutants. In Norway and the Netherlands, new passenger cars emitted 54% and 38% less CO in 2017 than in 2001 respectively due to the combination of the electrification of the fleet and the decrease in new ICE vehicle's emissions, both driven by policies that favored low-emitting vehicles (European Environment Agency, 2019).

However, electric vehicles (EVs) face several disadvantages when compared to internal combustion engine (ICE) vehicles. Firstly, the sticker price of EVs before subsidies is generally higher, with the average purchase price of a new electric car in 2021 being about $10,000 more than the industry average for gas-powered vehicles.[9] Although this gap is expected to narrow with technological advancements, it still presents a barrier to many potential buyers. Secondly, the range of EVs is typically shorter, with the most affordable EV in 2023 offering an estimated range of 415 kilometers, compared to around 700 kilometers for a typical ICE vehicle.[10] Lastly, charging times for EVs are longer than standard ICE refueling times, even with fast charging options (using a Direct Current Fast Charging station typically takes between 20 minutes to 1 hour to charge a BEV to 80 percent)[11], adding inconvenience for users and potentially limiting the practicality of EVs for long-distance travel. Given the challenges faced by electric vehicles, policy support is essential to foster their adoption and competitiveness with ICE vehicles. By providing support through favorable policies, governments can accelerate the transition to cleaner transportation, reduce greenhouse gas emissions, and stimulate innovation and growth in the electric vehicle industry.

Government intervention can take place on both the supply and demand sides, through a combination of incentives and/or restrictions. A classic distinction is made between binding regulatory measures (e.g. emission standards and speed limits) and economic tools of an incentive nature (such as taxes, purchase incentives, and penalties). These different types of policies do not all target the same types of uses and the same types of actors in the transport sector, and may also pose problems of equity. However, they all aim to improve the energy efficiency of transport vehicles and to increase the share of renewable or non-fossil fuels in the transport sector. Countries with proactive EV policies have seen substantial reductions in emissions. Challenges include providing sufficient charging infrastructure, managing increased electricity demand, and large-scale battery production (European Environment Agency, 2022). Publicly accessible chargers are essential for EV adoption, especially in dense urban areas where home charging is limited. As of 2022, there were 2.7 million public charging points worldwide, over 900,000 of which were

[9] "Electric vs Gas Cars: Is It Cheaper to Drive an EV?" Natural Resources Defense Council (NRDC), https://www.nrdc.org/stories/electric-vs-gas-cars-it-cheaper-drive-ev.

[10] Chevrolet, "Bolt EV: Electric Car,", https://www.chevrolet.com/electric/bolt-ev.

[11] United States Department of Transportation, "Charger Types and Speeds," 2023, https://www.transportation.gov/rural/ev/toolkit/ev-basics/charging-speeds.

installed that year - a 55% increase from 2021 and in line with pre-pandemic growth (International Energy Agency, 2023). Public charging infrastructure is expanding, supported by initiatives like the European Union's Alternative Fuels Infrastructure Regulation (AFIR) and the United States' National Electric Vehicle Infrastructure Formula Program (NEVI) (International Energy Agency, 2023). Despite a growth in the EV market, consumer purchasing behavior and public policy must align to promote low-carbon vehicles.

The European Commission has set specific targets for transport, focusing on a 55% reduction in GHG emissions by 2030 compared to 1990 levels.[12] Governments are employing a blend of regulatory and economic incentives to increase energy efficiency and renewable fuel use. Recent policies include the Fit for 55 package, requiring a 55% and 50% reduction in emissions of new cars and vans by 2030 (compared to 2021) and 100% for both by 2035 (International Energy Agency, 2023). This is part of the EU's increasing ambitions for decarbonization through electrification.

In the United States, the Inflation Reduction Act emphasises the strengthening of domestic supply chains for EVs, EV batteries and battery minerals, laid out in the criteria to qualify for clean vehicle tax credits. It includes various tax incentives and funding programs to accelerate EV adoption, such as the Clean Vehicle Tax Credit. It also introduced supply-side Advanced Manufacturing Production Tax Credits, providing subsidies for domestic battery production. However these measures are conditional on the vehicle being assembled in the U.S. (International Energy Agency, 2023). The California Air Resources Board approved the Advanced Clean Cars II (ACC II) rule in November 2022, aiming to gradually increase the share of zero-emission vehicles (ZEVs) until all vehicles sold from 2035 onwards are ZEVs or PHEVs. Several US states have followed suit (International Energy Agency, 2023). Several European countries strengthened their policies to accelerate EV adoption: The UK plans to end the sale of fully Internal Combustion Engine (ICE) cars and vans by 2030, transitioning to 100% ZEV sales by 2035. Greece now only allows the sale of ZEVs from 2030. Other countries like Italy, Spain, Denmark, Finland, Austria, Croatia, and Cyprus introduced various subsidies and tax changes (International Energy Agency, 2023). Policy has played a significant role in the growth of EVs. In major EV markets like China, Europe, and the U.S, early adoption was often stimulated by policies like vehicle purchase incentives and direct

[12] European Commission, "2030 Climate Target Plan," Climate Action, https://climate.ec.europa.eu/eu-action/european-green-deal/2030-climate-target-plan_en.

incentives for carmakers (International Energy Agency, 2023). However, countries like Norway, the United Kingdom, Germany, Ireland, Netherlands, Sweden, and France have begun reducing EV incentives or subsidies as EVs become more affordable and widespread (International Energy Agency, 2023).

Despite a certain development of the electric vehicle market (the market share in Europe reaches 10.5% in 2020 for BEV and PHEV) , a large amount of BEV's in the vehicle fleet is not yet in sights. The low rate of fleet renewal raises two questions, i) one of understanding consumer purchasing behavior and ii) one on the optimal design of public policies to stimulate and promote the diffusion of low-carbon passenger vehicles. While the development of innovative, low-carbon transportation solutions may encounter challenges without support from public decision-makers, the abundance of public policies prompts the question of how they can be effectively coordinated to ensure efficiency without becoming overly burdensome for governments.

Since the events of the "Dieselgate" (2015) incident, we have seen an increase in implications from these public actors and at different scales of application (urban, interurban, national, international). These different initiatives can have contradictory or undesired effects. For example, the fact that some cities are beginning to introduce traffic bans on old diesel vehicles (Paris 2024) could both accelerate the change in the fleet and exclude the poorest households from this process by causing the resale price of these vehicles to plummet on the second-hand market. In addition, these policies are not easy to implement, the city of Paris had in 2014 the objective to ban diesel cars by 2017; that objective had to be postponed for four years and was finally implemented in 2021.[13] This mirrors a real difficulty to implement strong measures against ICE cars into policy, even in very favorable areas such as the city of Paris where pollution and health is a particularly acute issue, given the density of inhabitants, and where a truly efficient alternative to car transport is already in place.

In order to be achieved, the objectives set by the European Union in terms of reducing greenhouse gas emissions or treating local pollution will have to combine improving the efficiency of internal combustion engines with the development of alternative energies or alternative vehicle technologies such as hybrid vehicles, alter-

[13]"La maire de Paris déclare la guerre au diesel," Capital.fr, December 7, 2014, [Online]. Available: https://www.capital.fr/economie-politique/la-maire-de-paris-declare-la-guerre-au-diesel-996759.

native fuels, electric motors and fuel cells.

The effectiveness of environmental policies, such as carbon taxes, low emission zones, and regulatory standards, hinges on public acceptance. A lack of public support can lead to the failure of well-intentioned policies, even if they are economically and environmentally sound. Several instances where public rejection resulted in the abandonment or alteration of policies, like the Australian carbon tax and France's "écotaxe." The case of France's "écotaxe" demonstrates that substantial resources can be wasted on planning, designing, and implementing a policy only to have it canceled due to public opposition. The sunk costs associated with such cancellations can strain government budgets and divert resources away from other vital areas. Additionally, social movements opposing environmental policies, such as the "Yellow Vests" in France, can lead to social unrest and broader dissatisfaction with government authorities. This can erode trust in governance and fuel further polarization. Addressing public acceptability is not just a matter of policy efficacy but also a critical aspect of maintaining social cohesion and confidence in government.

The underlying reasons for rejection may vary, including a lack of understanding, perceived infringement on individual interests, political polarization, or concerns about social and environmental justice. Without broad public acceptance, policies may face resistance, protests, or legal challenges, undermining their implementation and effectiveness. Engaging with public sentiment and fostering understanding are therefore crucial for policymakers to ensure that environmental objectives are achieved.

Addition to the research

Building medium to long-term scenarios, as well as anticipating technological breakthroughs, radical changes in public policy or changes in user behavior, remains a difficult exercise. This is what this research seeks to achieve by focusing on i) understanding the main determinants of the purchasing behaviour of private vehicles (passenger cars), ii) the criteria and conditions for the more or less rapid diffusion of low-carbon vehicles in the fleet on the road, iii) and the necessary accompanying public policies. It is indeed the joint analysis of this triptych - technology supply, purchasing demand and, at the intersection of the first two, the optimal design of the policy-mix that will make it possible to model optimally the demand for European road transport and its consequences in terms of pollutant emissions by 2040.

Following the European SCelecTRA project, IFPEN has developed a road transport demand model: the $DRIVE^{RS}$ model for DiscRete choIce modeling for low-carbon VEhicles fleet scenaRioS. This integrated simulation model allows to establish scenarios for the development of the road fleet in France and Europe by 2040 by studying the dynamics of the passenger vehicle market by technology type (propulsion mode). It also makes it possible to study the effects of a wide range of instruments and public policies and to evaluate the environmental impacts (CO_2, CH_4, CO, SOx, NOx, particles) of these policies in the transportation field (SCelecTRA, 2015).

The DRIVERS model focuses on individual behavior in that it simulates changes in consumer behavior in response to changing economic conditions. It consists of two modules. The first module consists of an econometric model for road transport demand (Gastineau, P., Chèze, B., 2018). This module provides projections for road transport demand up to 2040, by year and country. It is expressed either in terms of total number of vehicles (i.e., stock), without distinction of vehicle type or technology, or in terms of distance traveled (i.e., mobility). The second module consists of a discrete choice model that allows new sales to be broken down for each year into the different types of existing vehicles, i.e. by type of car and technology. The predictions from this module operate using a total cost of ownership (TCO) calculus, which assign disutility to each cost component such as purchase price, fuel costs and maintenance costs. The unit energy consumption of the different vehicles and their pollutant emissions are then deducted. This type of transportation demand modeling using discrete choice models is relatively common in the literature. The MoMo model, for example, used by the IEA in its transport demand projections, is based on this methodology (Fulton et al., 2009). The structure of the DRIVERS model is thus largely based on that of the TREMOVE model (De Ceuster et al., 2007) originally developed for the European Commission.

Generally, the purchasing behavior for traditional vehicles (ICEs), and their diffusion in the total vehicle stock are fairly well described by discrete choice models. However, this is not the case for low-carbon vehicles, particularly in the DRIVERS model. Factors other than simple cost comparisons may need to be taken into account to explain individuals' preferences for low-carbon vehicles, and more generally for any new technology. These factors may include the individual's socio-economic and cultural characteristics, such as their environmental awareness, their affinity with new technologies, or their tolerance for the risk of adopting a new technology.

When looking beyond the understanding of individuals' preferences for green technologies, the issue of government intervention for these low-carbon emitting vehicles needs to be investigated. Due partly to the very high fixed costs (for the installation of charging infrastructures, for example), it is very difficult to see these technologies emerge without a supporting policy to help launching them. Similarly to technologies like solar or wind power energy, very significant cost reductions are to be expected for these technologies as they develop. Once a certain critical mass of production of these vehicles has been reached, and that the vehicle upfront costs resembles that of ICE vehicles, public aid may therefore be reduced thanks to the effects of "learning-by-doing", and of economies of scale" on production costs.

The original contribution of this thesis lies first in the development of an integrated model of road transport demand, in order to formulate coherent scenarios for the diffusion of the different vehicle technologies, per country and at the European level, for private vehicles. These models are highly data intensive, which explains why there are relatively few of them that match the scale of the DRIVERS model.

Then, from a theoretical point of view, the originality of this thesis compared to the literature consists in integrating insights from behavioral economics into the DRIVERS modeling method, which so far mainly relies on a TCO based analysis, in order to better model the development and diffusion in the European low carbon vehicle fleet. The aim is to "endogenize" the purchasing behaviour for these types of vehicles by making it depend on a certain number of explanatory factors specific to each vehicle type.

The first factor is the impact of the different public policies that exist: the use of subsidies, the development of recharging infrastructures, increased taxation, even traffic bans introduced by certain cities for the most polluting vehicles, etc. The second factor are the preferences for the vehicle characteristics in themselves : purchase price, fuel and maintenance costs, current state of recharging infrastructures. However, the spread of these vehicles will also depend on characteristics such as the recharging time required, the autonomy of the batteries and their costs, for example. These characteristics may change positively over time as these technologies become more widespread through network effects, economies of scale, or learning effects. These are all elements that need to be properly modeled to define the best policy mix - and its temporal dynamics - in order to trigger the launch of these new technologies and support their development.

To encourage the rapid deployment of these vehicles, public authorities must implement policies targeting both the purchase of these new modes of transportation and the development of their recharging infrastructure. In the first case, the government acts primarily on the demand side by creating incentives, which may or may not be monetary incentives for consumers, thus making the ownership of such vehicles more favorable. The resulting demand for energy refueling is expected to naturally accelerate the deployment of recharging points. In the second case, the government acts more on the supply side by pushing for infrastructure deployment through subsidies or coordinated public-private partnerships, which in turn will encourage demand for these vehicles.

Ever since the contribution of Bass (1969), diffusion-adoption models for new technologies have been based on the assumption that a population of purchasers can be divided into two distinct classes: "the adopters" and "the followers". The former are tech-savvy, in the sense that their interest in (owning) new technologies outweighs the often (higher) costs associated with purchasing them.

In order to classify the population of potential purchasers, we need to understand that in the case of EVs, adopters take several risks. Firstly, the availability and sufficiency of charging infrastructure pose a significant barrier to the adoption of battery electric vehicles (BEVs). The uncertainty around the future level of electric fast-charging infrastructure, combined with the current low proportion of charging stations, creates apprehension among potential users. This uncertainty has a negative effect on vehicle adoption rates. Additionally, range anxiety, or the fear of running out of battery power before reaching a charging station, persists as an influential factor, despite technological advances. The driving range of BEVs is still considered a disadvantage when compared to conventional vehicles.

This why eliciting risk preferences is important for understanding and addressing the barriers to EV adoption. Different individuals may perceive the risks associated with electric vehicles differently, based on factors such as their knowledge about electric cars, attitude towards technology, environmental quality, and personal risk tolerance. Recognizing these variations in risk preferences can help policymakers and manufacturers tailor strategies to specific groups, such as "early adopters" or "environmentally minded" individuals who may have higher trust in BEVs. By incorporating uncertainty and attitudes towards risk into the analysis, it becomes possible to create more realistic and effective public policies and incentives to overcome barriers and increase electric vehicle adoption rates. The inclusion of risk and uncertainty in the research methodology can thus provide deeper insights into the factors affecting EV adoption and facilitate the development of targeted interventions to support the transition towards clean mobility.

The current literature still lacks consumer surveys to properly characterize vehicle users' classes in the case of low-carbon vehicles, and their resulting incentive policies. By conducting such surveys, using stated preference revelation methods, this thesis will make definite contributions to the field of transport economics. More precisely, it will observe the heterogeneity and distribution of preferences of the demand. The results will be statistically analyzed using the most advanced micro-econometric estimation methods to process choice experiment questionnaires to study household behavior, their sensitivity to different policy tools (incentives), and the heterogeneity of their preferences for low-carbon vehicles.

Methodology

The analysis of the transition to alternative vehicle technologies is a complex endeavor that necessitates a range of methodologies. Each has its strengths and limitations, making them suitable for specific areas of study, which we will delve into shortly.

The Discrete Choice Experiment Method

Discrete choice experiments (DCE) present individuals with exclusive alternatives and ask them to select their preference, usually via a survey. Each alternative is described by a set of attributes, and the levels of these attributes vary across alternatives. These alternatives might span a range of possibilities, from competing products to distinct courses of action. In all these situations, the outcome of the decision, can only adopt specific, countable values. By observing the choices individuals make across different sets of alternatives, researchers can infer the underlying preferences and the trade-offs individuals are willing to make between different attributes. By observing the choices individuals make across different sets of alternatives, researchers can infer the underlying preferences and the trade-offs individuals are willing to make between different attributes.

One of the primary strengths of DCEs is their ability to estimate the value individuals place on non-market goods or attributes. For instance, DCEs can be used to estimate the value people place on preserving a natural habitat or reducing air pollution. In transport economics, discrete choice experiments are particularly useful at modeling and analysing transport decisions, whether it's choosing a mode of transportation, route, or even the time of travel, which are inherently about making choices among discrete alternatives. For instance, when evaluating public transportation options, individuals might consider factors such as travel time, cost, convenience, and reliability. By presenting individuals with hypothetical scenarios that vary these attributes, DCEs can help researchers understand the trade-offs commuters are willing to make. Beyond individual preferences, DCEs in transport economics can also shed light on the potential uptake of new transportation initiatives or the of effect of investing into infrastructure such as charging stations.

The data from DCEs is then analysed through the use of a discrete choice model. According to the work by Train (2009), a discrete choice model is a conceptual approach aimed at understanding and predicting the decisions made by entities, whether they be individuals or firms. The primary objective here is to uncover the behavioral mechanism driving these choices. From a causal perspective, choices aren't made in isolation; they are influenced by various factors. On one hand, we have observed factors, which are measurable elements like price or brand reputation that can sway a decision. On the other, there are unobserved factors, which are elusive variables such as personal preferences or past experiences. These observed and unobserved factors interplay to shape the agent's choice, termed the behavioral process, this function works in a deterministic manner. Given the known and unknown variables, it can precisely predict the agent's decision. Therefore, at its core, a discrete choice experiment aims to unravel how different tangible and intangible elements influence a decision among set options (Train, 2009).

At the core of discrete choice models is the assumption that individuals make decisions to maximize their utility or satisfaction. This is often examined using a random utility model (RUM). Drawing inspiration from the seminal transport application study by Domencich and McFadden (1975), researchers commonly employ logit or probit models to determine the choice probabilities of each option and to identify the various factors influencing these probabilities.

However, one of the main challenges to the credibility of the stated-preference method is the issue of hypothetical bias (L'Haridon, 2018). People may make decisions that deviate from their real world behavior because the question is asked in a hypothetical context without real economic commitments or consequences. This issue is particularly important in a political context, where individuals might not be willing to admit their true opinions, or may make over-virtuous decisions, when faced with a survey.

The Lab Experiment Method

In experimental economics, a lab experiment is a controlled study conducted in a laboratory setting to investigate economic behaviors and decision-making processes. Unlike field experiments or observational studies, lab experiments are conducted in a controlled setting, typically a room equipped with computers where participants make decisions that often have real monetary consequences. This setting allow researchers to manipulate specific variables and observe the effects on participants' choices and behaviors (L'Haridon, 2018).

In economic research, the use of games in lab experiments has become a cornerstone methodology to study strategic interactions, cooperation, and decision-making processes. Games, such as the Prisoner's Dilemma, Ultimatum Game, and Public Goods Game, simulate real-world scenarios where participants must make decisions that have implications for both themselves and others. Lab experiments provide the opportunity to observe the effects of group-based social influence. Within the controlled confines of a laboratory, researchers can systematically introduce and manipulate group dynamics to observe how individuals' decision-making processes are affected by the presence and opinions of others. For instance, by placing participants in groups and allowing them to discuss or observe each other's choices, researchers can discern whether individuals conform to group norms, succumb to peer pressure, or exhibit herd behavior. This process is crucial, as decisions made under the influence of peers can significantly deviate from those made in isolation.

According to Roth (1988), lab experiments in economic science serve three vital purposes. Laboratory experiments first and foremost enable the evaluation of theoretical models by putting them to empirical tests. By doing so, they validate or refute the applicability of these models in mimicking real-life economic behaviors and outcomes. Beyond just testing existing theories, experiments also proactively delve into reality to unearth new facts and observations. In this context, experiments function as 'exhibits' instead of merely 'tests', as outlined by Sugden (2005). These 'exhibits' of real behaviors and outcomes in controlled settings can then be used to refine or even construct new theoretical models. Lastly, experiments are not just confined to academia. By harnessing insights from both theoretical tests and real-world exhibits, lab experiments can directly influence policy-making. They act as valuable advisors, offering evidence-based insights that can guide policy decisions towards more effective and efficient outcomes. This is particularly true when it comes to informing regulators or other key decision-makers about the potential outcomes of new or revisited public policies. The underlying principle is to harness experiments as testing grounds for different decision environments, whether they be market mechanisms, organizational structures, or policy modifications (L'Haridon, 2018).

To ensure the experiment's internal validity, it's crucial to establish a clear causal relationship between changes in the independent variable and observed changes in the dependent variable. Building on the research by Smith (1982), monetary incentives were incorporated into lab experiments. These incentives are pivotal for drawing inferences about behaviors in the experiment, which are believed to be influenced by the environment and institutions set up in the lab. By introducing these incentives, the lab experiment can be perceived as a microeconomic system where: more is always preferable to less, the differences in payoffs make choices meaningful and the overall experiment offers enough value to offset the opportunity cost of participation.

Monetary incentives also help with concerns about external validity, ensuring that behaviors observed within the experiment can be generalized outside the lab setting. Relying on the principle of parallelism, we argue that 'propositions about individual behavior and institutional performance tested in laboratory micro-economies are also applicable to non-laboratory micro-economies, provided similar ceteris paribus conditions are met' (Smith, 1982).

Summary

This thesis seeks to understand changes in vehicle user behaviour, anticipate technological breakthroughs and define the best possible public policies to support sustainable mobility by integrating them into a discrete choice model, with the aim to develop integrated and coherent scenarios for the diffusion of different technologies for passenger vehicles in France at an aggregated level. Our analysis is divided into

three parts. The first chapter uses a discrete choice experiment to analyze user's preferences for new vehicle technologies. The second chapter uses experimental economics methods, also called "lab experiment", in order to seek subjects preferences for different public policies promoting sustainable mobility such as taxes or regulations on car purchases. The third chapter uses the economical and behavioral insights from the first chapter and applies them into the "DRIVERS" model, which seeks to give projections on the future French fleet composition according to different public policy scenarios. The "DRIVERS" model up to now, only relies on total cost of ownership factors and economical data to make projections about fleet size and fleet composition.

Building on the empirical insights from these three chapters, the thesis concludes with a set of policy recommendations. Policy actions should encompass conditions that actively promote clean vehicles, including substantial investment in charging infrastructure, targeted subsidies for electric and alternative vehicle technologies, and comprehensive public awareness campaigns. These strategies are vital for extending the appeal of EVs beyond early adopters and enthusiasts, ensuring that they become an attractive option for a broader segment of the population. This is particularly important in regions outside of urban areas, where accessibility and acceptance of electric vehicles may be more challenging. By fostering these conditions, policymakers can facilitate a smoother transition to cleaner transportation, aligning with environmental goals and making electric vehicles a viable choice for an increasingly diverse range of consumers. It also advocates for context-aware policy implementations. To effectively reduce the number of ICE vehicles in the fleet and consequently decrease air pollution, a combination of price incentives and targeted restrictions on ICE vehicles will be essential. These restrictions may take various forms, including outright vehicle bans in certain areas, the implementation of tolls specifically for ICE vehicles, or the creation of low emission zones that limit or exclude their access. By making ICE vehicles less attractive or practical in certain contexts, these restrictions can accelerate the transition to cleaner transportation alternatives. Coupled with incentives that make these cleaner options more financially appealing, these strategies can form a comprehensive approach to reducing the environmental impact of transportation and promoting a more sustainable future.

The order and choice of implementation of the policies must depend on the cultural considerations of the area where they are implemented, and for the case of taxes, may require a policy trial in order to improve acceptability. Together, these recommendations aim to accelerate the shift towards environmentally friendly vehicle alternatives, in order to reach the emission reduction goals.

In summary, this thesis aims to unravel the complex web of factors shaping the transition towards a low-carbon transport sector in France. Through a multifaceted exploration encompassing consumer behavior, policy acceptability, and modeling improvements, it seeks to provide a more nuanced understanding of this transition. The insights gained from this study should serve as valuable inputs for policymakers as they navigate towards the goal of sustainable mobility.

Chapter 1

This chapter originates from a study written in collaboration with Benoît Chèze[14] and Johanna Etner.[15] It investigates the barriers to electric vehicle adoption in France through a stated preference study, using an online survey conducted in January 2021. Two discrete choice experiments were carried out, focusing on small "city" sized vehicles and medium "family" sized vehicles. The study's originality lies in its consideration of uncertainty around the future level of electric fast-charging infrastructure, a significant barrier to electric vehicle adoption.

The results reveal that factors such as purchase price, fuel cost, driving range, GHG emissions, and charging infrastructure are primary determinants for vehicle adoption across both vehicle sizes. Respondents prioritized immediate costs, such as purchase price, over other monetary attributes, and showed a non-linear preference for vehicle range. The presence of uncertainty regarding future charging infrastructure negatively impacted adoption rates, particularly for medium-sized vehicles.

Psychological profiles, including knowledge about electric cars, early adopter tendencies, and environmental consciousness, were found to significantly influence preferences. Knowledge about electric vehicles, interest in car technology, risk tolerance, and environmental consciousness were associated with a higher acceptance of alternative vehicle technologies. These profiles were often correlated with younger, wealthier, and more educated individuals.

The study concludes with policy recommendations, emphasizing the need to increase subsidies for electric vehicles, penalize higher GHG emitting vehicles, and

[14]EconomiX-CNRS, Paris Nanterre University
[15]EconomiX-CNRS, Paris Nanterre University

invest in fast-charging public infrastructure. The uncertainty surrounding charging infrastructure is identified as a significant barrier, especially for medium vehicle users. The high purchase price remains the main obstacle to widespread electric vehicle adoption.

This first chapter sets the stage for the rest of the thesis by demonstrating the importance of the behavioral dimension in the adoption of low-carbon vehicles. In the following chapters, these insights will be further developed and integrated into a transport simulation model to enhance its predictive accuracy and policy relevance.

Chapter 2

This chapter originates from a study written in collaboration with doctoral student Maria J. Montoya-Villalobos.[16] It explores the issues around public policy acceptability, particularly focusing on environmental policies aimed at reducing carbon emissions in the transport sector. Through a laboratory experiment, the study compares two types of policy instruments: taxes with equal redistribution and regulatory standards. It also investigates the influence of cultural worldviews on acceptability and examines how policy trials may affect support for these policies.

The experiment simulates the transportation market by presenting participants with options corresponding to different modes of transportation, including electric vehicles, public transportation, and conventional vehicles. Two policy interventions, taxation and regulatory standards, are introduced and subjected to a majority vote to measure acceptability. The study is enriched by drawing real-world examples such as Paris's 2024 ZFE[17] and London's ULEZ[18].

The findings reveal a nuanced picture of policy support. Regulatory standards are generally more accepted than taxes, with 57.8% of participants voting in favor of implementation. Furthermore, support is enhanced through experience with a policy trial for regulatory standards but not for taxation. The study uncovers the role of cultural dimensions, particularly hierarchical-egalitarian worldviews, in shaping the rejection of taxation policies.

The chapter emphasizes that regional culture and context matter significantly when

[16]EconomiX-CNRS, Paris Nanterre University
[17]"Zone à faibles émissions"
[18]"Ultra Low Emission Zone"

implementing public policies. It underscores the importance of understanding cultural variations and suggests engaging public participation through referendums and deliberative institutions to enhance acceptance. The results also hint at the difficulty of changing preferences even after pedagogical efforts, particularly when strong policy aversion exists.

The study's novelty lies in its experimental design that enlarges possibilities of choice, adding heterogeneity and proposing bans with available alternatives. This offers a more realistic representation of public policy scenarios, particularly in the field of transportation.

Chapter 3

In the context of European energy transition and the collective goal to reduce greenhouse gas (GHG) emissions, this chapter explores the integration of behavioral economics into the existing DRIVERS fleet model (DiscRete choIce modeling for low-carbon VEhicles fleet scenaRioS). This integrated approach aims to provide a more nuanced representation of private vehicle purchasing dynamics in France and Europe up to 2040, particularly focusing on the transition towards low-carbon mobility.

The original DRIVERS model has been developed to assess various public policies and strategies for decarbonizing transport, based on discrete choice modeling. However, its predictions for low-carbon vehicles could show more realism with the integration of the insights in behavioral economics from chapter 1. This chapter presents the methodology and process of incorporating these behavioral insights, modifying the DRIVERS model to better explain the initiation and deployment of low-carbon vehicles.

The modified model projects vehicle stocks and distances traveled up to 2050, with distinct scenarios for electric and thermal vehicles. It also calculates energy consumption and emissions under real driving conditions. The results highlight a propensity for higher thermal vehicle sales, with total emissions exceeding those predicted by the original model. The revised model's outcomes also display a heightened sensitivity to public policies, technological advancements, and economic conditions affecting vehicle affordability.

The chapter further discusses the profound impact of banning thermal vehicle sales by 2035, emphasizing the urgent need for specific public policies to close the gap between predicted vehicle emissions and targets set by the French state. The new, less optimistic predictions underscore the critical role of affordability, and the need for ICE vehicle bans in the transition towards greener vehicle technologies.

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Chapter 1

Preferences for alternative vehicles, an analysis of barriers to adoption through a discrete choice experiment

1.1 Introduction

In France, the transportation sector accounts for 34% of all the final energy consumed, and accounts for 92% of all petroleum products consumed (ADEME, 2020). It is responsible for 26% of the national green house gas emissions, which makes the transportation sector the biggest GHG emitting sector in France. The transportation sector is also a source of health concerns at the local level because of the emanation of carbon dioxide and particle pollution that results from the use of transport vehicles. The city of Paris has taken the initiative to ban starting in 2025 the use of diesel vehicles within it's vicinity, other cities such as Strasbourg and Grenoble have followed Paris's lead by banning those vehicles starting in 2025. The French government has set an aim of reducing its emissions by 6 by 2050 (SNCB, 2020). In order to deal with the emissions from the transport sector, the French government has created several public policies. In 2021, French car manufacturers will have to conform by 2021 to a limit of 95g/km of CO2 emissions for their new vehicles. The French government has also contributed towards the switch towards alternative vehicle technologies such as Plug-in Hybrid vehicles (PHEV) and Battery electric vehicles (BEV) through the implementation of subsidies called "bonuses" for the purchase of those vehicle technologies.

However, in 2019, only 200 000 vehicles out of 32 million vehicles in France were battery electric vehicles (ADEME, 2020). This low proportion of electric vehicles in the total fleet may be caused by internal factors such as vehicle characteristics or external factors such as the technology reputation or the development of it's refueling infrastructure. The issue of social and economic barriers for electric vehicles' adoption has been the subject of research in recent years (Tanaka et al., 2014; Hackbarth and Madlener, 2016a; Kim et al., 2014; Barth et al., 2016; Giansoldati et al., 2020). The literature reports varying magnitudes and directions of the different factors. Behavioral economics applied to transport allows the identification of barriers to the entry of electric vehicles based on stated preference methods, including choice experiments. Our study focuses on respondent's knowledge about electric cars, attitude towards technology, environmental quality and risk, in order to seek the effects of attitudes or of belonging to a group of "early adopters", coined by Rogers (1962), has any effect on BEV adoption rates.

We aim to identify the main barriers to electric vehicle adoption in order to find out what we can do in terms of public policies to overcome the barriers to entry and increase the electric vehicle adoption rates. The originality of our work is twofold.

First, we use two discrete choice experiment: one for small "city" sized vehicles, and one for medium "family" sized vehicles. Second, and for the first time to our knowledge, we propose to take into account the uncertainty around the future level of electric fast-charging infrastructure and inputting this uncertainty into one attribute inside our choice experiment.

Our results show that purchase price, fuel cost, driving range, GHG emissions and level of charging infrastructure are the main determinants for vehicle adoption for both vehicle sizes. The presence of uncertainty for the future level of charging infrastructure has a negative effect on vehicle adoption rates. The differences between the two choice experiments reveal that medium vehicle users have higher charging infrastructure needs when making decisions for purchasing vehicles. Respondents that were either well learned about BEV's, part of an "early adopter" profile, or "environmentally minded" had higher trust in BEV's and ceteris paribus preferred alternative vehicles over conventional ones.

This paper is structured as follows. Section 1 provides a literature review on stated preference methods applied to transport and behavioral economics. Section 2 details the design of the experiment and the methodology for producing our data, as well as characterising the socio-economic characteristics of our sample. Section 3 presents the modelling framework for our choice experiment, as well as the econometric theory for the models used in this paper. Section 4 presents the results, which are then discussed in a general conclusion.

1.2 Related Literature

The literature on private vehicle stated preference methods is extensive. For a comprehensive summary of transport DCE studies and their associated attributes, please see Table 1.9 in the appendix. However it agrees on a few points. The purchase price, vehicle ownership costs, range and charging time have the greatest impact on vehicle adoption rates (Carley et al., 2013; Graham-Rowe et al., 2012). A higher price, recharging time, operating cost, maintenance cost and sales tax lowers the probability that the vehicle is chosen (Jones et al., 2013). Unsurprisingly, the most critical decision criterion seems to be the purchase price (Danielis et al., 2018; Wicki et al., 2022). Electric cars are not ready for uptake until the government provides substantial subsidies (Inci et al., 2022). In the same way, Vehicle usage costs appear in most studies under different forms (Giansoldati et al., 2020). In addition to monetary attributes, most studies on vehicle adoption included technical attributes such as the vehicle's driving range or the amount of emissions during use. When compared to conventional vehicles, the driving range for BEV's is still considered a disadvantage (Wicki et al., 2022). Several studies have shown that despite the technological progresses in electric car, range anxiety is still considered as an important factor for respondents (Thøgersen and Ebsen, 2019; Broadbent et al., 2019; Guerra and Daziano, 2020; Haustein et al., 2021; Chen et al., 2020; Haustein et al., 2021). Daziano (2013) finds that even when accounting for operating costs saving, electric vehicles would still need to have a range equivalent to that of a hybrid vehicle in order to account for the difference in purchase price. Vehicle emissions are also included into choice-experiments, either represented by the amount of GHG emitted during use or in the case of our study represented as an environmental label. The amount of emissions during use of the vehicle had a significant effect on adoption rates, (Achtnicht et al., 2012; Jensen et al., 2013; Tanaka et al., 2014) and vehicle emissions brought higher disutility for environmentally friendly people (Hackbarth and Madlener, 2013). Lastly, several studies have shown a clear negative connection between BEV adoption rates and charging time (Hackbarth and Madlener, 2016b; Kim et al., 2020; Ščasnỳ et al., 2018). The low proportion of charging stations available and the duration to charge a vehicle to full charge are significant barriers to battery electric vehicle adoption. The availability and affordability of recharging infrastructure can be important in the purchasing decision based on where the respondents are located (Guerra and Daziano, 2020; Haustein et al., 2021). Moreover, the uncertainty and the anxiety around the amount of charging stations and the amount of government support can significantly influence the decision to adopt (Broadbent et al., 2021; Guerra and Daziano, 2020; Haustein et al., 2021).

An important factor that happens before the choice of vehicle technology, is the choice of vehicle size. However, in most stated preference methods, choices between vehicles are limited due to the complexity of adding too many alternatives. Some papers deal with these limitations by using a "pivoting" experimental design to adapt the levels of the attributes in their choice experiment to the respondent's desired vehicle (Yoon et al., 2017). Hess et al. (2012) uses a survey design mixing stated and revealed methods. The revealed preference survey ask respondents before the experiment what type of vehicle they have or would like to obtain, and how they would use it. This vehicle is then used as the status quo alternative during the survey.

Finally, most studies using stated preference methods end their choice experiment with a post experiment questionnaire on respondent's socio-economic characteristics. Psychological questions are also used in order to assess the respondent's positioning on some topics or their belonging to some social groups. For example, people with pro-environmental attitude or who are highly educated had higher BEV adoption rates than others (Kim et al., 2014; Daziano, 2013; Carley et al., 2013). Some studies that young or middle aged men are more likely to adopt BEV's than others. (Haustein and Jensen, 2018; Zhuge and Shao, 2019; Chen et al., 2020; Westin et al., 2018). (Haustein and Jensen, 2018; Zhuge and Shao, 2019; Chen et al., 2020; Westin et al., 2018; Gehrke and Reardon, 2022) find that higher earning households are more likely to adopt EV's than others. Early adopters tend to own their own home and own more than one car (Haustein and Jensen, 2018; Gehrke and Reardon, 2022; Brückmann et al., 2021).

In addition, Giansoldati et al. (2020) seek to find the effect of different attitudes and knowledge about electric vehicles on vehicle adoption rates, and then interact these effects with the car attributes. In a Hybrid Mixed Logit model, they find that the inclusion of electric car knowledge improves the explanatory power of their results, they also find that this knowledge changes the importance placed on car attributes, specifically that users with more knowledge about electric cars have fewer concerns with the density of electric fast-charging infrastructure.

Our study contributes to the reviewed literature in several ways. First, we assume that different vehicle sizes mean different transport behaviors and thus different adoption factors and barriers. We consider that smaller vehicles tend to be used more often in cities, while medium-sized and above vehicles are more often used outside rural areas. This difference could mean that users see a different use for a vehicle presented to them depending on its size. From this assumption, we separate our choice experiment into two sub-samples, one choice experiment for small vehicle users and one choice experiment for medium vehicles users. Our study is the first to use a stated-preference method on the topic of vehicles in France. Second, based on the recommendation from Liu and Cirillo (2017) we include a notion of uncertainty in the levels of one of our attributes used in our choice experiment. Liu and Cirillo (2017) find that contrary to the rest of the transport literature, stated preference methods rely solely on fixed vehicles attributes in their choice experiment. We know that in real life, several characteristics surrounding the vehicle are prone to fluctuations, such as for fuel costs, battery health and duration, and the presence, density and availability of charging infrastructure. Excluding uncertainty when talking about vehicle range, charging availability may reduce realism of presented choice tasks. In order to take account of uncertainty and attitude towards risk, we use a methodology similar to the one used by Glatt et al. (2019), by making respondents answer a choice experiment as well as a questionnaire with a choice of lotteries to assess their risk preferences. This will allow us to interact the effects of attitudes towards risk with the car attributes. We give our charging infrastructure attribute, several possible levels according to different projected scenarios in order to incorporate the notion of risk in our choice experiment. To the best of our knowledge, our study is the first to use a vehicle attribute with risk.

1.3 Empirical Data

The survey was conducted in France in January 2021 and implemented online, with a sample representative of the general French population. Data are from two stated-choice experiments: 1022 respondents were divided into 512 respondents for the small vehicle choice experiment, and 510 respondents for the medium vehicle choice experiment. The survey provided respondents with detailed information on the different types of vehicles and the attributes that characterize it. A questionnaire with sociodemographic questions followed. Then, respondents were tested of their perceived knowledge about electric cars. They answered which type of vehicle they would most likely purchase if they had to purchase a new vehicle or replace an old one. Following this answer, respondents participated in one of the two discrete choice experiments. In one experiment, values correspond to small, city-type vehicles, while in the other, it follows bigger vehicles called here ”Medium sized vehicles”. The remaining vehicles under the ”Medium sized vehicles” are grouped, assuming that the types of use for family sized vehicles and bigger ones wouldn't significantly differ. The design used here is based on a labelled experiment with quasi-customed alternatives (Daziano et al., 2017).

1.3.1 The Discrete Choice experiment

Vehicles were characterized by seven attributes: purchase price, annual fuel cost, annual maintenance cost, vehicle range (km), proportion of stations equipped with fast-charging and emissions amount, represented through an environmental label. We chose not to include charging time as an attribute, assuming that respondents would not accept to charge their electric vehicle in public in a non fast-charging station with a charging time above 30 minutes. Other characteristics such as the installation cost of home charging station (”wall box”), the safety of the vehicle, the motor power of the vehicle and the driving comfort could not be presented in this survey for fear of over complicating the decision process. The effect of all these ”omitted variables” will be captured by an alternative specific constant. We designed the attribute levels according to recommendations from experts from the vehicle transport field. The attribute levels are based on the average value of a reference vehicle (RV) of the same vehicle technology and vehicle size (small or medium). The values for the attributes of the small vehicle and medium choice experiment are described in tables 1.1 and 1.2. The values for the attributes in each

Attributes	BEV	PHEV	CV
Purchase Price:			
Base -30%	22 400 €	19600 €	
Base -15%	27 200 €	23 800 €	
Base	32 000 €	28 000 €	14 000 €
Base +15%			16 100 €
Base + 30%			18 200 €
Annual Fuel Cost:			
Base -30%	140 €	315 €	560€
Base	200 €	450 €	500 €
Base + 30%	260 €	585€	1040€
Annual Maintenance Cost:			
Base -30%	105€	175€	210€
Base	150€	250€	300€
Base + 30%	195€	325€	390€
Vehicle Range:			
Base -30%	210 km		
Base	300 km	750 km	700 km
Base + 30%	390 km		
Infrastructure Amount(with risk):			
	(50% 3; 50% 1)		
	(50% 5; 50% 1)		
	(50% 5; 50% 3)		
Infrastructure Amount(no risk):	1/5		
	3/5	5/5	5/5
	5/5		
Environmental Label:		A	B
	A	B	C
		C	D

Table 1.1: Small Vehicle Choice Experiment Attribute Values

choice experiment sub-sample for each technology represent the status quo value for

Attributes	BEV	PHEV	CV
Purchase Price:			
Base -30%	28 000€	24 500€	
Base -15%	34 000€	29 750€	
Base	40 000€	35 000€	
Base +15%			31 050€
Base + 30%			35 100€
Annual Fuel Cost:			
Base -30%	245€	615€	875€
Base	350€	880€	1 250€
Base + 30%	455€	1 145€	1 625€
Annual Maintenance Cost:			
Base -30%	175€	300€	490€
Base	250€	425€	700€
Base + 30%	325€	550€	910€
Vehicle Range:			
Base -30%	280 km		
Base	400 km		
Base + 30%	520 km		
Infrastructure Amount(with risk):			
	(50% 3; 50% 1)		
	(50% 5; 50% 1)		
	(50% 5; 50% 3)		
Infrastructure Amount(no risk):	1/5		
	3/5	5/5	5/5
	5/5		
Environmental Label:		A	C
	A	B	D
		C	E

Table 1.2: Medium Vehicle Choice Experiment Attribute Values

their respective reference vehicle, plus the variations on the status quo value. The variations on the purchase price attempt to emulate french public policies such as environmental "bonuses" and "penalties". It is believed that current prices are high and one of the paper's purpose is to support policy decision-making, therefore we only test negative variations of the status quo BEV prices. Thus the purchase price values for BEV and PHEV are : -30% , -15% , SQ. The purchase price values for conventional vehicles are : SQ, +15% , + 30%. For the annual fuel cost, annual maintenance cost, and vehicle range the values are : -30% , SQ , +30%. The vehicle range represents the maximum distance travelled with a single charge. Note that for Conventional Vehicles (CV) and PHEV the values are fixed as they don't represent a source of concern for these specific vehicle technologies.

We choose to represent the vehicle emissions attribute as an environmental label, such as those found on washing machines or cars in France. The label starts from the A label which is the "cleanest" vehicle with the lowest green house gas emissions up to the E label which is the "dirtiest" vehicle with the most emissions. Note that this label only characterises emissions resulting from the use of the vehicle, not from the manufacturing or the recycling of said vehicle.

Since the recharging time for an electric vehicle using regular charging infrastructure is eight hours, while it is thirty minutes with fast-charging, we make the assumption that users will only charge in public using electric fast-charging. The level of fast-charging infrastructure is represented as a ratio out of all service stations in France that equipped with electric fast-charging infrastructure.

When talking about battery electric vehicles, the price of energy, battery lifetime and range, charging infrastructure may be subject to fluctuations or uncertainty. The future proportion of electric stations may depend on public or private investment and the popularity of electric vehicles. We choose to take into account uncertainty around the future level of charging infrastructure in order to add realism to the discrete choice experiment, as suggested by Liu and Cirillo (2017) in their literature review. We present the infrastructure amount attribute as a projected scenario on the proportion of fast-charging infrastructure that will be available in the near future. The attribute is either certain or includes risk. Some scenarios present for the level of infrastructure two projected values that are equally likely to be realised, while other cases show just one certain value for the level of infrastructure.

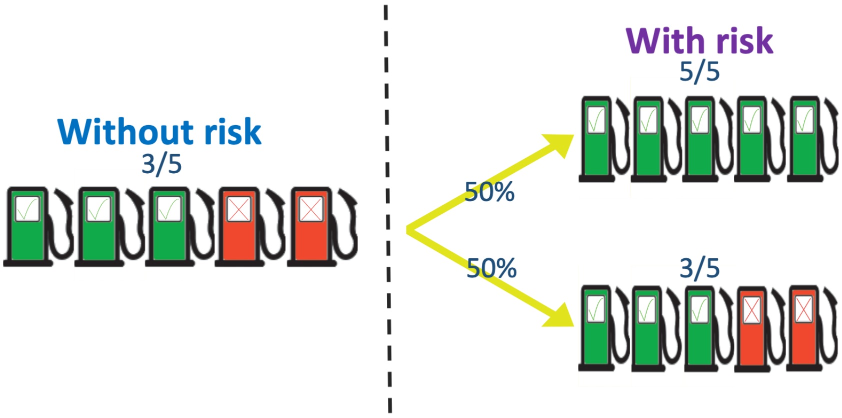

Figure 1.1: Example of the infrastructure attribute.

Figure 1.1 shows two examples of levels of the infrastructure attribute. The example on the left presents the attribute without risk, where the total proportion of service stations equipped with electric fast charging stations is three out of five. We explained to respondents that if they were presented with a service station without electric fast charging , they would loose time to find another one with the right equipment. The example on the right presents the attribute with risk, where it is equally likely that the future proportion of electric fast charging is five out of five or three out of five.

The attributes were explained in detail on separate screens of the survey prior to the discrete choice experiment. The discrete choice experiment consisted of a sequence of eight choice tasks as illustrated in figure 1.2. Every task included three different vehicle technologies, out of which respondents were asked to choose their most preferred option. There were one scenario with a conventional diesel/gas car (CV), one scenario with a plug-in hybrid car and one scenario with a battery electric car.

Attribute level combinations were determined using a D-Efficient design Bliemer and Rose (2010), with priors taken from a survey with a sample of N = 100 respondent, N=50 for the small vehicle choice experiment and N = 50 for the medium vehicle choice experiment [1].The questions about socio-economic background, electric vehicle knowledge, environmental and risk attitudes were the same for all respondents. The survey took around 15 minutes to complete. Respondent were informed that all their responses and information would remain anonymous and that this questionnaire was issued by the University of Paris Nanterre for scientific purposes.

[1]We used the dcreate Stata module in order to generate the experimental design Hole (2015).

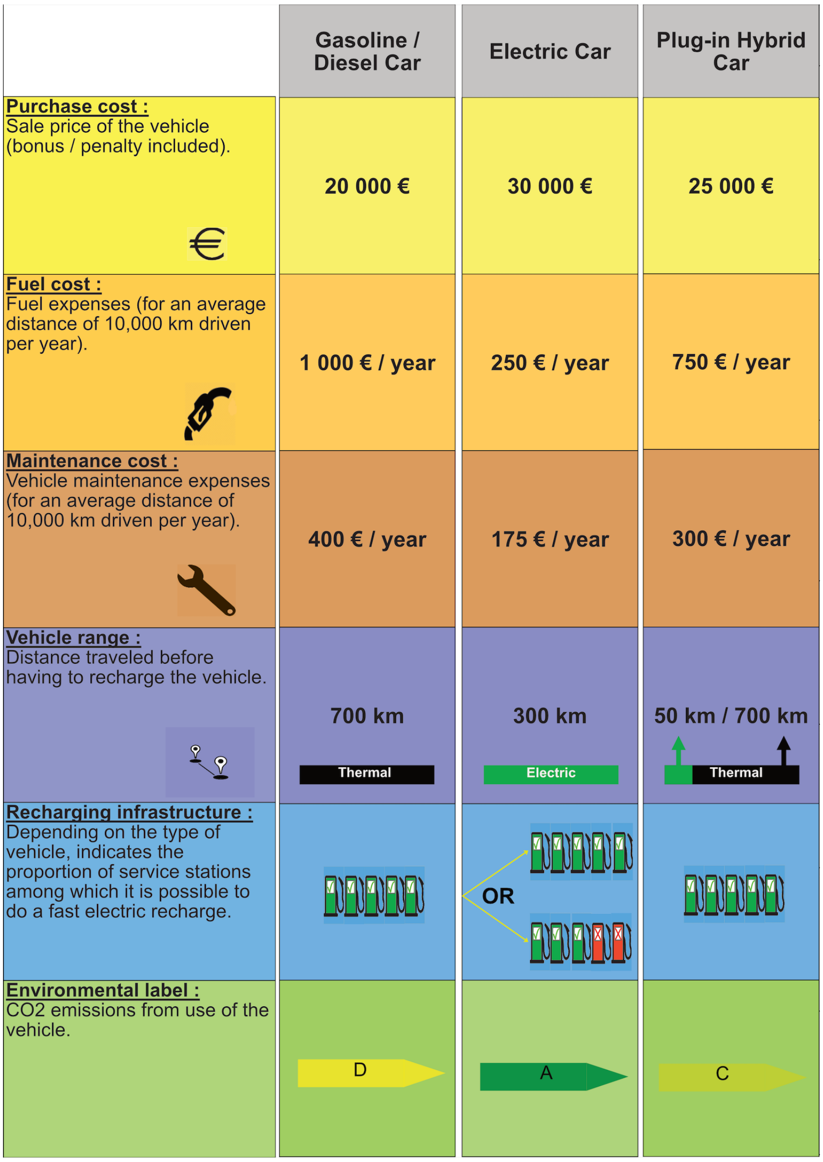

Figure 1.2: Example of a choice card presented to respondents.

1.3.2 Socio-demographic Characteristics

Table 1.3 reports the demographic statistics for the respondents in both our samples. Welsch's tests are performed between the small vehicle and medium vehicle samples in order to identify potential significant biases in the respondent's characteristics. The null hypothesis of mean equality between both samples was tested for the sample characteristics : *Gender*, *Working Situation*, *Age*, *Level of diploma* and *Monthly net income of the household*. The results of these tests reported in table 1.12 in the Appendix section, show that there is no significant mean difference between each of the vehicle samples. Since the respondents were randomly allocated to each of the two vehicle sample, these results allows us to study and compare the effects of the

Socio-economic - information/Sample Type	Small	Medium
Gender		
• Males	49%	50%
• Females	51%	50%
Age		
• From 18 to 29	8%	10%
• From 30 to 44	26%	29%
• From 44 to 65	35%	32%
• More than 65	30%	29%
Level of education		
• Low	47%	49%
• Middle	34%	33%
• High	19%	18%
Monthly Income		
• Less than €1000	7%	8%
• Between €1000 and €2000	23%	23%
• Between €2000 and €3000	30%	32%
• Between €3000 and €4000	24%	21%
• More than €4000	16%	16%
Place of residency		
• Urban	51%	50%
• Non Urban	49%	50%
Professional Activity		
• Top socio professional category	11%	15%
• Middle socio professional category	22%	23%
• Low socio professional category	33%	28%
• Retiree/Inactive	34%	34%
No. of owned cars in the family		
• 0 cars	7%	5%
• 1 car	53%	54%
• 2 cars	34%	35%
• more than two	5%	5%
Availability of a garage or car box		
• Yes	78%	77%
• No	22%	23%

Table 1.3: Summary statistics of the sample

difference in vehicle types and characteristics on the respondent's preferences and adoption choices. We can now claim that the respondent's allocated different vehicle usages depending on the vehicle characteristics that were presented to them.

1.3.3 Knowledge and Preferences

Information about car knowledge and preferences about risk and environment was collected before the discrete choice experiment. The statistics for those questions are reported in table 1.4. We start by reporting the statistics used for our latent

Socio-economic - information/Sample Type	Small	Medium
Assessed car knowledge		
• Level 0	60%	59%
• Level 1	32%	34%
• Level 2	8%	7%
Self-assessed car knowledge		
• Reply 1	13%	13%
• Reply 2	29%	28%
• Reply 3	40%	41%
• Reply 4	15%	14%
• Reply 5	4%	4%
Social Electric Car		
• Yes	37%	39%
• No	63%	61%
EC Driving Experience		
• Yes	16%	16%
• No	84%	84%
Self-assessed risk attitude		
• Level 0	6%	8%
• Level 1	6%	7%
• Level 2	10%	10%
• Level 3	8%	8%
• Level 4	8%	6%
• Level 5	22%	22%
• Level 6	10%	11%
• Level 7	12%	12%
• Level 8	11%	10%
• Level 9	3%	4%
• Level 10	3%	3%
Assessed risk attitude		
• Reply 1	35%	37%
• Reply 2	39%	35%
• Reply 3	11%	14%
• Reply 4	6%	7%
• Reply 5	9%	7%
Preference for innovation in cars		
• Reply 1	15%	15%
• Reply 2	27%	25%
• Reply 3	23%	22%
• Reply 4	30%	30%
• Reply 5	5%	7%
Environmental donation		
• Yes	13%	14%
• No	87%	86%
Self-assessed Environment		
• Reply 1	0%	0%
• Reply 2	3%	2%
• Reply 3	23%	26%
• Reply 4	58%	53%
• Reply 5	16%	19%
Environmental Mobility		
• Reply 1	3%	5%
• Reply 2	9%	8%
• Reply 3	29%	31%
• Reply 4	45%	47%
• Reply 5	14%	10%

Table 1.4: Latent statistics of the sample

attribute car knowledge. Similarly to Giansoldati et al. (2020), car knowledge is measured through a self-assessment with a Likert scale that ranges from 1, lowest BEV knowledge, to 5, highest BEV knowledge. In both samples, most of the respondents declared to have an average or below average knowledge on BEV's. In terms of assessed car knowledge, we asked respondents one question about BEV range (Q13 in table 1.10) and one question about BEV charging time (Q14 in table 1.10). Respondents were given a level for each question answered correctly. Most respondents answered incorrectly for the two questions on BEV characteristics with 60% in the small sample and 59% in the medium sample. Only 8% in the small sample, and 7% for the medium, responded correctly to both questions. We also asked respondents if they had previously driven an BEV (Q37 in table 1.11) or if they knew someone who had driven one (Q36 in table 1.11), most respondents in both samples responded no to both questions.

We now describe the results for the attitudinal questions for the latent variable "early adopter" reported in table 1.4. This latent variable includes attitudinal questions on risk preference and the preference for innovation when purchasing cars. We asked respondents to provide their preference for risk in general (Q19 in table 1.10), then towards their own health and professional career with a Likert scale that ranges from 0, no tolerance for risk, to 10, full tolerance to risk for the respondent. For the preference for innovation, we asked respondents how important innovation was for them when purchasing a new car(Q21 in table 1.10) with a scale ranging from 1, no importance for innovation, to 5, innovation being crucial for the vehicle choice. These questions are displayed in table 1.10 in the appendix section. However we chose to only use the results for the question regarding the preference for risk in general for further analysis. Then we used a risk lottery game in the win domain (Q20 in table 1.10), taken from the study by Glatt et al. (2019) which represents a modification of the original game by Harrison et al. (2010). This consisted in asking respondents to choose between different lotteries, shown in figure 1.6 in the appendix section, with the first lotteries having no risk and the last ones having higher risk but also higher rewards.

In both samples, most respondents replied that their risk-tolerance was medium to high, whereas their choices in the assessed risk attitude reflected a low tolerance for risk by choosing the safest lotteries. For the preference for innovation in cars, we observe in both samples a high heterogeneity in answers, with the mean being the medium response.

Finally, we describe the results for the last attitudinal questions used for the "environmental attitude" latent variable reported in table 1.5. We asked respondents questions related with environmental behavior (Q23 in table 1.11), with the answers to these questions we made a score called self-assessed environment. We also asked respondents to what extent they worried about their GHG emissions for their mobility (Q24 in table 1.11) with a scale ranging from 1, no concern for environmental mobility, to 5, representing full concern. In both samples, we observe that most respondents responded that they adopt "environmental friendly" behavior and care about their emissions for their mobility. Finally, we asked respondents if they had ever donated money for an environmental organisation (Q22 in table 1.10) and in both samples, most respondent responded no.

1.4 Empirical Strategy

This section outlines the various hypotheses formulated to address the research question of this chapter: "What are the barriers to electric vehicle adoption?" Subsequently, we introduce the available modeling tools and provide a rationale for our selected hybrid choice model approach. Lastly, we detail the latent variables incorporated into our chosen modeling methodology.

1.4.1 Hypotheses

Hypothesis 1. *states that the attributes used in the experiment are the main determinant of vehicle adoption and have the expected effect on vehicle preferences.* The null hypothesis follow the previous results from the literature, which predicts that the monetary attributes have a negative effect on vehicle adoption and the vehicle characteristics have a positive effect on vehicle adoption. Lower vehicles emissions is also expected to have a positive effect on adoption following the results of (Achtnicht et al., 2012; Jensen et al., 2013; Hackbarth and Madlener, 2013; Hidrue et al., 2011; Potoglou and Kanaroglou, 2007).

Hypothesis 2. *states that respondents have different preferences and different uses for the different vehicle sizes presented to them.* The null hypothesis predicts that there is a difference in coefficients for the attributes and the constants between the small vehicle model and the medium vehicle model. Rejecting the null indicates that there are no observed differences between the small and medium vehicle sample.

Hypothesis 3. *states that respondents prioritize direct monetary costs over usage costs.* The null hypothesis predicts that the utility related to vehicle adoption is more elastic to changes in the purchase price than changes to fuel or maintenance costs. This follows the results by Giansoldati et al. (2020), which suggest that respondents were more receptive to immediate lump sum costs rather than future savings made by purchasing an alternative vehicle technology with lower fuel costs.

Hypothesis 4. *states that respondents who have good BEV knowledge, are "early adopters" or are "environmentally minded" tend to adopt BEV's more often than other respondents.* The null hypothesis predicts that latent variables and their interaction with the vehicle attributes are positive and significant.

Hypothesis 5. *states that respondents dislike uncertainty around the level of recharging infrastructure.* The null hypothesis predicts that the levels of infrastructure including risk have more of a negative effect on utility the levels without any risk.

1.5 Econometric Analysis

This section provides an overview of the theoretical foundation for analyzing discrete choice experiments. We then delve into the specific models utilized in this chapter. The models are articulated and explained based on the work presented by Chèze et al. (2021).

1.5.1 Random Utility Model

Lancaster's theory posits that a product can be characterized by its attributes, with its value being an aggregate of these attributes' values (Lancaster, 1966). In the context of the Discrete Choice Experiment (DCE) approach, an option i is defined by K observable attributes, denoted X_i. Similarly, an individual n is characterized by A socio-economic and attitudinal traits, represented as Z_n. The resulting indirect utility $V_{n,i}$ is expressed as:

$$V_{n,i} = V(X_i, S_n) \quad \forall n \in [1, N], i \in [1, I] \tag{1.1}$$

Building on this, McFadden and Zarembka (1974) suggest that individuals base their choices on a deterministic component, influenced by their characteristics S and option attributes X, and a random component ϵ. The random utility $U_{n,i}$ for a choice i by respondent n is the sum of the deterministic indirect utility $V_{n,i}$ and the random factor $\epsilon_{n,i}$:

$$U_{n,i} = V(X_i, S_n) + \epsilon_{n,i} \tag{1.2}$$

Assuming rational decision-making, a respondent will opt for choice i if its utility $U_{n,i}$ surpasses that of other options j, represented as $U_{n,j}$:

$$U_{n,i} > U_{n,j} \implies V_{n,i} + \epsilon_{n,i} > V_{n,j} + \epsilon_{n,j} \quad \forall j \neq i \tag{1.3}$$

As articulated by Train (2009), the likelihood of a respondent selecting option i equates to the probability that its utility exceeds that of any other choice in the set:

$$P_{n,i} = P\left(U_{n,i} > U_{n,j}\, \forall j \neq i\right) \tag{1.4}$$

$$P_{n,i} = P\left(V_{n,i} + \epsilon_{n,i} > V_{n,j} + \epsilon_{n,j}\, \forall j \neq i\right) \tag{1.5}$$

$$P_{n,i} = P\left(\epsilon_{n,j} - \epsilon_{n,i} < V_{n,i} - V_{n,j}\, \forall j \neq i\right) \tag{1.6}$$

1.5.2 Specification of the Indirect Utility Functions

The random utility $U_{n,i}$ comprises a deterministic component, $V_{n,i} = V(X_i, S_n)$, and a stochastic element, $\epsilon_{n,i}$. For simplicity, a linear specification is commonly adopted in literature.

For our labeled alternatives experiment, the baseline Conditional Logit (CL) model, excluding interactions with respondent socio-economic traits, defines the utility of an option as:

$$U_{ni} = ASC_i + \beta_{n,i} X_i + \epsilon_{n,i} \tag{1.7}$$

Here, Asc signifies the alternative-specific constant for propulsion type i. It captures the effects of either the battery electric or hybrid electric propulsion systems, holding other factors constant. This dummy variable assumes a value of 1 when the associated propulsion type is selected and 0 otherwise. The error term ϵ is i.i.d. based on the assumptions of this baseline CL model.

1.5.3 Econometric Models

A variety of econometric models are available for discrete choice data analysis. This section introduces the Conditional Logit (CL), Random Parameter Logit (RPL), Latent Class (LC), and Integrated Choice and Latent Variable (ICLV) models.

Conditional Logit models

The CL model stands as a foundational tool for discrete choice data analysis and has been extensively employed in DCEs. However, it has its limitations, notably its assumption of uniform preferences across respondents. The (multinomial) logit probability of a respondent n selecting a specific option i is:

$$P_{n,i} = \frac{e^{V_{n,i}}}{\sum_j e^{V_{n,j}}} \tag{1.8}$$

The hypothesis of irrelevant alternatives suggests that the relative probabilities of two choices, i and h, being selected remain unaffected by the addition or removal of other options:

$$\frac{P_{n,i}}{P_{n,h}} = \frac{e^{V_{n,i}}}{\sum_{j \neq h} e^{V_{n,j}}} \times \frac{e^{V_{n,h}}}{\sum_{j \neq i} e^{V_{n,j}}} \tag{1.9}$$

Random Parameter Logit models

The RPL model, as discussed in Tversky (1992); Train (2009), offers a more flexible approach than the CL model by relaxing the IIA assumption and accommodating heterogeneity in respondents' preferences. The probability of selecting an alternative in the RPL model is given by:

$$P_{n,i|\beta} = \frac{e^{V_{n,i}(\beta)}}{\sum_j e^{V_{n,j}(\beta)}} \tag{1.10}$$

In the absence of socio-demographic cross-effects, the individual-specific utility is modeled as:

$$U_{n,i} = \beta_n X_i + \epsilon_{n,i} \tag{1.11}$$

where $\epsilon_{n,i} \sim$ iid extreme value type I and $\beta_n \sim g(\beta|\Omega)$.

Given that β_n is unknown, the unconditional choice probability of person n choosing alternative i is the integration of $P_{n,i|\beta}$ over the distribution of β:

$$P_{n,i} = \int L_{n,i}(\beta) f(\beta|\Omega) d\beta \tag{1.12}$$

Here, $f(\beta|\Omega)$ is the density that describes the distribution of preferences across individuals. Ω represents the true parameters of taste variation, such as the fixed parameters of the distribution indicating the mean and standard deviation of β_n in the population. A prevalent assumption in literature is that random parameters are normally distributed, except for the cost attribute, which is either fixed or assumed to follow a log-normal distribution to prevent a negative sign for a subset of respondents.

The simulated probability of individual n choosing alternative i is:

$$SP_{n,i} = \frac{1}{R} \sum_{r=1}^{R} L_{n,i}(\theta_r) \tag{1.13}$$

Latent Class

The Latent Class model offers another approach to relax the IIA assumption and account for heterogeneity in respondents' preferences.

Unlike Equation (1.10), the logit probability for respondent n favoring a specific alternative i over alternatives j is no longer defined for a given β but is conditional on class c. Here, the β's are assumed to follow a discrete distribution, belonging to one of the C classes. The conditional probability for respondents in class c choosing alternative i is:

$$P_{n,i|\beta_c} = \frac{e^{V_{n,i}(\beta_c)}}{\sum_j e^{V_{n,j}(\beta_c)}} \quad \forall c \in \{1, \ldots, C\} \tag{1.14}$$

where β'_c is the vector of class-specific preference parameters, representing the average importance of each attribute for respondents in class c.

The unconditional probability of individual n selecting choice option i is:

$$P_{n,i} = \sum_{c=1}^{C} \Pi_{n,c} P_{n,i|\beta_c} \tag{1.15}$$

$$= \sum_{c=1}^{C} \frac{e^{\beta_c X_i}}{\sum_j e^{\beta_c X_j}} \tag{1.16}$$

where $\Pi_{n,c}$ denotes the probability of respondent n belonging to class c:

$$\Pi_{n,c} = \frac{e^{\phi_c Z_n}}{\sum_h e^{\phi_h S_n}} \tag{1.17}$$

Z_n is the vector of psychometric constructs and socioeconomic characteristics, and ϕ is the vector of parameters associated with Z_n (Boxall and Adamowicz, 2002).

According to Equation (1.17), the probability of belonging to a class with specific preferences is probabilistic and is influenced by the respondent's socio-economic and attitudinal characteristics. By combining Equations (1.16) and (1.17), the LC model assumes that respondent characteristics indirectly influence their choice through their impact on segment membership. Note that ϕ_c includes $C-1$ class membership parameters, with ϕ_C normalized to zero for identification purposes. All other coefficients ϕ_c are interpreted relative to this normalized class.

Hybrid Choice Model

Hybrid models integrate both a Discrete Choice Model (DCM) and a Structural Equation Model (SEM). The DCM mirrors the previously discussed models but incorporates Latent Variables into the deterministic utility function V:

$$U_{n,i} = V(X_i, S_n, \eta_n) + \varepsilon_{n,i} \tag{1.18}$$

where η_n is a $Q \times 1$ vector of the Q latent variables for individual n, and ε_n is the $I \times 1$ vector of iid error terms for the I alternatives.

Drawing from Soto et al. (2018) and Giansoldati et al. (2020), the structural equation, given by 1.19, describes the individual-specific latent attribute η_j for each of the three latent attributes: car knowledge, early adopter, and environmentally minded.

$$\eta_{jin} = \sum_r \alpha_{ri} S_{rin} + \upsilon_{n,i} \tag{1.19}$$

Here, S_{rin} refers to the socio-economic attributes of the n respondents for i vehicle technology and r explanatory variable. The parameters to be estimated are represented by α, and υ_{in} are the error terms with zero mean.

Our measurement equations are modeled as an ordered logit model. Each discrete choice response k is derived from the individual-specific latent attribute plus an error term through a censoring mechanism that identifies different response categories. The categorical response, represented by Z_{in}, is defined using a set of threshold parameters (τ):

$$Z_{in} = \begin{cases} 1 \text{ if } (-\infty) < Z_{in} \leq \tau_1 \\ 2 \text{ if } \tau_1 < Z_{in} \leq \tau_2 \\ 3 \text{ if } \tau_2 < Z_{in} \leq \tau_3 \\ \ ... \\ K \text{ if } \tau_{K-1} < Z_{in} \infty \end{cases} \tag{1.20}$$

$$Z_{in} = \gamma_i \upsilon_{in} + \xi_{in} \tag{1.21}$$

In this chapter, our most advanced model employs a hybrid choice approach, drawing on data related to stated preferences, respondents' understanding of battery electric vehicles (BEV), their disposition towards technology, and their perspectives on risk and the environment. We adopt the methodology from Tran et al. (2013) to discern if a portion of our sample can be classified as "early adopters" or "followers". This distinction will enable us to understand how these two groups differ in their vehicle technology preferences.

The utility in each Hybrid Choice model is specified as:

$$U_{n,i,j} = ASC_i + \sum_x \beta_{xi} X_{xin} + \theta_i \eta_{jin} + \sum \varphi_{gi} X_{in} \eta_{jin} + \epsilon_{n,i} \tag{1.22}$$

Here, Asc represents the alternative-specific constant for propulsion type i. In our context, it captures the effects of either the battery electric propulsion system or the hybrid electric propulsion system, holding other factors constant. This dummy variable assumes a value of 1 when the associated propulsion type is selected and 0 otherwise. We aim to estimate the parameters θ, β, and φ for the car attribute x

for respondent n, which are linked with the level of the vehicle attribute X, and the latent specific attribute η_{jn}. The error term ϵ is i.i.d. based on the assumptions for the MNL model presented in equation 1.7.

1.5.4 Latent variables used in the model

Group	Variable	Type	Description
Design attributes	*Purchase Price*	Continuous	€1 000
	Fuel Cost	Continuous	€1 000
	Maintenance Cost	Continuous	€1 000
	Vehicle Range	Continuous	Km 100
	Environmental Label	Ordinal (1-5)	1: lowest; 7: highest
	Level of infrastructure	Ordinal (1-6)	Ratio out of 5 with or without risk 1: 1/5 stations available 2: 3/5 or 1/5 stations available 3: 5/5 or 1/5 stations available 4: 3/5 stations available 5: 5/5 or 3/5 stations available 6: 5/5 stations available
Socio-economic characteristics	*Gender*	Dummy (0-1)	1: female; 0: male
	Age	Ordinal (1-5)	1: youngest; 7: oldest
	Diploma	Ordinal (1-3)	1: lowest; 3 highest
	Income	Ordinal (1-3)	1: lowest; 3 highest
Measurement indicators	*Self-assessed car knowledge*	Ordinal (1-5)	1: lowest; 5: highest
	Assessed car knowledge	Ordinal (1-3)	1: lowest; 3: highest
	Driving Experience	Dummy (0-1)	1: driven; 0: not driven
	Social car	Dummy (0-1)	1: acquainted with EC driver; 0: not acquainted with EC driver
	Self-assessed risk preference	Ordinal (1-11)	1: lowest; 11: highest
	Assessed risk preference	Ordinal (1-5)	1: lowest; 5: highest
	Car Innovation preference	Ordinal (1-5)	1: lowest; 5: highest
	Self-assessed environmental preference	Ordinal (1-5)	1: lowest; 5: highest
	Environmental donation	Dummy (0-1)	1: donation given; 0: no donation given
	Green Mobility	Ordinal (1-5)	1: lowest; 5: highest

Table 1.5: Variables used in the model

Table 1.5 shows in the first part the different attribute used for describing the hypothetical vehicles shown to respondents. These attributes are either represented as a continuous or ordinal variable. In the second part, we can see the different socio-economic characteristics used for the structural models in our three Hybrid Mixed Logit (HMXL) models. The third part describe the variables used for each of the measurement models for the three HMXL models.

The measurement variables for the Electric car knowledge equation are, (*Self-assessed car knowledge*) ranging from a minimum of 1, which indicates the absence of knowledge on BEV, to a maximum of 5, which indicates that the respondent see himself as an "BEV expert". The measurement indicator for the variable "objective knowledge", *Assessed car knowledge*, takes a value depending on the respondent's answer to two questions i.e. 1) "What is the maximum range for a standard electric car (i.e. Renault Zoe) and 2) "What is the minimum time required to recharge an electric car using fast-charging infrastructure ?". The value of the indicator corresponds to the number of correct answers to the previous two questions based on BEV characteristics at the time of the survey. The measurement indicator for the BEV driving experience (*Driving Experience*) takes the value of 1 if the respondent has at least driven an BEV once, 0 otherwise. The measurement indicator for having an BEV driver as an acquaintance (*Social car*), takes the value of 1 if the respondent know someone who drives an BEV, 0 otherwise.

The measurement indicators for the "early adopter" latent equation are, the respondent's self described tolerance for risk *Self-assessed risk preference* ranging from a minimum of 1, which indicates zero tolerance for risk, to a maximum of 5, which indicates that the respondent frequently engages in risky behavior. The assessed risk tolerance *Assessed risk attitude*, takes a value depending on the respondent's choice between 5 lotteries, where the minimum 1 corresponds to choosing the safest lottery, and the maximum 5 corresponds to choosing the riskiest lottery. The respondent's preference for innovation in car, *Preference for innovation in cars*, ranges from a minimum of 1, indicating the respondent doesn't car at all about technology when purchasing a new car, to a maximum of 5, indicating the respondent only purchases a car if it brings new technology and innovation.

The measurement indicators for the "environmental attitude" are, the respondent's view of their own behavior as "environmentally friendly", *Self-assessed Environment*, takes a value depending on the respondent's answer to several questions on their habit of recycling or purchasing environmentally friendly products, which was then calculated into a score, with a minimum of 1, indicating they don't care about the environment, to a maximum of 5, indicating they only partake in "environmentally friendly" behavior. Whether the respondent donated to an environmental organisation (*Environmental donation*), takes the value of 1 if the respondent donated at least once and 0 if the respondent never donated.

1.6 Results

1.6.1 Mixed Logit Model

To investigate the impact of vehicle attributes and fast charging network density on preferences for alternative vehicles, we estimate the mixed logit model (MXL) in

		MXL Model (Small Sample)		MXL Model (Medium Sample)	
		Coefficient (T.rat)	Coeff. Std. (T.rat)	Coefficient (T.rat)	Coeff. Std. (T.rat)
. ***Attributes***					
. ASC Electric		-0.226242	3.584724***	-1.126147**	-3.813379***
		(-0.36997)	(7.59768)	(-2.3556)	(-8.6324)
. ASC Hybrid		0.423217*	-3.163132***	-0.792059***	-3.094026***
		(1.62575)	(-13.84433)	(-3.5699)	(-12.1071)
. Purchase Price		-3.3579e-04***	-2.7068e-04	-2.8998e-04***	-1.9414e-04***
		(-13.50292)	(-7.07566)	(-13.2423)	(-11.4597)
. Fuel Cost		-0.002160***	0.002453***	-0.002431***	0.001847***
		(-6.62057)	(5.51622)	(-11.3478)	(8.1590)
. Maintenance Cost		-0.003157***	-0.003450***	-0.002882***	0.004197***
		(-5.60274)	(-3.24903)	(-7.2205)	(10.4066)
. Vehicle Range (ln)		1.451906***	1.510565***	2.022135***	3.098812***
		(3.56066)	(4.21927)	(4.2900)	(6.3351)
. Environmental Label		0.195786***	-0.562470***	0.291206***	0.329417***
		(3.12799)	(-2.94077)	(5.3593)	(3.0566)
. Recharging Infrastructure :					
. (RI_1)	*1/5 Stations*	-1.220412***	1.767976***	-1.812170***	-1.582598**
		(-3.20339)	(4.47323)	(-4.7721)	(-2.0305)
. (RI_2)	*50% 1/5 Stations*	-0.758856**	-0.847976	-0.889568***	-0.327087
	50% 3/5 Stations	(-2.40786)	(-1.35032)	(-2.6190)	(-0.5638)
. (RI_3)	*50% 1/5 Stations*	-1.055063***	-0.686936	-1.509114***	0.699295**
	50% 5/5 Stations	(-3.44753)	(-0.51467)	(-4.9924)	(2.1704)
. (RI_4)	*3/5 Stations*	-0.013544	0.324817	-0.633828**	1.218201***
		(-0.06409)	(0.93958)	(-2.4647)	(3.0400)
. (RI_5)	*50% 3/5 Stations*	0.123727	0.214686	-0.422133*	0.743168
	50% 5/5 Stations	(0.55844)	(0.48014)	(-1.8669)	(1.4124)
N (ind.)		512		510	
N (obs.)		4096		4080	
Adjusted R2		0.3861		0.3692	
Log Likelihood		-2738.448		-2803.327	
AIC		5524.9		5654.65	
BIC		5676.52		5806.19	

ASC: Alternative Specific Constant. **** indicates significance at 1%, ** at 5% and * at 10%.*

Table 1.6: MXL Results

utility space.[2]

We use a log-transformation of the vehicle range attribute to estimate the effect of a change in vehicle range, instead of the effect of the range in itself. Concerning the recharging infrastructure attribute, which includes risk, we ordered levels according expected values and level of risk. We consider that a level without risk would be ranked higher than the level with risk at the same expected value. In order to find the effect of each infrastructure level compared to a full infrastructure level, we modeled the attribute as a dummy variable with the full level of infrastructure as a reference level in order to avoid the dummy trap. Hence, each infrastructure level represented in table 1.6 represents the change in utility resulting from the change in infrastructure from the reference level.

Table 1.6 provides two versions of the model. One version with the small vehicle choice experiment and the other version with the medium vehicle choice experiment. In each sample, the left column shows the coefficient for the estimator of the attribute, while the right column shows the coefficient for the standard deviation of the estimator. We choose to display in parentheses the t-ratio for each of the coefficients in order to point out the statistical significance of each estimator. We can see from the results in both vehicle samples that the standard deviation of most coefficients are significant, which confirms the presence of heterogeneity in the preferences for the attributes in the experiment.

When looking at the MXL results, we find that in the small sample only the alternative specific constant (ASC) for PHEVs is positive and significant, whereas both ASCs are negative and significant for the medium vehicle sample. These results for the small sample reveal that respondent's utility increases if the car is PHEV, meaning, that *ceteribus paribus*, attributes other than those specified in the model positively affect the utility that respondents derive from an BEV. Thus, the results for the medium sample, show that respondents utility decreases from factors outside our model for BEVs and PHEVs. Hence in the small sample, respondent's preferred PHEVs over ICVs, while in the medium sample, respondents preferred ICVs over PHEVs and BEVs. The differences in results for the ASCs in the two sample, show that respondent's attributed different uses to the vehicle's that were presented to them.

[2]Results for the Multinomial Conditional Logit models with fixed preferences are available in table 16 in the appendix section.

All the vehicle's direct attributes (purchase price, fuel cost, maintenance cost, vehicle range, environmental label) are significant and have the expected sign.
In both samples, the vehicle range has the expected sign and is significant.
Both samples show that vehicle emissions negatively affect respondent's utility, suggesting that respondents do take into account environmental factors when reviewing a vehicle.
Looking at the effect of the level of recharging infrastructure on the respondent's preference. We estimate this attribute as a dummy variable, ranging from the lowest (1) to the fullest (6) level of infrastructure, with the fullest level serving as a reference for the other values. For the small vehicle sample we can see, that the coefficients for the first three infrastructure levels are negative and significant. Whereas for the medium vehicle sample we can see, that the coefficients are negative and significant for all infrastructure levels. This suggests that respondents in the small sample were indifferent between vehicles with a full infrastructure coverage and vehicle with more than 3 levels of coverage, while respondents in the medium sample are significantly concerned about recharging infrastructure without a full level of infrastructure coverage. Once again, our results suggest that respondent found different uses for the vehicles that were presented to them and were more accepting of the level of infrastructure for smaller vehicles.

1.6.2 Elasticities

Let us now look more into details at the monetary attributes (purchase price, fuel cost and maintenance cost). The elasticity of the choice probability with respect to an independent variable is calculated by dividing the changes in the probability and the independent variable by the values at which the elasticity is being calculated Glasgow (2022). We observe, in table 1.7, that for all categories, the purchase price has the highest effect on the respondents preferences among the three monetary attributes, followed by fuel cost and thereafter maintenance cost.

1.6.3 Willingness To Pay Estimates

Welfare can be measured in the form of a marginal WTP/WTA by estimating the marginal rate of substitution (MRS) between the considered attribute and income (Louviere et al., 2000). Here the implied utility from income is represented by one of the monetary costs for each vehicle. We choose the *purchase price* attribute $\beta price$ as the representation of the marginal utility of income. Since we study the barriers

Attributes	Small Model	Medium Model
Conventional Elasticities		
.Purchase Price	-1.082375	-2.529367
.Fuel Cost :	-0.3294652	-0.7147667
.Maintenance Cost :	-0.1781723	-0.33044
Electric Elasticities		
.Purchase Price	-1.64362	-1.586954
.Fuel Cost :	-0.1309902	-0.1589469
.Maintenance Cost :	-0.1297877	-0.1374121
Plug-In Hybrid Elasticities		
.Purchase Price	-1.635799	-1.536038
.Fuel Cost :	-0.232132	-0.3763653
.Maintenance Cost :	-0.181076	-0.1989276
N (ind.)	512	510

Table 1.7: Elasticities

Table 1.8: WTP estimates for the Mixed Multinomial Logit models.

		Small Sample	Medium Sample
		Mean (95% CI)	Mean (95% CI)
. Attributes			
	. Driving Range :	4324	8300
		(1874 ; 6774)	(5416,84 ; 11183,16)
	. Environmental Label	583,1	1015
		(232,064 ; 934,136)	(635,348 ; 1394,652)
	. Available Infrastructure		
	(Station 1/5)	-3634	-6097
		(-5891,92 ; -1376,08)	(-8092,28 ; -4101,72)
	(50% Station 1/5; 50% Station 3/5)	-2260	-3236
		(-4047,912 ; -472,088)	(-5280,28 ; -1191,72)
	(50% Station 1/5; 50% Station 5/5)	-3142	-5131
		(-4962,056 ; -1321,944)	(-7033,376 ; -3228,624)
	(Station 3/5)	-40,33	-2554
		(-1274,15 ; 1193,49)	(-4209,612 ; -898,388)
	(50% Station 3/5; 50% Station 5/5)	368,5	-1816

to adoption of alternative vehicles, it is easier to interpret this MRS as a WTP. This is consistent with the fact that most of our non-monetary attributes of our choices are valued positively by respondents, with the exception of the *infrastructure level* attribute. Since utilities are modelled as linear functions of the attributes, the MRS between two attributes is the ratio of the coefficients of the two attributes. For attributes modelled as discrete variables, the WTP_k associated with attribute k is $WTP_k = -\frac{\beta_k}{\beta price}$. This applies for the *range* and *environmental label* attributes. For the *infrastructure level* attribute, which we modelled as dummy-coded variable with as a reference level the highest infrastructure level, it is easier to think of the MRS as a WTA. Where the WTA_k^l associated with attribute k and category l is $WTP_k^l = -\frac{\beta_k^l}{\beta price}$.

We have derived the implied willingness to pay estimates (WTP) for the MXL models (Table 1.8) for each of the two vehicle categories. The estimated standard deviations and confidence intervals around the mean of the WTP estimates are obtained using the delta method at a 95 % confidence interval. The WTP for increasing the *Environmental Label* by one level is €583 for the small sample and €1015 for the medium sample. We can see that by this level our respondents are concerned about their potential vehicle emissions. The difference in WTP between both samples could be explained by a concern of respondents for future environmental regulations, explained by the fact that medium sized vehicle tend to emit more than small ones.

1.6.4 Hybrid Choice Model

In order to further investigate on the source of heterogeneity in vehicle preferences we include in the next model specifications different latent variables, with the aim of finding psychological profiles that are more favorable to the adoption of low-carbon vehicles. These psychological profiles are related to the respondent's socio-economic characteristics and influence the respondent's preferences for each vehicle attribute and thus determines which vehicle they adopt. We choose to include three separate latent profiles, an "electric car knowledge" profile similar to the one used by Giansoldati et al. (2020), an "early adopter profile" and an "environmentally minded" profile. In order to estimate if respondents are part of the latent profile we used for each profile the results of different attitudinal questions asked to respondents. The list of each questions asked to respondents can be found in Table 1.10 and 1.11 in the appendix.

We start by describing the model incorporating the variable electric car (BEV) knowledge, which is based on the design used by Giansoldati et al. (2020) but with the addition of a variable indicating whether the respondent knows someone who has driven a BEV. This latent variable is based on questions about the respondent's knowledge about BEVs and their experience driving one or knowing someone who has. The questions about BEV knowledge are divided in one question where the respondent self-assesses their knowledge about BEVs and another question where their knowledge is tested.

The second model incorporating the variable "early adopters profile", investigates whether the respondent is interested in new car technologies and if they are comfortable with taking risks in general. This is in order to find if the respondent's are "early adopters" a term coined by Everett M Rodgers (1962) describing a part of the population that is keen on adopting new products or technology at an early stage, before it is fully mature and advantageous over other existing products or technology. This latent variable is based on one question about the respondent's self-assessed tolerance for risk in general, one question that tests the respondent's tolerance for risk with a game about choosing between different risky lotteries, and one question about the respondent's self-assessed preference for new technologies in cars.

The third model incorporating the variable "Environmental profile", investigates whether the respondent shows "environmentally minded" behaviour. This latent variable is firstly based on a score calculated from the respondent's answer to several questions about their daily "environmental friendly" behavior, secondly a question asking if the respondent has ever donated to an environmental association, and lastly one question asking the respondent's how concerned they are about the carbon footprint of their mobility habits.

Table 1.5 shows in the first part the different attribute used for describing the hypothetical vehicles shown to respondents. These attributes are either represented as a continuous or ordinal variable. In the second part, we can see the different socio-economic characteristics used for the structural models in our four HMXL models. The third part describe the variables used for each of the measurement models for the four HMXL models.

For each latent variable specification, we include one hybrid mixed model (HMXM) that account for the latent variable interacting with the ASC's, and additionally for the "early adopter" latent variable, one HMXM accounting for the latent variable interacting with the ASC's and the vehicle attributes of interest. When comparing the results for the MXL model in table 1.6 and the results from the different HMXL models in both samples in table 1.3, 1.4 and 1.5 we see that LL (choice) is lower for the HMXL models. The implications are that the introduction of a latent variable for each model improves the ability of the model to explain respondent's choice.

Electric Car Knowledge Results

Table 1.3 presents the results for the equation with the car knowledge latent attribute presented in equation 1.7. The results here are for both samples and present results with and without the interaction of the latent attribute with the vehicle attributes. Since in this case, the interaction is not significant in both samples, we will only comment for the results without the interaction between the latent attribute and the car attributes.

Similarly to the findings by Giansoldati et al. (2020), we see that the positive parameter associated with the $LV * ASCElectric$ variable in the HMXM models for both samples, indicate that a higher BEV knowledge reduces the aversion towards towards BEV. Looking more into detail, we can see that in both samples the ASC's are not significant, meaning that respondents were indifferent between their trust for each of the three vehicle technologies (CV, PHEV, BEV). While the interactions $LV * ASCElectric$ and $LV * ASCHybrid$ are significant and positive in both samples. With the interaction coefficients in the medium sample completely offseting the negative original values for the ASC's. This shows that respondents with good BEV knowledge, in contrast with the rest of the sample, trust and prefer alternative technologies over conventional ones. This result illustrates the HMXL model's ability to disentangle heterogeneity.

In the small sample, the structural model indicates that the Gender, Age, Level of education, and income are related with the LV *BEV knowledge*, the level of electric car knowledge is higher for young, rich and highly educated men. In the medium sample, none of the socio-economic variables are significant and thus related to the level of $BEVknowledge$.

For the measurement model, we find in the small sample that the three indicators (self-assessed knowledge, assessed knowledge and driving experience) are all positively correlated to the level of BEV knowledge. While the medium sample does not show any correlation between having driven an BEV and knowing someone who has on the level of BEV knowledge. For both samples almost all of the thresholds in our measurement model are significant and related to the level of BEV knowledge.

Early Adopters Profile Results

We now look at the model incorporating the variable Early Adopter profile, which indicates whether a respondent is willing to take risks to adopt a new technology. Similarly to the previous latent attribute, the interaction between the latent attribute and the car attribute is not significant. We will therefore, only comment the result with the model without the interaction with the car attributes. We find that for both samples, the coefficient for the interaction between the latent variable and the ASC for BEV's and PHEV's is positive and significant. We also find that for the medium sample the coefficients for the interaction with the ASC for BEV's and PHEV's completely offsets the negative sign of the respective original ASC's.This shows that respondents that are interested in new car technologies and more risk tolerant have a higher trust in alternative vehicle technologies when compared with the rest of the respondents. However they show no differences in risk tolerance concerning the level of infrastructure than the rest of the sample.

Environmental Profile Results

We finally look at the model incorporating the environmental profile latent variable. This latent variable indicates whether a respondent is "environmentally minded" through answering questions about their donations to environmental association, environmental preferences and environmental behaviour. We find that for both samples , the interaction between the latent variable and the ASC Electric and ASC Hybrid are both positive and significant. In the small sample, the coefficient for the interaction between the latent variable and the ASC Electric completely offsets the negative and significant coefficient of the original ASC Electric. While in the medium, sample the interaction for both ASCs completely offset the negative coefficient of both original ASCs. This means that in both samples, most respondents

	HMXL Model (Small Sample-LV1)		HMXL Model (Small Sample-LV1)		HMXL Model (Medium Sample-LV1)		HMXL Model (Medium Sample-LV1)	
	Coefficient (T.rat)	Coeff. Std. (T.rat)	Coefficient (T.rat)	Coeff. Std. (T.rat)	Coefficient (T.rat)	Coeff. Std. (T.rat)	Coefficient (T.rat)	Coeff. Std. (T.rat)
. Attributes								
. ASC Electric	0.495268	-2.813754***	0.012538	3.834936***	-0.948125*	-2.555059***	-2.075346**	-3.407150***
	(0.7853)	(-9.1931)	(0.02055)	(9.09909)	(-1.8109)	(-8.5424)	(-2.28576)	(-8.80368)
. ASC Hybrid	0.612946	-3.225489***	0.447874	3.338914***	-1.079945***	-0.604240	-1.297164***	2.855285***
	(1.2874)	(-11.8742)	(1.14442)	(12.07034)	(-2.8367)	(-0.8366)	(-2.97747)	(9.45950)
. Purchase Price	-3.4170e-04***	-2.3959e-04***	-3.2332e-04***	-2.6190e-04***	-2.7763e-04***	-1.7952e-04***	-2.8389e-04***	1.8679e-04***
	(-14.0642)	(-10.9091)	(-12.91635)	(-11.38984)	(-14.5990)	(-9.5944)	(-13.79959)	(10.43657)
. Fuel Cost	-0.002251***	-0.003060***	-0.002287***	0.002509***	-0.002495***	0.001713***	-0.002362***	0.001858***
	(-6.6370)	(-8.8164)	(-6.64949)	(5.07703)	(-11.3591)	(4.8865)	(-10.15790)	(3.33893)
. Maintenance Cost	-0.002836***	0.004360***	-0.003221***	0.004674***	-0.002538***	0.002760***	-0.002901***	-0.004508***
	(-5.0651)	(4.9583)	(-5.26899)	(4.33813)	(-7.0335)	(4.1138)	(-6.18200)	(-5.68371)
. Vehicle Range (ln)	1.913044***	2.369989***	1.236711***	1.310078***	2.485083***	3.602119***	1.905610***	2.512756***
	(4.0894)	(6.9426)	(2.97008)	(4.10306)	(5.0498)	(7.2137)	(4.16628)	(5.56164)
. Environmental Label	0.172518***	-0.596044***	0.175239***	0.634612***	0.284912***	-0.251350***	0.308498***	0.467726**
	(2.6740)	(-7.9206)	(2.79332)	(6.77382)	(5.3420)	(-3.3506)	(4.77505)	(2.14770)
. Recharging Infrastructure :								
. (RI_1) *1/5 Stations*	-1.215732***	1.696220***	-1.316532***	-2.015923***	-1.814814***	-1.358071**	-1.798696***	-1.925317***
	(-3.7177)	(5.0527)	(-3.42131)	(-4.80274)	(-5.4333)	(-2.4838)	(-4.75029)	(-4.27105)
. (RI_2) *50% 1/5 Stations*	-0.962938***	-1.453917***	-0.883927***	-0.950380**	-0.817156***	0.165422	-0.443886	0.411899
50% 3/5 Stations	(-3.3502)	(-4.7561)	(-2.65632)	(-2.25111)	(-2.7404)	(0.5505)	(-0.90044)	(0.53878)
. (RI_3) *50% 1/5 Stations*	-1.061965***	0.264068	-1.174976***	-0.679325	-1.341126***	0.397482	-1.164489***	0.017844
50% 5/5 Stations	(-3.8645)	(0.6371)	(-3.37418)	(-1.18415)	(-4.9993)	(0.8843)	(-3.06461)	(0.01929)
. (RI_4) *3/5 Stations*	-0.073229	-0.754927	0.003397	0.119993	-0.665379***	-1.229541**	-0.449655	-1.028362**
	(-0.3321)	(-1.5083)	(0.01497)	(0.22102)	(-2.6519)	(-2.5668)	(-1.18374)	(-2.09167)
. (RI_5) *50% 3/5 Stations*	0.102155	-0.201429	0.101718	0.327485	-0.559305***	0.343772	-0.098883	-0.557097
50% 5/5 Stations	(0.4646)	(-0.9084)	(0.39978)	(0.41035)	(-2.6325)	(0.5081)	(-0.26981)	(-1.16868)
. Estimated parameters of the structural model	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)
. LV_Female	-0.953959***	(-6.86)	-0.887813***	(-6.67)	-	(-)	-0.701417***	(-3.71028)
. LV_Age (30-44)	-0.184055	(-0.74)	-0.518291*	(-1.85)	-	(-)	-	(-)
. LV_Age (45-64)	-0.555939**	(-2.22)	-0.650567**	(-2.22)	-	(-)	-	(-)
. LV_Age (65 +)	-0.729289***	(-2.96)	-0.993180***	(-3.15)	-	(-)	-	(-)
. LV_Diploma (Mid)	0.382810**	(2.3664)	0.322369*	(1.79)	0.154859	(1.0730)	0.488617**	(2.39402)
. LV_Diploma (High)	0.504910***	(2.70)	0.451519**	(2.17)	0.455380**	(2.3470)	0.657589***	(2.96369)
. LV_Income (Mid)	0.647027**	(2.47)	0.707768***	(2.71)	-	(-)	0.480624*	(1.63762)
. LV_Income (High)	0.795611***	(3.05)	0.984795***	(3.43)	-	(-)	0.951573***	(3.07379)
. Estimated parameters of the measurement model	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)
. LV * ASC Electric	1.612030***	(5.0598)	1.113208***	(2.74975)	3.578716***	(6.8269)	1.478455**	(2.04540)
. LV * ASC Hybrid	1.378647***	(4.2483)	0.914834***	(4.31592)	3.780954***	(8.6691)	0.790731*	(1.86479)
. LV * RI_1	-	(-)	1.8196e-04	(4.8824e-04)	-	(-)	0.082607	(0.23108)
. LV * RI_2	-	(-)	0.281989	(0.73470)	-	(-)	-0.679827*	(-1.99012)
. LV * RI_3	-	(-)	0.426314	(1.22920)	-	(-)	-0.572946**	(-2.09223)
. LV * RI_4	-	(-)	-0.097383	(-0.35856)	-	(-)	-0.269681	(-0.72533)
. LV * RI_5	-	(-)	-0.288128	(-1.16932)	-	(-)	-0.545084*	(-1.89820)
. zeta_self_assessed_car_knowledge	1.224453***	(7.4061)	1.195071***	(6.71559)	0.289392**	(2.1249)	0.997941***	(5.66760)
. zeta_assessed_car_knowledge	0.310294***	(3.0440)	0.330852***	(3.08178)	0.359788***	(2.9968)	0.553387***	(4.58295)
. zeta_social_car	1.065051***	(4.4035)	1.072281***	(4.07651)	0.261493*	(1.8445)	0.973767***	(3.81786)
. zeta_driving_experience	1.298219***	(4.1269)	1.504398***	(3.69790)	0.389796*	(1.9370)	1.186430***	(3.77855)
. tau_self_assessed_car_knowledge_1	-2.665193***	(-5.7857)	-2.768532***	(-5.52621)	-1.926053***	(-14.0371)	-1.829223***	(-5.27977)
. tau_self_assessed_car_knowledge_2	-0.581470	(-1.4291)	-0.690137	(-1.55080)	-0.340008***	(-3.5020)	0.029175	(0.09929)
. tau_self_assessed_car_knowledge_3	1.866752***	(4.6907)	1.762269***	(4.00842)	1.586964***	(12.4813)	2.403612***	(7.77996)
. tau_self_assessed_car_knowledge_4	4.132638***	(8.7023)	3.997510***	(7.77798)	3.282460***	(13.9367)	4.328823***	(10.75501)
. tau_assessed_car_knowledge_1	0.394843***	(2.9749)	0.364959**	(2.48268)	0.443836***	(4.4223)	0.712670***	(3.62768)
. tau_assessed_car_knowledge_2	2.474744***	(13.2175)	2.451131***	(12.39272)	2.722527***	(14.2986)	3.085028***	(10.93503)
. tau_social_car_1	0.626347*	(1.7870)	0.535070	(1.36348)	0.493958***	(5.0247)	1.078419***	(2.85480)
. tau_driving_experience_1	2.240515***	(4.7976)	2.288437***	(3.81818)	1.777605***	(11.7985)	2.828531***	(5.34845)
N (ind.)	512		512		510		510	
N (obs.)	4096		4096		4080		4080	
Log Likelihood (Choice)	-2719.326		-2722.053		-2752.211		-2796.24	
AIC	8754.69		8754.34		8980.3		8953.71	
BIC	9063.96		9097.23		9249.07		9276.24	

ASC: Alternative Specific Constant. ****** indicates significance at 1%, ** at 5% and * at 10%.*

Figure 1.3: LV1 (Electric car) Results

	HMXL Model (Small Sample-LV2)		HMXL Model (Small Sample-LV2)		HMXL Model (Medium Sample-LV2)		HMXL Model (Medium Sample-LV2)	
	Coefficient (T.rat)	Coeff. Std. (T.rat)	Coefficient (T.rat)	Coeff. Std. (T.rat)	Coefficient (T.rat)	Coeff. Std. (T.rat)	Coefficient (T.rat)	Coeff. Std. (T.rat)
. Attributes								
. ASC Electric	0.694966	-1.613269**	1.543205	0.054761	-1.018379*	-2.235906***	-0.507802	2.681784***
	(0.64893)	(-2.38037)	(1.5978)	(0.1974)	(-1.7231)	(-10.3486)	(-0.3516)	(3.1712)
. ASC Hybrid	0.693270	-2.861032***	1.606095***	3.060395***	-0.879550***	1.461142*	-0.725500	2.843054***
	(0.94342)	(-9.19048)	(2.9661)	(14.4129)	(-2.6045)	(1.8401)	(-0.9068)	(8.4902)
. Purchase Price	-3.3664e-04***	-2.4564e-04***	-3.0665e-04***	-2.2253e-04***	-2.8588e-04***	-1.8687e-04***	-2.8546e-04***	2.1661e-04***
	(-12.43983)	(-9.70928)	(-13.7576)	(-9.3421)	(-12.5023)	(-11.3751)	(-10.6473)	(8.5023)
. Fuel Cost	-0.002237***	-0.003056***	-0.002207***	0.001883***	-0.002541***	0.001771***	-0.002619***	0.001845***
	(-6.82169)	(-8.16354)	(-6.8723)	(5.9176)	(-11.0451)	(6.5064)	(-10.9318)	(3.8624)
. Maintenance Cost	-0.002970***	0.003931***	-0.003058***	0.002792*	-0.002650***	-0.002499***	-0.002882***	-0.004043***
	(-5.12074)	('3.56834)	(-5.3803)	(1.9734)	(-6.9912)	(-3.8053)	(-6.7357)	(-4.8557)
. Vehicle Range (ln)	2.008486***	2.712783***	0.923494**	0.371670	2.508747***	-3.418790***	2.400594***	3.496488***
	(4.58876)	(9.88390)	(2.3549)	(0.7900)	(5.1731)	(-7.6094)	(3.6800)	(4.2525)
. Environmental Label	0.172877***	-0.584926***	-1.366841***	-1.883661***	0.283651***	-0.235088**	0.331263***	0.461312*
	(2.67077)	(-7.05007)	(-3.4807)	(-4.4394)	(5.4756)	(-2.2316)	(4.5861)	(1.7844)
. Recharging Infrastructure :								
. (RI_1) *1/5 Stations*	-1.272275***	2.077068***	-0.724919**	1.172989**	-1.818856***	-1.669382***	-2.058269***	1.930553***
	(-3.39004)	(4.70924)	(-2.2936)	(2.2165)	(-5.4736)	(-4.6679)	(-3.4077)	(3.5231)
. (RI_2) *50% 1/5 Stations 50% 3/5 Stations*	-0.858064***	-1.378887***	-1.152193***	-0.263499	-0.777746**	0.273344	-0.831507*	0.076951
	(-3.00302)	(-3.26203)	(-3.5225)	(-0.6362)	(-2.5422)	(0.8536)	(-1.8105)	(0.1974)
. (RI_3) *50% 1/5 Stations 50% 5/5 Stations*	-0.969116***	0.200391	-0.092744	-0.126172	-1.396110***	-0.703858*	-1.532061***	-0.096921
	(-3.63222)	(0.29646)	(-0.4295)	(-0.4118)	(-5.0285)	(-1.7206)	(-4.6472)	(-0.1084)
. (RI_4) *3/5 Stations*	-0.045556	-0.610975	-0.096574	-0.616625	-0.630735**	-1.120554***	-0.651750*	-1.434173***
	(-0.20537)	(-0.63369)	(-0.4325)	(-1.4530)	(-2.3267)	(-3.6101)	(-1.8368)	(-3.9263)
. (RI_5) *50% 3/5 Stations 50% 5/5 Stations*	0.049762	-0.498416	0.142535**	0.584228***	-0.603928**	0.564050*	-0.504618	-0.721139
	(0.21455)	(-1.24789)	(2.3164)	(8.4669)	(-2.4500)	(1.9774)	(-1.2194)	(-0.7462)
. Estimated parameters of the structural model	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)
. LV_Female	-0.540057***	(-3.28)	-0.469792***	(-4.59)	-	(-)	-0.472434*	(-1.95)
. LV_Age (30-44)	0.027738	(0.08)	0.090539	(0.65)	-	(-)	-0.550266*	(-1.70)
. LV_Age (45-64)	-0.659183**	(-2.26)	-0.480446***	(-3.19)	-	(-)	-0.618232*	(-1.97)
. LV_Age (65 +)	-0.638316*	(-1.84)	-0.465070***	(-3.21)	-	(-)	-0.918755***	(-2.78)
. LV_Diploma (Mid)	-	(-)	0.108672	(0.98)	0.142641	(1.2562)	-0.034321	(-0.15)
. LV_Diploma (High)	-	(-)	0.160114	(1.13)	0.351318**	(2.0706)	0.242958	(0.63)
. LV_Income (Mid)	0.645219***	(3.26)	0.103080	(0.79)	-	(-)	0.703497	(1.49)
. LV_Income (High)	0.619566***	(2.95)	0.100037	(0.73)	-	(-)	0.845921	(1.53)
. Estimated parameters of the measurement model	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)
. LV * ASC Electric	3.193693***	(8.01271)	4.668862***	(10.2806)	4.390352***	(7.3332)	2.468736	(1.5227)
. LV * ASC Hybrid	2.269044***	(5.70577)	2.626599***	(8.5035)	3.818129***	(4.7864)	1.476542	(1.5019)
. LV * RI_1	-	(-)	0.322475	(0.5800)	-	(-)	0.733456	(1.1495)
. LV * RI_2	-	(-)	0.790001	(1.3800)	-	(-)	-0.472224	(-1.0072)
. LV * RI_3	-	(-)	0.618989	(1.3446)	-	(-)	-0.320472	(-0.8888)
. LV * RI_4	-	(-)	0.149975	(0.3919)	-	(-)	-0.310026	(-0.5424)
. LV * RI_5	-	(-)	0.243695	(0.5417)	-	(-)	-0.683705	(-1.3458)
. zeta_self_assessed_risk	0.450196***	(3.10578)	0.360501***	(3.2327)	0.277583**	(2.16631)	0.703410**	(2.0783)
. zeta_assessed_risk	0.441055***	(3.49759)	0.354741***	(3.1894)	0.330084**	(2.29212)	0.663874***	(3.5426)
. zeta_car_innovation	0.587286***	(3.65765)	0.498792***	(4.4101)	0.471198***	(3.62308)	0.811125**	(2.3050)
. tau_self_assessed_risk_1			-2.867469***	(-14.2616)			-2.795284***	(-4.8619)
. tau_self_assessed_risk_2	-1.937817***	(-8.05017)	-2.144897***	(-13.1701)	-1.732021***	(-13.4844)	-2.043991***	(-3.8806)
. tau_self_assessed_risk_3	-0.443181**	(-2.12833)	-1.427300***	(-10.0585)	-0.347804***	(-3.6388)	-1.317057***	(-2.7288)
. tau_self_assessed_risk_4	0.590783***	(2.88828)	-0.978419***	(-7.5483)	0.598440***	(6.1137)	-0.888564*	(-1.9585)
. tau_self_assessed_risk_5	2.985504***	(10.96510)	-0.621537***	(-4.8929)	2.760297***	(14.7131)	-0.611351	(-1.3881)
. tau_self_assessed_risk_6	-0.693792***	(-4.22665)	0.285896**	(2.3803)	-0.518803***	(-5.5107)	0.401168	(1.0580)
. tau_self_assessed_risk_7	1.081229***	(6.35142)	0.757982***	(6.2698)	1.005771***	(9.2959)	0.971487***	(2.7657)
. tau_self_assessed_risk_8	1.785242***	(9.91122)	1.470760***	(10.7148)	1.901821***	(13.9323)	1.711514***	(5.2147)
. tau_self_assessed_risk_9	2.356096***	(11.59456)	2.607092***	(13.5882)	2.647287***	(14.7589)	2.829868***	(8.4804)
. tau_self_assessed_risk_10	-2.811645***	(-11.70800)	3.371112***	(13.1004)	-2.453442***	(-14.7824)	3.674604***	(9.4495)
. tau_assessed_risk_1	-2.081566***	(-10.00457)	-0.779380***	(-6.7792)	-1.746501***	(-13.8074)	-0.705332*	(-1.8951)
. tau_assessed_risk_2	-1.353817***	(-7.09119)	0.956514***	(8.0380)	-1.081586***	(-10.4308)	0.966205**	(2.5501)
. tau_assessed_risk_3	-0.896922***	(-4.93050)	1.650045***	(12.1491)	-0.697630***	(-7.3028)	1.930621***	(4.7527)
. tau_assessed_risk_4	-0.532924***	(-2.97306)	2.216327***	(13.6738)	-0.448543***	(-4.8528)	2.706817***	(6.3024)
. tau_car_innovation_1	0.394787**	(2.27977)	-2.032402***	(-11.3219)	0.452827***	(4.9143)	-2.095566***	(-3.4847)
. tau_car_innovation_2	0.877353***	(5.09391)	-0.571096***	(-4.1007)	0.961430***	(9.5453)	-0.573663	(-1.1670)
. tau_car_innovation_3	1.603833***	(8.57934)	0.435916***	(3.2572)	1.643320***	(13.4983)	0.489061	(1.1348)
. tau_car_innovation_4	2.750953***	(11.65719)	2.786457***	(12.9665)	2.708764***	(14.5886)	2.844101***	(6.9310)
N (ind.)	512		512		510		510	
N (obs.)	4096		4096		4080		4080	
Log Likelihood (Choice)	-2699.244		-2697.736		-2746.062		-2775.625	
AIC	10692.03		10710.96		10824.14		10844.36	
BIC	11043.75		11109.13		11149.12		11242.3	

ASC: Alternative Specific Constant. *** indicates significance at 1%, ** at 5% and * at 10%.*

Figure 1.4: LV2 (Early Adopter) Results

	HMXL Model (Small Sample-LV3)		HMXL Model (Small Sample-LV3)		HMXL Model (Medium Sample-LV3)		HMXL Model (Medium Sample-LV3)	
	Coefficient (T.rat)	Coeff. Std. (T.rat)	Coefficient (T.rat)	Coeff. Std. (T.rat)	Coefficient (T.rat)	Coeff. Std. (T.rat)	Coefficient (T.rat)	Coeff. Std. (T.rat)
. Attributes								
. ASC Electric	-0.903134*	-3.054312***	-0.295500	3.277065***	-1.851265***	3.019514***	-1.769700***	-1.662395***
	(-1.94988)	(-8.74476)	(-0.6196)	(8.7848)	(-3.7944)	(6.5973)	(-3.1254)	(-7.1771)
. ASC Hybrid	0.201421	-2.966406***	0.205907	-3.059636***	-1.465065***	2.783921***	-1.314574***	-2.474271***
	(0.76664)	(-10.83699)	(0.6933)	(-8.7712)	(-5.1947)	(9.1024)	(-3.8457)	(-9.1310)
. Purchase Price	-3.2053e-04***	-2.3203e-04***	-3.1955e-04***	2.4605e-04***	-2.7474e-04***	-1.9158e-04***	-2.8116e-04***	-1.9604e-04***
	(-12.40900)	(-8.89069)	(-13.6260)	(10.9081)	(-14.1887)	(-9.7259)	(-14.0355)	(-11.1569)
. Fuel Cost	-0.002209***	-0.002060***	-0.002233***	0.002277***	-0.002410***	0.001637***	-0.002456***	0.001264***
	(-6.88681)	(-4.05119)	(-6.8186)	(6.0772)	(-9.9099)	(5.8412)	(-11.2839)	(6.0155)
. Maintenance Cost	-0.003046***	0.002967*	-0.003088***	0.003895***	-0.002699***	-0.004303***	-0.002712***	0.002981***
	(-5.45775)	(1.92694)	(-5.4392)	(4.1678)	(-5.5858)	(-3.1520)	(-7.2258)	(4.3555)
. Vehicle Range (ln)	1.211091***	-1.175313***	1.351408***	1.249115***	1.973766***	-2.374020***	2.215572***	2.661422***
	(3.19420)	(-3.09249)	(3.2916)	(3.1188)	(4.5561)	(-5.0871)	(5.0978)	(8.4990)
. Environmental Label	0.145729**	-0.561024***	0.167204**	0.597827***	0.270418***	-0.285758	0.274530***	0.143630*
	(2.35240)	(-6.76280)	(2.5928)	(8.1860)	(5.3220)	(-1.2537)	(5.3015)	(1.6801)
. Recharging Infrastructure :								
. (RI_1) 1/5 Stations	-1.198223***	1.654322***	-1.264055***	-1.830182***	-1.763500***	1.382957***	-1.861519***	-1.414626***
	(-3.58348)	(4.22725)	(-3.5945)	(-4.4454)	(-4.9917)	(2.8315)	(-5.4265)	(-3.2899)
. (RI_2) 50% 1/5 Stations	-0.608528**	-1.015734***	-0.842841***	1.420541***	-0.852535**	0.291634	-0.827076***	0.506441
50% 3/5 Stations	(-2.28416)	(-2.73787)	(-3.0701)	(4.1431)	(-2.3671)	(0.7133)	(-2.7729)	(1.1387)
. (RI_3) 50% 1/5 Stations	-1.018356***	0.851437**	-1.093847***	-0.744897	-1.369634***	0.270007	-1.349438***	-0.408715
50% 5/5 Stations	(-3.66743)	(2.07628)	(-3.9777)	(-1.5128)	(-4.1767)	(0.5297)	(-4.8906)	(-0.8869)
. (RI_4) 3/5 Stations	-0.019471	-0.103922	-0.074247	0.110287	-0.582102**	1.031124*	-0.546879**	1.034907***
	(-0.09313)	(-0.23782)	(-0.3460)	(0.2212)	(-2.1073)	(1.8190)	(-2.4215)	(3.5017)
. (RI_5) 50% 3/5 Stations	0.079427	0.294659	0.060967	-0.237652	-0.394279*	-0.218441	-0.531181**	-0.322117
50% 5/5 Stations	(0.36081)	(0.53187)	(0.2714)	(-0.8282)	(-1.8322)	(-0.2879)	(-2.4768)	(-0.5601)
. Estimated parameters of the structural model	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)
. LV_Female	-	(-)	-	(-)	0.420082***	(2.65)	0.226707**	(2.0292)
. LV_Age (30-44)	-	(-)	-	(-)	-	(-)	-	(-)
. LV_Age (45-64)	-	(-)	-	(-)	-	(-)	-	(-)
. LV_Age (65 +)	-	(-)	-	(-)	-	(-)	-	(-)
. LV_Diploma (Mid)	0.228230	(1.32217)	0.134920	(1.1614)	0.502711***	(3.05)	0.208784	(1.3957)
. LV_Diploma (High)	0.400344**	(2.36202)	0.484643***	(3.4583°	0.739440***	(3.91)	0.429040***	(2.8851)
. LV_Income (Mid)	-	(-)	-	(-)	-	(-)	-	(-)
. LV_Income (High)	-	(-)	-	(-)	-	(-)	-	(-)
. Estimated parameters of the measurement model	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)	Coefficient	(Coeff T.rat)
*. LV * ASC Electric*	2.478000***	(7.51841)	2.478128***	(7.0474)	2.146560***	(4.8337)	4.105723***	(8.9008)
*. LV * ASC Hybrid*	1.619255***	(5.80615)	1.547640***	(5.7701)	1.615280***	(4.5446)	2.734715***	(6.3008)
*. LV * Environmental label*	-	(-)	0.149375**	(2.1019)	-	(-)	0.163610**	(2.3932)
. zeta_environment_donation	0.955149***	(3.97423)	0.900817***	(3.8479)	1.153275***	(4.8581)	0.782164***	(3.4830)
. zeta_self_assessed_green	1.701074***	(5.55270)	1.700519***	(6.5064)	1.120641***	(5.8497)	0.661616***	(4.0950)
. zeta_green_mobility	1.452645***	(6.27991)	1.656348***	(6.5839)	1.397916***	(4.9404)	0.813305***	(4.8135)
. tau_environment_donation _1	2.385263***	(9.55909)	2.293053***	(9.9591)	2.790431***	(8.3673)	2.210330***	(9.3506)
. tau_self_assessed_green_1	-6.623681***	(-8.43412)	-6.701077***	(-8.7613)	-6.494205***	(-6.2966)	-6.297468***	(-6.2483)
. tau_self_assessed_green_2	-4.330204***	(-10.93143)	-4.379101***	(-11.4748)	-3.923670***	(-11.1000)	-3.782244***	(-12.2206)
. tau_self_assessed_green_3	-1.261946***	(-6.57312)	-1.334787***	(-6.7498)	-0.677535***	(-3.9855)	-0.840046***	(-6.8869)
. tau_self_assessed_green_4	2.701708***	(8.30897)	2.614870***	(9.4926)	2.332993***	(8.7938)	1.749744***	(9.3179)
. tau_green_mobility_1	-4.072001***	(-11.61362)	-4.342030***	(-10.4184)	-3.228927***	(-10.2546)	-3.036745***	(-14.1491)
. tau_green_mobility_2	-2.459193***	(-10.83983)	-2.663945***	(-9.7184)	-1.931935***	(-8.1414)	-1.906950***	(-12.2084)
. tau_green_mobility_3	-0.298350*	(-1.98050)	-0.377640**	(-2.2818)	0.284448	(1.3602)	-0.073798	(-0.5520)
. tau_green_mobility_4	2.711858***	(10.36993)	2.819874***	(10.7755)	3.633264***	(8.3352)	2.699060***	(11.4753)
N (ind.)	512		512		510		510	
N (obs.)	4096		4096		4080		4080	
Log Likelihood	-2715.374		-2716.399		-2783.767		-2745.87	
AIC	8179.72		8174.2		8351.42		8354.07	
BIC	8445.17		8446.29		8623.35		8632.63	

ASC: Alternative Specific Constant. **** indicates significance at 1%, ** at 5% and * at 10%.*

Figure 1.5: LV3 (Environmentally minded Results)

don't trust the BEV technology, while the part of the sample that is "environmentally minded" prefers the technology over the conventional one.

The HMXL models with interaction for both ASCs and for the amount of vehicle emissions show that for both samples, the added interaction with the vehicle emissions is positive and significant. This means that respondents who were "environmentally minded" had higher preferences for vehicles with lower emissions than the rest of the sample.

The structural model indicates that in the small sample the level of diploma, and in the medium sample the level of education plus gender, are related to being part of the "environmentally minded" profile. This means that for the medium sample, women with a high level of education were more likely to be part of the "environmentally minded" profile. For the the measurement model, we find in both samples that donating to environmental associations, being concerned about green mobility and adopting environmental behavior are all related to the environmental profile. All of the threshold levels for the questions in the ordered logit model are significant and related to the "environmentally minded" profile, meaning that the questions were effective at discriminating respondents that were part of the profile or not.

1.7 Conclusion and discussion

This paper describes a stated preference study taken in France in January 2021, using an online survey, on individual's preferences between a conventional diesel/gas car, a battery electric car and a plug-in hybrid car. We seek to evaluate the impact of the proportion of electric fast-charging infrastructure and the uncertainty on it's future level, on the adoption rate of electric cars. We used two choice experiments that each characterized a different vehicle size according to a survey on respondent's vehicle preferences. We analyzed the data of both choice experiments by using for each sample a MNL, MXL and four HMXL models. This study has dealt with issues such as the credibility of public policies by including a notion of uncertainty regarding the future level of charging infrastructure. We have also investigated the heterogeneity of demand for vehicles, as well as the effect of the segmentation of the car market on user behaviour.

The findings are the following. In both vehicle categories, all the monetary attributes are significant and have the expected sign. We have shown that respondents prioritised immediate costs such as the purchase price compared to the other monetary attributes for their vehicle purchasing decision. The vehicle range is significant in both vehicle categories and shows that respondent's preference for vehicle range exhibits a non-linear relationship, meaning that range becomes less important as it increases in value. The environmental label is significant in both categories meaning that respondents care about the impact of their vehicle emissions or are cautious about future polluting vehicle bans in cities such as Paris in 2025. The PHEV ASC is positive and significant for the small vehicle sample, while both BEV and PHEV ASCs are negative and significant for the medium category. When all attributes are taken into account, medium vehicle users prefer conventional vehicles, while PHEVs and BEVs are more popular for small vehicles. This shows that respondent's have different preferences and different uses for the vehicles that are presented to them. When we compare the full level of infrastructure to the the other levels, only the lower levels of infrastructure amounts are negative and significant for the small category, while all the infrastructure amounts are negative and significant for the medium vehicle category. This shows that medium vehicle users require higher infrastructure amounts for their usage.

With regards to the psychological profiles and their respective latent variable, we find that in both vehicle categories, the interaction between the "electric car knowledge" variable and the BEV and PHEV ASCs are positive and significant. This means that an increase in knowledge about electric vehicles increases the adoption rate of alternative vehicle technologies. With regards to the "early adopters" profile, we find that in both vehicle categories, the interaction between the latent variable and both ASC's are positive and significant. While the interaction between the latent variable and the different levels of infrastructure are not significant for both vehicle categories. This means that individuals that are interested in car technology and have a higher risk preference tend to adopt more alternative vehicles technologies than others. For the the "environmental profile" latent variable, we find that in all vehicle categories the interaction between the ASC for BEVs and PHEVs is positive and significant. The interaction between the latent variable and the environmental label is positive and significant in both vehicle categories but the effect is stronger in the medium vehicle category. This means that for all vehicle sizes "environmentally minded" individuals tend to adopt more frequently alternative vehicle technologies, and that when compared to the rest of the population, these individuals tend to choose medium vehicles with a lower carbon footprint.

All three of the latent attributes used in our HMXL models improve the precision of our model and allow us to better explain respondent's car choices. Our findings are similar to those by Giansoldati et al. (2020), in that an increase in the general population's knowledge and experience with BEV will lead to a higher acceptance of the vehicle technology. According to our results, the part of the population that is currently willing to adopt BEVs over CVs consists of "early adopters", with a high interest in vehicle technology and a high risk tolerance, or people that are "environmentally minded". These three profiles seem to be related to the young, rich and highly educated part of the population. In order for the general population to adopt BEV's, it is important to deal with the main barriers to adoption that are the high purchase price and the low level of fast-charging infrastructure. We have seen that including psychological profiles in our estimation allows to find specific population targets for public policies. To the best of our knowledge, no publication has so far explored the relation between the respondent's tolerance for risk and their preference for electric vehicles.

To sum up, we suggest that policy makers should focus on increasing subsidies on electric vehicle and increasing penalties on higher green house gas emitting vehicles as the high purchase price is the main barrier for widespread electric vehicle adoption, and these policies will be more effective than fuel taxes in order to help promote alternative vehicle adoption. We also suggest that the BEV range is less of a critical issue than the lack of charging infrastructure. The uncertainty surrounding the future level of charging infrastructure is a factor preventing electric vehicle adoption, especially for medium vehicle users. Thus policy-makers need to focus on investing into electric fast-charging public infrastructure to help promote electric vehicles, especially in areas outside of cities where users are more demanding of the level of infrastructure.

This study could be developed further by extending the notion of risk to the other attributes used in the experiment. We suggest applying this notion to fuel costs, as we are observing at the time of this study important fluctuations in gas prices due to disruptions in the global supply. Another suggested area of improvement would be to account for public transport in addition to conventional and alternative technologies. This would result in a study that is more representative of the general population, since this study only allowed participants with a driving-license to participate.

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1.8 Appendix

Literature Attributes

Attributes	Number	References
Operation cost	All studies	All studies
Purchase cost	All studies	All studies
Fuel cost	10	[32] [34] [12] [21] [25] [26] [27] [4] [2] [37]
Fuel efficiency	6	[32] [33] [4] [15] [28] [36]
Fuel Type	14	[4] [16] [2] [5] [11] [16] [20] [22] [23] [24] [27] [30] [1] [3] [38]
Maintenance costs	5	[4] [34] [35] [22] [27]
Subsidy amount	2	[26] [32]
Tax amount	9	[30] [4] [27] [9] [16] [1] [35] [16] [1]
Leasing Charge	1	[16]
Driving range	30	[1] [2] [3] [4] [5] [6] [7] [8] [9] [10] [13] [16] [17][20] [21] [25] [11] [12] [26] [24] [29] [15] [18] [30] [31] [33] [34] [35] [37] [38]
Battery lifetime	1	[12]
Expected resale price	1	[18]
Car performance	15	[4] [33] [35] [2] [12] [21] [29] [9] [14] [23] [28] [27] [32] [5] [7]
Acceleration time	11	[20] [25] [8] [10] [4] [20] [2] [8] [17] [4] [35]
Infrastructure amount	29	[1] [3] [13] [12] [26] [24] [15] [10] [4] [18] [27] [28] [30] [9] [2] [4] [13] [15] [26] [27] [6] [14] [22] [23] [21] [29] [34] [18] [20]
Infrastructure detour	4	[16] [11] [18] [30]
Home Plug-In Cost	1	[15]
Refuel time	16	[16] [13] [25] [11] [18] [30] [4] [6] [35] [16] [7] [21] [29] [2] [18] [37]
CO2 emission	17	[13] [25] [15] [27] [5] [6] [7] [12] [14] [18] [23] [32] [8] [25] [27] [28] [36]
Road tax reduction	4	[16] [13] [11] [1]
Free parking	6	[16] [4] [11] [27] [24] [1]
Access to vehicle lane	7	[1] [16] [4] [11] [27] [24] [28]
Policy incentives	7	[6] [9] [11] [13] [16] [24] [27]
Road toll exemption	1	[1]
Vehicle Size	5	[2] [5] [27] [31] [36]
Vehicle Brand	3	[1] [20] [3]
Vehicle Speed	1	[38]
Brand Diversity	3	[16] [16] [11]
Warranty Coverage	1	[26]

them and which studies included them from the references below :

1.	Wang et al. (2017)	20.	Helveston et al. (2015)
2.	Brownstone et al. (2000)	21.	Kim et al. (2014)
3.	Giansoldati et al. (2018)	22.	Shin et al. (2012)
4.	Hess et al. (2012)	23.	Achtnicht et al. (2012)
5.	Daziano (2013)	24.	Qian and Soopramanien (2011)
6.	Hackbarth and Madlener (2016b)	25.	Hidrue et al. (2011)
7.	Link et al. (2012)	26.	Mau et al. (2008)
8.	Mabit and Fosgerau (2011)	27.	Potoglou and Kanaroglou (2007)
9.	Bahamonde-Birke and Hanappi (2016)	28.	Horne et al. (2005)
10.	Valeri and Danielis (2015)	29.	Rasouli and Timmermans (2016)
11.	Hoen and Koetse (2014)	30.	Dimitropoulos et al. (2016)
12.	Jensen et al. (2013)	31.	Liu and Cirillo (2017)
13.	Hackbarth and Madlener (2013)	32.	Axsen et al. (2009)
14.	Ziegler (2012)	33.	Dagsvik et al. (2002)
15.	Tanaka et al. (2014)	34.	Yoon et al. (2017)
16.	Chorus et al. (2013)	35.	Jones et al. (2013)
17.	Christensen et al. (2010)	36.	Sierzchula et al. (2014)
18.	Bockarjova et al. (2014)	37.	Daziano et al. (2017)
19.	Axsen and Kurani (2013)	38.	Munshi et al. (2022)

Table 1.9: List of Citations

Questions asked in the DCE

Number	Question
Q1.	Do you have a driver's license?
Q2.	Are you male/female?
Q3.	What is your date of birth?
Q4.	What is your postal code?
Q5.	What is your most recent degree?
Q6.	What is your net monthly household income?
Q7.	Are you currently employed?
Q8.	What is your current situation?
Q9.	What is your profession/activity?
Q10.	How many people are in your household?
Q11.	Among the propositions below, which type of bodywork corresponds best to this car?
Q12.	Concerning electric vehicles (your knowledge on 5 levels):
Q13.	What is the maximum range of a small electric car (for example: Renault Zoé) today?
Q14.	What is the minimum time to recharge a small electric car (e.g. Renault Zoe) in a gas station today?
Q15.	(To be asked if the choice is systematically "The gasoline/diesel car") Why don't you prefer to buy an electric or plug-in hybrid vehicle?
Q16.	Are there any features that you did not consider when making your choices?
Q17.	If so, which one(s)?
Q18.	For what reason(s)?
Risk preference questions:	
Q19.	On a scale of 0 to 10, what is your attitude toward risk in general ?
	On a scale of 0 to 10, what is your attitude toward risk to your health:
	On a scale of 0 to 10, what is your attitude toward risk to your professional career:
	On a scale of 0 to 10, what is your attitude toward risk in general:
Q20.	I prefer the coin toss:
Technology preference questions:	
Q21.	In general, I am interested in new technologies
	When it comes to cars, I am always looking for an innovative model
Environmental preference questions:	
Q22.	Over the past five years, have you been a member or donor of an environmental organization?

Table 1.10: Questions asked in the DCE 1

Number	Question
Q23.	I buy/consume food products labeled "Organic
	I buy/use "Green" labeled household products
	I practice plastic recycling
	I recycle glass
	I buy products with the least amount of packaging
Q24.	To what extent would you say you are concerned about the impact of your travel on climate change?
Q25.	How many people are in your household?
Q26.	How many motorized vehicles does your household use regularly?
Q27.	How often do you use your vehicle?
Q28.	How many miles do you drive per year on average (excluding 2020)?
Q29.	Do you make trips of more than 400 km by car in a year (excluding 2020)?
Q30.	Do you live in an apartment or a house?
Q31.	Does your household have private parking available at your home?
Q32.	Is a charging station for electric vehicles (e.g. wall-box with Type 2 plug) available at your home?
Q33.	Do you think it would be possible to install one?
Q34.	Is a charging station for electric vehicles (e.g. CCS Combo or Type 2 socket) available at your workplace?
Q35.	Do you think it would be possible to install one?
Q36.	Do you know anyone who drives, or has driven, an electric car?
Q37.	Have you ever driven an electric car?
Q38.	Do you own/use an electric or plug-in hybrid car?
Q39.	Do you regularly recharge this vehicle at a gas station?
Q40.	Do you currently work?
Q41.	What is the distance between your home and your workplace? (6 level distance)
Q42.	Do you travel to work by : (Among 5 transportation modes)
Q43.	Would you say that the current context of the Covid-19 will lead you to rather :

Table 1.11: Questions asked in the DCE 2

Welsch test

Description	Small Sample	Medium Sample	Chi2 pvalue Small:Medium
Gender			
Male	*251*	255	0.75
Female	*261*	255	
Working Situation			
Active	*337*	337	0.93
Non-Active	*175*	173	
Age			
18-29	*42*	52	0.16
30-44	*133*	146	
45-59	*181*	165	
60+	*156*	147	
Level of diploma			
BEPC/BEP/CAP or lower	*130*	113	0.69
Baccalaureat to Bac +2	*227*	242	
Bac +3 and higher	*154*	155	
Monthly net income of the house hold (€)			
<1000	*34*	*45*	0.73
1000-2000	*120*	*115*	
2000-3000	*156*	*161*	
>3000	*202*	*189*	
N (ind.)	512	510	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 1.12: Welsch Test

Risk lottery

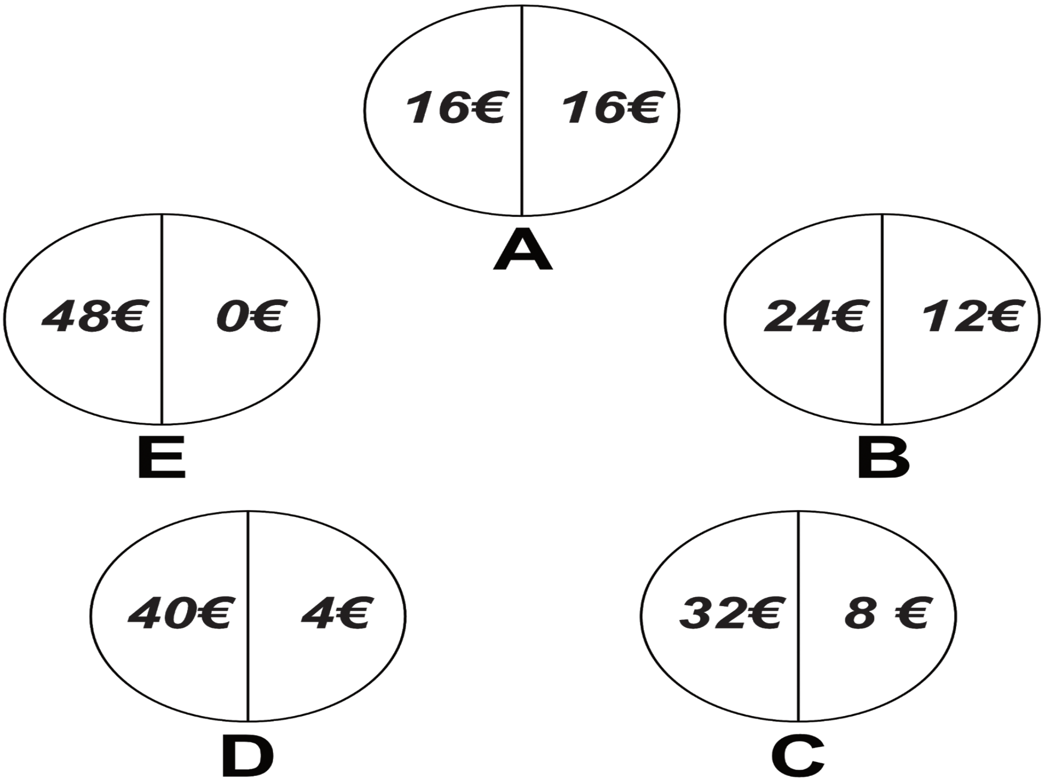


Figure 1.6: Risk assessment lottery game.

MNL Results

	MNL Model (Small Sample)	MNL Model (Medium Sample)
	Coefficient (T.rat)	Coefficient (T.rat)
. ***Attributes***		
. ***ASC Electric***	0.015768	-0.41547**
	(0.08593)	(-2.1018)
. ***ASC Hybrid***	0.026466	-0.30828***
	(0.24879)	(-3.3939)
. ***Purchase Price***	(-9.515e-05***	-9.494e-05***
	(-12.59316)	(-16.8959)
. ***Fuel Cost***	-7.2951e-04***	-7.9488e-04***
	(-5.46114)	(-9.6866)
. ***Maintenance Cost***	-0.001069***	-9.7942e-04***
	(-4.85100)	(-5.8019)
. ***Vehicle Range (ln)***	0.324904**	0.56227***
	(2.14890)	(2.8964)
. ***Environmental Label***	0.031540	0.11031***
	(1.29968)	(5.7203)
. ***Recharging Infrastructure :***		
. ***(RI_1)*** *1/5 Stations*	-0.411864***	-0.54859***
	(-3.77150)	(-5.1837)
. ***(RI_2)*** *50% 1/5 Stations*	-0.250094**	-0.19908
50% 3/5 Stations	(-2.10412)	(-1.3763)
. ***(RI_3)*** *50% 1/5 Stations*	-0.494821***	-0.31362***
50% 5/5 Stations	(-4.39630)	(-2.5988)
. ***(RI_4)*** *3/5 Stations*	-0.038682	-0.05787
	(-0.44388)	(-0.5574)
. ***(RI_5)*** *50% 3/5 Stations*	-0.057856	-0.01640
50% 5/5 Stations	(-0.70848)	(-0.1748)
N (ind.)	512	510
N (obs.)	4096	4080
Adjusted R2	0.0675	0.0886
Log Likelihood	-4184.166	-4073.288
AIC	8392.33	8170.58
BIC	8468.15	8246.34

ASC: Alternative Specific Constant. **** indicates significance at 1%, ** at 5% and * at 10%.*

Table 1.13: MNL Results

Chapter 2

Correcting negative externalities, an experiment on the acceptability of taxes and regulatory standards

2.1 Introduction

Reducing CO2 emissions has become an essential environmental target, particularly applicable to the transport sector, which contributes a quarter of the European Union's total CO2 emissions, with road transport being the most significant source (accounting for 72% of the EU's overall greenhouse gas emissions in 2019).[1] In an effort to curtail the negative externalities associated with pollution, policy designers often employ market-based tools to facilitate the internalization of additional costs arising from these environmental disruptions. Negative externalities manifest when the production or consumption of a commodity adversely impacts a third party, without any corresponding compensation. Prominent instances of negative externalities typically relate to environmental implications such as deforestation, water contamination, and air pollution. Among these, air pollution stands as the preeminent health risk globally and a primary agent of environmental degradation. The number of premature fatalities linked to PM2.5 fine particles pollution has observed a global surge.[2] To rectify these negative externalities, policymakers can introduce pricing strategies, like corrective taxes or subsidies. An alternative approach involves the execution of regulatory standards where the government dictates the production or consumption of quantities that align with societal optimal levels. In principle, both pricing policies and regulatory standards, when judiciously calibrated, can achieve similar outcomes in reaching societal optimality.

Environmental public policies have been implemented across different countries, such as carbon tax, removing subsidies to polluting agents, and bans on polluting goods. For example, the European Green Deal and the United Kingdom's Climate Change Act seek to reduce 90% of greenhouse gas emissions from transport by 2050 (compared to 1990).

In 2017, the Ultra Low Emission Zone (ULEZ) was created in central London and expanded in October 2021. Every diesel car produced before September 2015, and every petrol car produced before 2006, has to pay 12.5 pounds daily in order to enter the ULEZ. The effectiveness of this public policy has been demonstrated by a 44% reduction in toxic NO2 concentrations in 2020.[3]

[1] EEA Report No 2/2022. Decarbonizing road transport - the role of vehicles, fuels, and transport demand.

[2] OECD (2020), *Environment at a Glance 2020*, OECD Publishing, Paris, https://doi.org/10.1787/4ea7d35f-en.

[3] Press release, 5 times greater reduction in NO2 in London than rest of the country, 7 August 2020, https://www.london.gov.uk/press-releases/mayoral/5x-greater-reduction-in-toxic-no2-

In Italy, low emission zones are referred to as "Zona a Traffico Limitato" (ZTL), or Limited Traffic Zones. They have been established in numerous Italian cities as a measure to reduce congestion and pollution. The regulations governing each ZTL can vary significantly from one city to another, with some areas restricting access based on the vehicle type, its emission standards, or the time of day.[4] For instance, Milan has implemented an extensive LEZ known as Area B, which encompasses approximately 72% of the municipality. It operates from Monday to Friday, from 7:30 am to 7:30 pm. Vehicles that fail to meet the Euro 3 emission standards for petrol and diesel are prohibited from entering this zone.[5] In contrast, Rome has several ZTL areas, each with distinct regulations. Some areas enforce restrictions at all times, while others only during specific hours. Additionally, Rome has established a Green Zone, active from Monday to Friday, where only vehicles adhering to specific emission standards are permitted entry.[6]

In France, Paris implemented the "Zone à Faibles Emissions" (ZFE), or "low emission zone", in 2015, aimed at curbing the proliferation of polluting vehicles. This included a prohibition on diesel cars produced before 2006, which was enacted in 2021. Subsequent restrictions were planned for July 2023, including the prohibition of diesel cars manufactured before 2011 and petrol cars produced prior to 2006. A comprehensive ban on all diesel vehicles is anticipated in 2024, alongside restrictions on petrol cars produced before 2011. The ZFE covers the entire "Grand Paris" area, constituting 77 out of the 131 communes in the Paris metropolitan area, with an end goal of eliminating all polluting vehicles (diesel and petrol) by 2030 within the ZFE, thereby achieving a zero-emissions policy.[7]

The fist chapter of this thesis explored how vehicle users respond to changes in vehicle characteristics, which allowed us to formulate policy recommendations on how best to promote sustainable mobility and reduce the amount of negative externalities associated with pollution. However, public policies may fail in practice because of inadequate implementations or unintended consequences. They can also

in-london.

[4]Urban Access Regulations in Europe, "Italy", http://urbanaccessregulations.eu/countries-mainmenu-147/italy-mainmenu-81.

[5]Comune di Milano, "Area B", https://www.comune.milano.it/aree-tematiche/mobilita/area-b.

[6]Roma Mobilita, "Limited traffic zones", https://romamobilita.it/en/services/limited-traffic-zones.

[7]Ministère Ecologie Energie Territoires, "Zones à faibles emissions (ZFE)",https://www.ecologie.gouv.fr/zones-faibles-emissions-zfe

fail because of a lack of public support, which can be explained for some reasons. For instance, the population might not be aware of the policy's implications and mechanisms, the policy can go against individual interests, or a lack of communication from policy-makers generating a misunderstanding of the policy. Culture can shape political convictions and beliefs that will thus influence the support for public policies. Political polarization and lack of trust in government may lead to a lack of public support based on political affiliation, independently of the actual efficacy of the policy. Understanding the different determinants of public support is necessary before implementing a public policy to avoid side effects such as social movements that can undermine social cohesion or confidence in government.

For example, Australia's carbon tax, which priced businesses 23$ for every tonne of carbon they produced, was implemented in July 2012 despite the lack of public support. A majority of Australians (62 %) agreed that "The carbon tax will have no significant impact on reducing the total worldwide volume of carbon dioxide put into the atmosphere"[8]. Finally, in July 2014, the Australian government abolished the policy.

Furthermore, the rejection of environmental public policies may not be exclusively due to climate skepticism, as it can be shown by the yellow vests movement in France. This movement initially appeared to be "anti-environmental", however, the yellow vests were not rejecting environmental policies due to climate skepticism but would be bearers of an alternative vision of ecology, more "popular" and aiming at articulating the demand for social justice and environmental justice, since they do not appear to be more or less ecologist than the rest of the population.[9] Drawing upon this example, conducting a laboratory experiment that explores the acceptability of environmental policies without explicitly framing it in an environmental context becomes relevant since it allows us to study the motivations that influence policy acceptance beyond climate skepticism. It allows us to have a more comprehensive understanding of the factors that shape policy support.

It is essential to study the acceptability of public policies since their rejection prevents attaining the maximization of social welfare and the correction of negative

[8]Robson, A. (2014), Australia's Carbon Tax: An Economic Evaluation. Economic Affairs, 34: 35-45. https://doi.org/10.1111/ecaf.12061

[9]Dormagen, J., Michel, L. & Reungoat, E. (2021). Quand le vert divise le jaune: Comment les clivages sur l'écologie opèrent au sein des Gilets jaunes. Écologie & politique, 62, 25-47. https://www.cairn.info/revue–2021-1-page-25.htm.

externalities that can cause avoidable costs to the population. It can result in the removal of the policy, which can be costly for the government. For instance, the *Bonnets rouges* (“Red caps”) movement emerged as a protest in Brittany (France), in 2013, opposing the *écotaxe* – a tax designed to address the negative environmental externalities trucks produce. The ”écotaxe” was aimed at internalising externalities (including road wear and tear costs) for truck travel outside the tolled highway network. It should be noted that a substantial part of road freight traffic in France is on tolled highways, where tolls are quite high. For many of its proponents, the ecotaxe was justified as much as a way to prevent trucks from avaiding the toll network as it was considered a way to internalise externalities. It was a complex tax, where vehicle routes had to be reliably identified. The tax collection protocol was very costly (a standard tax costs 0.001€ per € collected; the ecotax would have cost 0.2€ per € collected). The ecotax was being designed and discussed for ten years before it was finally cancelled; it was cancelled very late in its implementation process, thus the sunk costs. Not all tax cancellation incur sunk costs.

However, the abandonment of the tax posed a burden on the government, as the tolls constructed to collect the tax were installed yet remained unused. The state was required to pay a termination indemnity of 776.79 million euros for abandoning the partnership contract with the tax collection operator.[10]

One way to increase public support is to raise awareness and improve information concerning public policies. The objective is to ensure that individuals are well-informed about the benefits of a public policy before its implementation. Dechezleprêtre et al. (2022) find that informing about climate policies significantly increases support for climate policies. One way to rise information about policies is through a policy trial. A policy trial increases the comprehension of the policy and makes its benefits more apparent. For example, the city of Stockholm introduced in 2006 a seven-month trial of congestion charges followed by a referendum, overcoming the initial hostility faced among the population (Eliasson, 2008).

However the lack of support for policies cannot be attributed to a lack of awareness alone. According to a survey realised in France by Steria (2022) concerning the burden of reducing carbon emissions, a significant majority (68%) of respondents believed that they should not be the ones to make sacrifices, and the responsibility

[10]Rapport public annuel 2017 - Tome I - L’écotaxe poids lourds : un échec stratégique, un abandon coûteux - février 2017, Cour des comptes. https://www.ccomptes.fr/fr/publications/le-rapport-public-annuel-2017 - Link available on April 19, 2023.

to act primarily lies with the government and companies. Pisani-Ferry and Mahfouz (2022) conclude that these results reflect a deep mistrust for french people in the state's green transition strategy, and that they fear nothing more than having to make sacrifices alone. Pisani-Ferry and Mahfouz (2022) outlines the importance of ensuring fairness in the distribution of efforts. This condition is particularly demanding: as illustrated by the rejection of the carbon tax, it requires nothing less than equality in sacrifices.

This chapter aims to provide some elements to the following scientific debates: To what extent does the acceptability vary among different policy instruments? How does previous experience from policy trials shape or influence the degree of acceptability? In what ways do individual attributes shape the perception and acceptance of various policies? We seek to compare the acceptability of regulatory standards and taxes to evaluate individuals' responses to future restrictions. Furthermore, we seek to study the extent to which users are biased toward public policies according to their beliefs.

In this chapter, we propose an unframed experiment where we study the acceptance rate of public policies through a majority vote to understand the different determinants of the acceptance rate of public policies.To that aim, we conduct a laboratory experiment in which participants play in a negative externalities game. Within this game, participants are tasked with allocating their preferred choice among three alternatives: A, B, and C. Notably, one of these options engenders a negative externality. While the experience is unframed, and, as such, designed to inform widely the issue of environmental policy acceptability, it is directly relevant to transportation. For example, we could consider option A as an electric vehicle, option B represents public transportation, and option C a conventional vehicle (diesel or petrol cars). We will see in section 2.3, that Option A and option C are constructed to yield the same gain, representing the utility of using a car, without accounting for discrepancies in vehicle range or access to recharging infrastructure. This earning is always higher than the gain from choosing option B, representing public transportation, which is less comfortable than using a car. Furthermore, the cost of using option A is the highest, representing higher prices for electric vehicles, despite being subsidised, than for public transportation or conventional cars despite the latter being taxed. The cost of choosing public transportation (option B) is the lowest. Furthermore, choosing option C yields a loss for every group member, which is not the case for other options. This loss represents a negative externality, and under this framework, all the damages caused locally by the air pollution generated by conventional vehicles. This experimental design is meant to replicate the situation around the access to city centers through different transport means and the different public policies available to regulate them.

To examine the impact of public policies, we introduced two distinct policy interventions - taxation and regulatory standards - to each experimental treatment, subjecting the participants to a policy trial. Furthermore, we ask the participants to vote for or against public policy implementation. Our unframed experiment simulates the transportation market by presenting participants with options corresponding to different transportation modes, such as electric vehicles, public transportation, and diesel or petrol vehicles. It is important to note that the experiment is conducted in an entirely unframed context. This gives us the advantage that the results can be widely applied to any market generating negative externalities such as a transportation mode choice framework..

Moreover, this experiment seeks to compare individual behavior under two cases of public policy implementations under the frameworks of transportation mode choice, with one being representative of the regulation treatment and the other of the tax treatment. We used the case of Paris's 2024 ZFE as the basis for the regulation treatment, while the basis for the tax treatment was London's congestion tax through the ULEZ.

In addition to acceptability, we seek to understand the psychological determinants driving a public policy rejection. The cultural construction of opinions may play a role in the beliefs and perception of public policies. Cultural worldviews shape how people access, process, and assess policy information (Kahan et al., 2011; Cherry et al., 2017). We seek to verify if cultural worldviews have an impact on the acceptability of public policies and see if this effect is stable after experiencing the game and a policy trial. Increasing the understanding of regulatory standards and taxation policies through a policy trial could diminish the importance of beliefs about policies through the comprehension of the mechanisms and positive impact of public policies. The novelty of this chapter is that we enlarge the possibilities of choice by proposing a market with three different goods, compared to the related literature that uses a one good market game (Cherchi, 2017) or a two way congestion game (Janusch et al., 2020), and adding heterogeneity. In contrast to previous experimental literature, we propose bans with available alternatives, offering a more realistic representation of public policy scenarios. For example, if we focus on transportation mode choice, support for climate public policies is more likely to be higher in a city with public transport available than in a city with none (Dechezleprêtre et al., 2022).

In this chapter, we find an increase in the acceptability of regulatory standards after a policy trial. However, we do not find this effect after a taxation trial. We also find that regulatory standards are more accepted than taxation policies. Furthermore, we find that possessing hierarchical worldviews decrease the acceptability of public policies, yet individualistic worldviews do not impact public policy support. Our results suggest that it is difficult to change people's preferences, even after pedagogical efforts, when specific policy aversion is high.

The chapter is organized as follows: section 2.2 presents the literature review, section 2.3 presents the experimental design, section 2.4 details the predictions of the experiment, and section 3.7 presents the results. Finally, section 3.8 concludes. The study that this chapter is based on was written in collaboration with doctoral student Maria J. Montoya-Villalobos [11].

2.2 Literature review

This chapter is related to the literature on attitudes towards climate policies (see the review by Fairbrother, 2022) and attitudes on the acceptability of carbon taxes (see the review by Carattini et al., 2018).

The experimental literature focuses mainly on laboratory experiments. Our chapter contributes to this literature. Some papers study the acceptability across public policies in an unframed setup, such as Cherry et al. (2012, 2017) and Heres et al. (2017), where the authors find that subsidies are more accepted than taxes. This result appears as a paradox since economists regard taxation as the least costly policy per unit of pollution abatement (Fairbrother, 2022). Cherry et al. (2012) find that individuals support more taxes than regulatory standards, claiming that the most coercive policy instrument usually receives the least support. However, Cherry et al. (2017) do not find any difference in the acceptability. In a survey, Dechezleprêtre et al. (2022) find that carbon taxes and taxes on fossil fuels appear to be amongst the least popular policies, and there is higher support for bans than for taxes. They find that the preference for different policy instruments varies across

[11] EconomiX-CNRS, Paris Nanterre University

countries. Overall, support is the lowest in Australia, France, and Germany and the highest in China and India. The survey by Douenne and Fabre (2022) finds that French people will largely reject a tax and a dividend policy. Douenne and Fabre (2020) find a significant rejection of the carbon tax, but most support stricter norms and green investments. Furthermore, surveys focus on the determinants of support for policies. In Kallbekken and Sælen (2011), the authors find that beliefs about environmental consequences influence support for environmental taxes. Carattini et al. (2017) find that distributional and competitiveness concerns reduce the acceptability of energy taxes. Dechezleprêtre et al. (2022) study the support for other climate policies such as a tax on flying and find that the support for a tax on kerosene is higher. These studies highlight the importance of beliefs about the impact of public policies in their lack of support. It is, therefore, necessary to study mechanisms to correct any misperceptions of the impact of public policies and account for individuals' beliefs.

The experimental literature also focuses on the determinants of support for climate policies. Janusch et al. (2021) and Cherry et al. (2014) studies how increasing comprehension of public policies through the implementation of a policy trial impacts acceptability. The authors study the impact of trial runs on the acceptability of a toll and an environmental tax, respectively, through a majority vote. Both studies find a positive impact of a policy trial on acceptability. Cherry et al. (2017) study the support across different instruments after having experienced the policy, they find that the level of policy aversion declines over time. However, they do not study how experiencing the instrument-specific regulatory standard impacts support, they also find that experience with efficiency-enhancing instruments increases the probability of supporting an instrument. However, it does not have any significant effect on the tax models. Cherry et al. (2017) and Janusch et al. (2021) focus on the impact of cultural worldviews on perceptions of social issues and policy on policy support. In the latter, the authors study how worldviews play a role in the acceptability of a toll with a heterogeneous impact of the toll among the participants. Tiezzi and Xiao (2016) examine the effect of delaying the benefits of taxation on support for taxes. They find that people are less willing to accept Pigouvian taxes when negative externalities are delayed.

Our experiment aims to enrich this literature by studying the acceptability of different public policies experimentally after experiencing a policy trial and the role of cultural worldviews in support of public policies. As seen above, the literature stud-

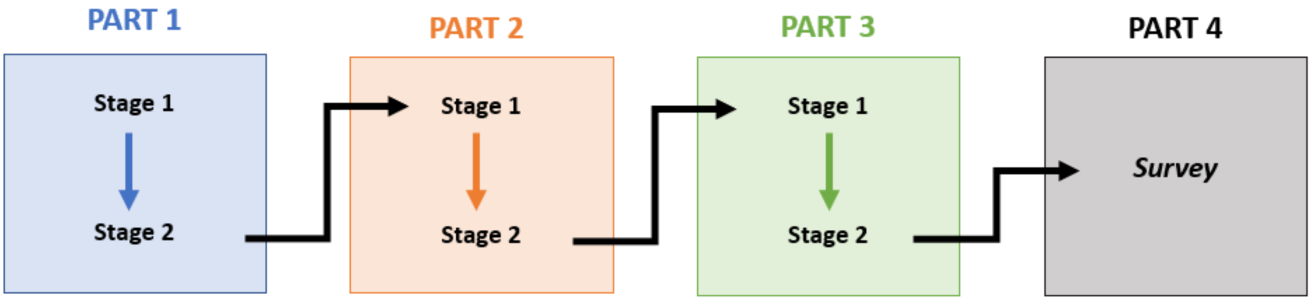


Figure 2.1: Summary of the experiment

ies these research questions, however, not in the same experiment. The novelty of this chapter is that we propose a market with imperfect substitutes to the polluting good which has not been studied to our knowledge. Finally, we analyze how experiencing the game and a policy trial can change the impact of cultural worldviews on the acceptability of instrument-specific policy, verifying the evolution of the impact of worldviews on the support of corrective policies.

2.3 Experimental design

2.3.1 Negative externalities game

The experiment aims to investigate if the acceptability of a public policy increases after experiencing its implementation. This design consists of two treatments: taxation and regulatory standards treatment. In the taxation treatment, a Pigouvian tax (a tax that completely internalizes negative externalities) is imposed on participants choosing the option generating a negative externality. In the regulatory standards treatment, the option generating the negative externality is banned.

At the beginning of the experiment, the computer randomly constitutes groups of six participants and assigns to the player a number: $player = \{1, ..., 6\}$. The composition and the number remain the same throughout. The negative externalities game comprises three parts, each consisting of two stages, as explained in Figure 2.1.

Stages

Stage 1

Stage 1 is repeated three times. It consists of participants voting for or against

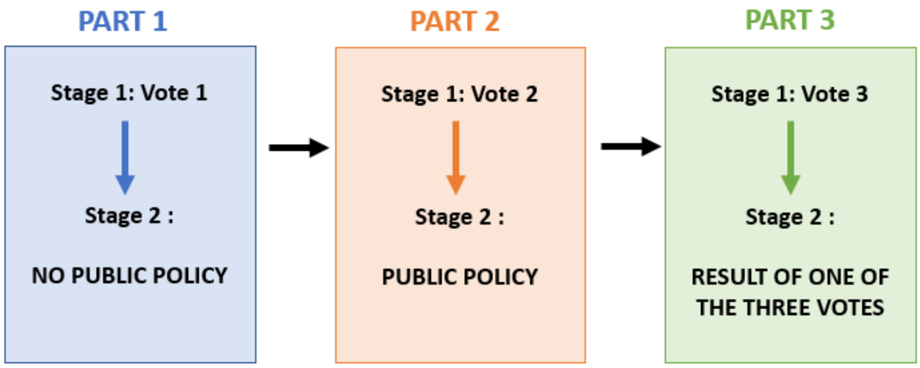


Figure 2.2: Summary of the game

implementing the public policy, depending on the treatment. It is important to note that there are only three votes in the experiment. The votes are only considered in Stage 2 of Part 3; this will be explained later in this section.

Stage 2

Stage 2 is repeated three times. It comprises five rounds for each part of the experiment (15 rounds in total). We included five rounds in each part of the experiment in order to create a learning effect, so that the participants could understand the effect of the negative externality and of the implementation of a policy. Having a repeated game allows the participants to understand the positive impact of the public policy. At the beginning of each round, the participant is endowed with 100 ECU (Experimental Currency Units) and must choose between options A, B, or C. At the end of each round, the participants know their payoff and how many group members choose each option. The public policy may or may not be implemented depending on the part of the experiment. No public policy is implemented in the experiment's first part. In the second part of the experiment, the public policy is implemented. Finally, in Stage 2 of the third Part, we randomly choose one of the three votes, and the result of the drawn vote is implemented in the third part of the experiment. The summary of the main task is shown in Figure 2.2.

Payoff

Heterogeneity is introduced to represent different preferences across individuals, as the earning from option B vary for each player type from 1 to 6 (the payoff tables for each player can be found in the Appendix A section), they are constant over the game. The costs of all options and the gross gains for options A and C are constant

Player 1

	Option A	Option B	Option C
Earning	200 ECU	80 ECU	200 ECU
Cost	100 ECU	20 ECU	50 ECU
Loss	0 ECU	0 ECU	15 ECU

Initial endowment in each round: 100 ECU

Figure 2.3: Earnings and costs for Player 1

for every type of player and over time. Option C generates the negative externality. If one group member selects option C, they impose an additional 15 ECU cost on themselves and to the other members of her group. If two members choose option C, each player incurs a 30 ECU supplementary cost, and so on. The game is constructed such that any participant's dominant strategy is selecting option C, resulting in a Nash equilibrium when all participants choose option C. The second best option for players 1, 2, and 3 is option A, while for players 4, 5, and 6, is option B. The Nash equilibrium and the social optimum of the game are further discussed in subsection 2.3.3. The gain matrix for player 1 is shown in Figure 2.3. The earnings and costs for the other players can be found in Appendix .1.

The payoff of the participant when there is no implementation of the public policy is represented by the following:

$$\pi_{ik} = w_0 + g_{ik} - c_{ik} - (n_c \times 15), i \in \{1, ..., 6\}\,, \quad k \in \{A, B, C\}$$

Where π_{ik} denotes the payoff of player i having chosen option k. w_0 denotes the initial endowment of 100 ECU, g_{ik} denotes the gross gain of participant i for choosing the option k, c_{ik} is the cost of participant i for choosing option k, and n_c is the number of members of the group having chosen option C. We will explain the participant's payoff when the public policy is implemented in subsections 2.3.2 and

2.3.2.

Policy implementation procedure

In Stage 2 of the third part of the experiment, the result of one of the three votes is implemented. During the third part of the experiment, after Stage 1 (vote 3) and before Stage 2, the experimenter creates an urn composed of 30 marbles: 10 blue, 10 orange, and 10 green. A volunteer participant randomly chooses one marble from the urn. If the blue marble is chosen, the first vote result of each group is implemented. If it is an orange marble, the result of vote 2 is implemented, and finally if it is a green marble, the result of vote 3 is implemented for each group. As a result, the public policy may or may not be implemented in Stage 2 of the third part of the experiment, depending on the draw and the voting outcomes. The procedure is summarized in Figure 2.4. In case of a tie within a group (three for and three against the implementation of the public policy), the experimenter will roll a die. If it is an odd number, the public policy will not be implemented, if it is an even number, the policy will be implemented.

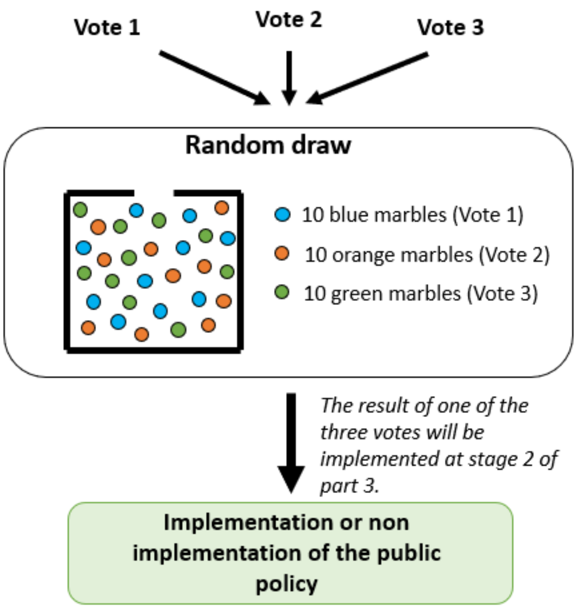


Figure 2.4: Random draw

2.3.2 Treatments

Regulatory standards treatment

In the regulatory standards treatment, participants are asked to vote for or against the implementation of a regulatory standard in the last part of the experiment (Part 3 - Stage 2). In the parts where the regulatory standard is implemented, the participants can no longer choose option C, but only option A or option B.[12] In this case, there is no negative externality or supplementary loss to the participants. Under the regulatory standard, the payoff function π_{ik} for player i becomes:

$$\pi_{ik} = w_0 + g_{ik} - c_{ik}, i \in \{1, ..., 6\}, \quad k \in \{A, B\}$$

Where π_{ik} denotes the payoff of player i having chosen option k. w_0 denotes the initial endowment of 100 ECU, g_{ik} denotes the gain of player i for choosing the option k, c_{ik} is the cost of participant i for choosing option k.

Taxation treatment

In the taxation treatment, we introduce a Pigouvian tax. The agent that generates the negative externality pays the tax and therefore takes into account the costs imposed on a third party. Under the framework of negative externalities, the external cost (the cost imposed on a third party) is not taken into account as a private cost by the agent producing the negative externality. The Pigouvian tax corresponds to the marginal external cost. In this game, the total external cost equals the negative externality imposed on the *other* members of the group multiplied by the number of group members having chosen option C. Therefore, choosing option C generates a supplementary cost to each other group member equal to 15; there are six group members, and the externality is imposed on all the members of the group, excluding the participant having chosen option C.[13] Considering a group of six members, the total external cost is equal to 75 ($15 \times 5 \times 1$) for one member having chosen option C. It is equal to 150 ($15 \times 5 \times 2$) for two members having chosen option C, etc.

[12] This policy seems highly restrictive. However, we decided to implement it in order to represent existing cases.

[13] We do not consider the supplementary loss that the participant that chooses option C incurs since it is considered a private cost for herself or an internality.

The total external cost (EC) is equal to:

$$EC = 75 \times n_c$$

where n_c is the number of participants choosing option C, the marginal external cost is equal to 75.

At every voting stage (Stage 1), participants have to vote for or against implementing a tax in Stage 2 of the third part of the experiment. In the parts where the tax policy is implemented, if the participant chooses option C, she will have to pay a Pigouvian tax of 75 ECU.[14] At the end of each round, the collected amount of taxes is equally redistributed among the six group members.[15] For example, if only one group member chose option C, thanks to the redistribution, each participant will receive a supplementary payoff of $\frac{75}{6} = 12.5$ ECU. If two group members choose option C, each group member will receive $\frac{2 \times 75}{6} = 25$ ECU, etc.
Under the taxation policy, the payoff function π_i for player i is:

$$\pi_{ik} = w_0 + g_{ik} - c_{ik} - (n_c \times 15) - t_k + \frac{n_c \times 75}{6}$$

with $i \in \{1, ..., 6\}$, and $k \in \{A, B, C\}$.

Where π_{ik} denotes the payoff of player i having chosen option k. w_0 denotes the initial endowment (100 ECU), g_{ik} corresponds to the gain of player i for choosing the option k. c_{ik} is the cost for the player i, having chosen option k. n_c is the number of participants in the group that chose option C. Finally, t_k is the tax that the player i has to pay for choosing option k, with $t_A = 0$, $t_B = 0$ and $t_C = 75$. The total amount collected from the tax is $n_c \times 75$.

2.3.3 Strategies: Nash equilibrium and social optimum

Negative externalities result in a discrepancy between private costs and social costs. In other words, the cost incurred by an individual or firm engaged in an economic activity may not reflect the true cost to society as a whole. This can lead to market failure, where the market fails to allocate resources efficiently. In this case, the

[14] The theoretical justification of the level of the Pigouvian tax can be found in our theoretical model in Appendix .2.

[15] We decided to equally redistribute the amount of tax collected as done in the literature (Cherry et al., 2012, 2017; Heres et al., 2017).

quantity produced or consumed of the good generating the negative externality will be larger than at the social optimum. The Nash Equilibrium is defined by the correspondence of each individual's best response function simultaneously. In this game, there is a dominant strategy for every player, which yields the Nash Equilibrium. Our theoretical model in Appendix .2 shows the predictions.

Under the framework of this experiment, when no public policy is implemented, the dominant strategy of each individual is to choose option C. Therefore, the Nash Equilibrium corresponds to the configuration where every player chooses option C.

The strategies that maximize welfare among each group is that players 1, 2, and 3 choose option A, and players 4, 5, and 6 choose option B, because of heterogeneity introduced in the gain matrix. The social optimum yields a welfare of 645, higher than the welfare at the Nash Equilibrium, equal to 450. At the social optimum, there are no external costs; no players choose option C, therefore, there are no negative externalities.

Introducing public policies aims to correct negative externalities by incentivizing individuals to adopt the strategies that yield the social optimum and maximize welfare. When implementing a public policy under this framework, the dominant strategies that result in the Nash Equilibrium are those that result in the social optimum. Figure 2.5 summarizes the strategies at the Nash equilibrium and the social optimum according to the implementation or non-implementation of a public policy.

2.3.4 Cultural worldviews

In the fourth part of the experiment, the participants must answer a post-experimental survey and some socio-demographic questions (age, gender, level of education, if the participant is a student or if she works). The survey seeks to elicit individuals' cultural worldviews (Kahan et al., 2011). This survey measures individual worldviews across two dimensions: individualistic opposed to communitarian worldviews and hierarchical opposed to egalitarian worldviews. As explained by Kahan et al. (2011), "individualism measures attitudes toward social orderings that expect individuals to secure their own well-being without assistance or interference from society versus those that assign society the obligation to secure collective welfare and the power to override competing individual interests". With statements such as: "The government should do more to advance society's goals, even if that means limiting

	No policy	Taxation	Regulatory standards
Nash equilibrium (NE)	NE = (C,C,C,C,C,C) Welfare = 360 Total External Cost = 75 x 5 = 450	NE = SO = (A,A,A,B,B,B) Welfare = 645 Total External Cost = 0	NE = SO = (A,A,A,B,B,B) Welfare = 645 Total External Cost = 0
Social optimum (SO)	SO=(A,A,A,B,B,B) Welfare = 645 Total External Cost = 0		

Figure 2.5: Nash equilibrium and social optimum

the freedom and choices of individuals". Furthermore, they define the dimension hierarchy-egalitarianism as "attitudes toward social orderings that connect authority to stratified social roles based on highly conspicuous and largely fixed characteristics such as gender, race, and class", with statements such as: "Society as a whole has become too soft and feminine". The detailed survey is in Appendix .5.

2.3.5 Experimental procedures

The experiment was conducted at the Laboratoire d'Economie Expérimentale de la Défense (Courbevoie, France), it obtained approval from the ethics committee of the University of Paris Nanterre (CER-PN). 120 individuals took part in the experiment and were randomly assigned to one of the two treatment groups: 60 participants were assigned to the tax treatment, and 60 were assigned to the regulatory standards treatment. Sessions took place in October 2022 and January 2023. 47 participants were male (39.17%), the average age of the participants was 38.09 years old, and 35.83% of the participants were students. The experiment was developed using oTree (Chen et al., 2016).

At the end of the experiment, one round among the fifteen rounds was randomly chosen in order to determine the final payoff of the participant. The payoff exclusively depends on the negative externalities game. The session lasted, on average, one hour for the regulatory standards treatment and one hour and fifteen minutes for the taxation treatment. The average payoff was 16.60 euros (including a show-up fee of 7 euros). One ECU in the experiment equals 0.05 €. All participants received their payoff by bank transfer at the end of the experiment. Note that participants had at their disposal a calculator integrated into the experiment to facilitate calculations. After each option choice round, the participants had feedback on their payoff and how the other group members behaved, they knew how many chose option A, B, or C.

The participants had to answer two comprehension questions: The result of which vote will be implemented in Stage 2 of Part 3? How many ECUs do you lose (without considering the cost of using the option you have chosen) if two participants in your group choose option C? 11 participants (9.17%) answered both questions incorrectly. We eliminated these participants from the database, which leaves us with 109 participants, 56 in the taxation treatment and 53 in the regulatory standards treatment. 47 participants (39.17%) answered at least one of the two questions incorrectly.

Likely, participants that answered one question incorrectly later understood the game's mechanism. Before each voting stage, a reminder message was prominently written: "This vote could only be applied to Part 3". In addition, feedback after each of the 15 rounds stated clearly how many group members chose option C and the additional cost that the choice yields. You can find screenshots of the reminder message and the feedback in Appendix .4. We ran the same analysis eliminating the 47 participants that answered at least one question incorrectly, and we found the same results as those presented in section 3.7. You can find the complementary analysis in Appendix .3.

2.4 Predictions

This experiment aims to test three main hypotheses. Our hypotheses are mainly taken from the literature.

Hypothesis 1 *Experience with the policy increases the level of acceptability.*

This result comes from the case study on Stockholm's adoption of a congestion tax (2006), where it was found that the policy was more popular after it had been first adopted through a policy trial. The advantage of a policy trial is that it allows individuals to be aware of the benefits of a policy instrument. We assume that the level of acceptability will be higher for vote 2 than for vote 1. Between vote 1 and vote 2, participants play the game without any policy implementation. After having experienced the game and the impact of negative externalities, participants will understand how the game works, how their choices and the others' choices will have a negative impact on their payoff. Furthermore, between vote 2 and vote 3, participants experience a policy trial (the implementation of the policy), increasing their comprehension of the policy and seeing more clearly the positive impact of a public policy, which is a limit for public support. This result is confirmed in both Janusch et al. (2021)'s and Cherry et al. (2014)'s experiments, in which participants voted to implement a policy before and after being subjected to a tax policy trial and adopted the tax more often in the later stages. We expect to find this effect in both treatments following the literature.

Hypothesis 2 *The level of acceptability is higher for taxes than for regulatory standards.*

We assume that taxation policies are likely to receive greater public support than regulatory standards. This is because regulatory standards are perceived as more coercive and restrictive in terms of limiting individual freedom of choices, whereas taxes may be viewed as less restrictive and more acceptable to the general population. Taxation can be perceived as less intrusive than regulation standards. Consumers can choose to continue consuming the good, while regulatory standards prohibit the consumption of the good completely, which can be perceived as more restrictive.

This hypothesis comes from the results of the experimental literature. Cherry et al. (2012), in which, when comparing the acceptability of subsidies, taxes, and quantity regulations in a market experiment, the less coercive policies are more popular than the latter. Meaning that subsidies are more accepted than taxes, and taxes are more accepted than attempts to regulate quantities. However, Cherry et al. (2017) find no significant difference in public support between taxes and quantity regulations. Moreover, Douenne and Fabre (2022), in a survey, find that the French largely reject taxes and dividend policies. Douenne and Fabre (2020) find that the French prefer green investments or regulations to a tax and dividend.[16]

Hypothesis 3 *The level of acceptability is lower for participants with individualistic and hierarchical worldviews.*

This hypothesis comes from the literature on the effect of worldviews on the acceptability of policies (Janusch et al., 2021; Cherry et al., 2017), which states that

[16]There is a lack of consensus in the literature, therefore, we decided to follow the results from the experimental literature.

individuals that fit the "individualistic" or "hierarchical" worldviews tend to be less accepting of re-distributive measures such as taxes or coercive measures such as regulatory standards. We assume that participants possessing communitarian worldviews will support more government interventions than those with individualistic worldviews. Furthermore, we also assume that participants possessing egalitarian worldviews will support more government interventions than those with hierarchical worldviews. We study if the result holds in a negative externalities game with heterogeneity and if cultural worldviews have an impact over time on the acceptability of taxes and regulatory standards. Furthermore, we also seek to study if experiencing the game without a policy and with a policy trial decreases the impact of cultural worldviews. Since cultural worldviews shape opinions and beliefs about policies, we could expect that increasing the understanding of the benefits of a policy, through the introduction of a policy trial, would decrease the impact of worldviews.

2.5 Results

2.5.1 Descriptive statistics

Descriptive statistics of the socio-demographic characteristics of the participants by treatment are summarized in Table 2.1.

Figure 2.6 presents the proportion of participants who chose option C by period, by treatment, and whether the policy was implemented in Part 3 or not. In the regulatory standards treatment, we can observe that the proportion is equal to 0 for rounds 5 to 10 and for rounds 11 to 15 if the policy was implemented since option C was no longer available. In rounds 11 to 15 without policy implementation, between 40% and 60% of the participants chose option C, which is the proportion seen in rounds 1 to 5, suggesting that even after having experienced the policy trial, around half of the participants behaved as predicted by the Nash equilibrium (i.e., choosing option C). This suggests that the effect of a policy trial does not have an impact on future choices without policy implementation. In the tax treatment, without policy implementation, we observe the same behavior as in the regulation treatment; the proportion of participants that chose option C in rounds 1 to 5 and 11 to 15 stays constant.

Tables 2.2 and 2.3 present the summary of option choice by treatment. As explained in subsection 2.3.3, the dominant strategy, when the public policy is not

Table 2.1: Summary statistics

	Regulatory standards	Tax	Total
Female (%)	58.5	64.30	61.5
	(0.497)	(0.483)	(0.489)
Age	37.83	34.64	36.19
	(17.49)	(14.45)	(16.00)
Level of education			
- No diploma(%)	1.89%	0.00	0.92%
	(0.00)	(0.00)	(0.00)
- CAP/BEP (%)	3.77	0.00	1.83
	(0.19)	(0.00)	(0.14)
- High school(%)	9.43	19.60	14.70
	(0.30)	(0.40)	(0.36)
- Two-year degree(%)	13.20	16.10	14.70
	(0.34)	(0.37)	(0.36)
- Bachelor(%)	24.50	14.30	19.30
	(0.43)	(0.35)	(0.40)
- Master(%)	41.50	48.20	45.00
	(0.50)	(0.50)	(0.50)
- Ph.D.(%)	5.66	1.79	3.67
	(0.23)	(0.13)	(0.19)
Student(%)	37.7	41.10	39.40
	(0.49)	(0.50)	(0.49)
In activity (%)	52.80	55.40	54.10
	(0.50)	(0.50)	(0.50)
# of observations	53	56	109

Notes: Standard errors are in parenthesis.d CAP/BEP are french vocational certificates obtained two years after the 8th/9th grade. Student is a dummy variable = 1 if the participant is a student. In activity is a dummy variable = 1 if the participant works. There are no significant differences in characteristics between the treatments (Chi-squared tests for all variables, except for age, continuous variable, for which we run a two-tailed t-test).

Figure 2.6: Share of participants having chosen option C, by period, by treatment, and whether or not the policy was implemented at the end of the experiment.

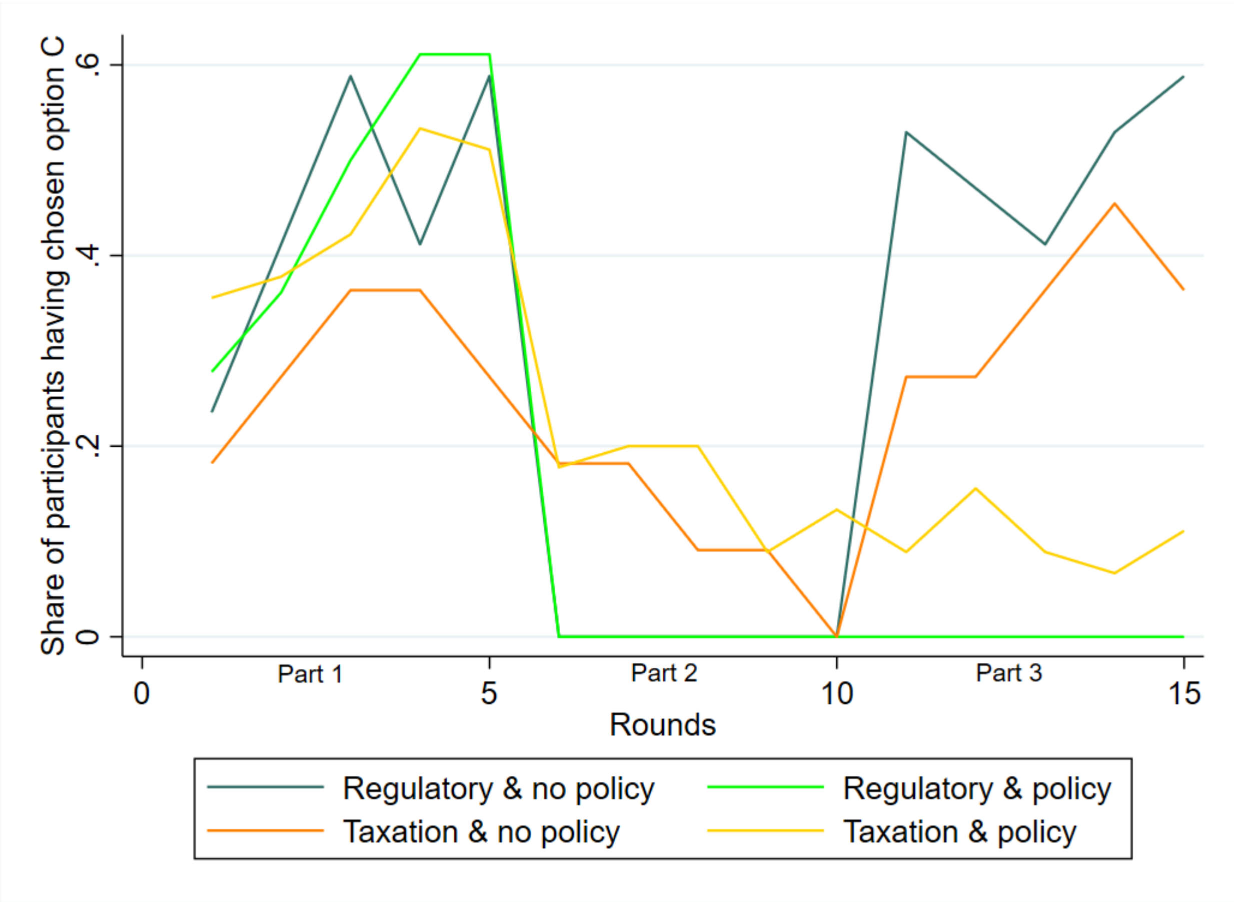


Table 2.2: Summary of option choice in the regulatory standards treatment

	No policy (Part 1)	Policy (Part 2)	No policy (Part 3)	Policy (Part 3)
Option B is not advantageous				
Option A (Social optimum)	40.00%	93.60%***	31.11%	97.50%
Option B	6.40%	6.40%	8.89%	2.50%
Option C	47.33%	N/A	60.00%	N/A
Number of individuals	25	25	25	25
Observations	125	125	45	80
Option B is advantageous				
Option A	17.86%	33.57%***	12.50%	29.00%
Option B (Social optimum)	42.14%	66.43%***	47.50%	71.00%
Option C	38%	N/A	40%	N/A
Number of individuals	28	28	28	28
Observations	140	140	40	100

Chi-squared tests in the group comparisons between Stage 1 and Stage 2. *** p<0.01, ** p<0.05, * p<0.1

Notes: Share of participants' choice in the regulatory standards treatment. Note that the dominant strategy is option C if the policy is not implemented and equal to the strategy yielding the social optimum if the policy is implemented.

Table 2.3: Summary of option choice in the taxation treatment

	No policy (Part 1)	Policy (Part 2)	No policy (Part 3)	Policy (Part 3)
Option B is not advantageous				
Option A (Social optimum)	46.67%	71.85%***	44.00%	76.36%
Option B	13.33%	11.11%	36.00%	10.91%
Option C	40.00%	17.03%***	20.00%	12.73%
Number of individuals	27	27	27	27
Observations	135	135	25	110
Option B is advantageous				
Option A	21.38%	21.38%	20.00%	22.61%
Option B (Social optimum)	36.55%	65.52%***	33.33%	69.57%
Option C	42.07%	13.10%***	46.67%	7.83%
Number of individuals	29	29	29	29
Observations	145	145	30	115

Chi-squared tests in the group comparisons between Stage 1 and Stage 2. *** p<0.01, ** p<0.05, * p<0.1

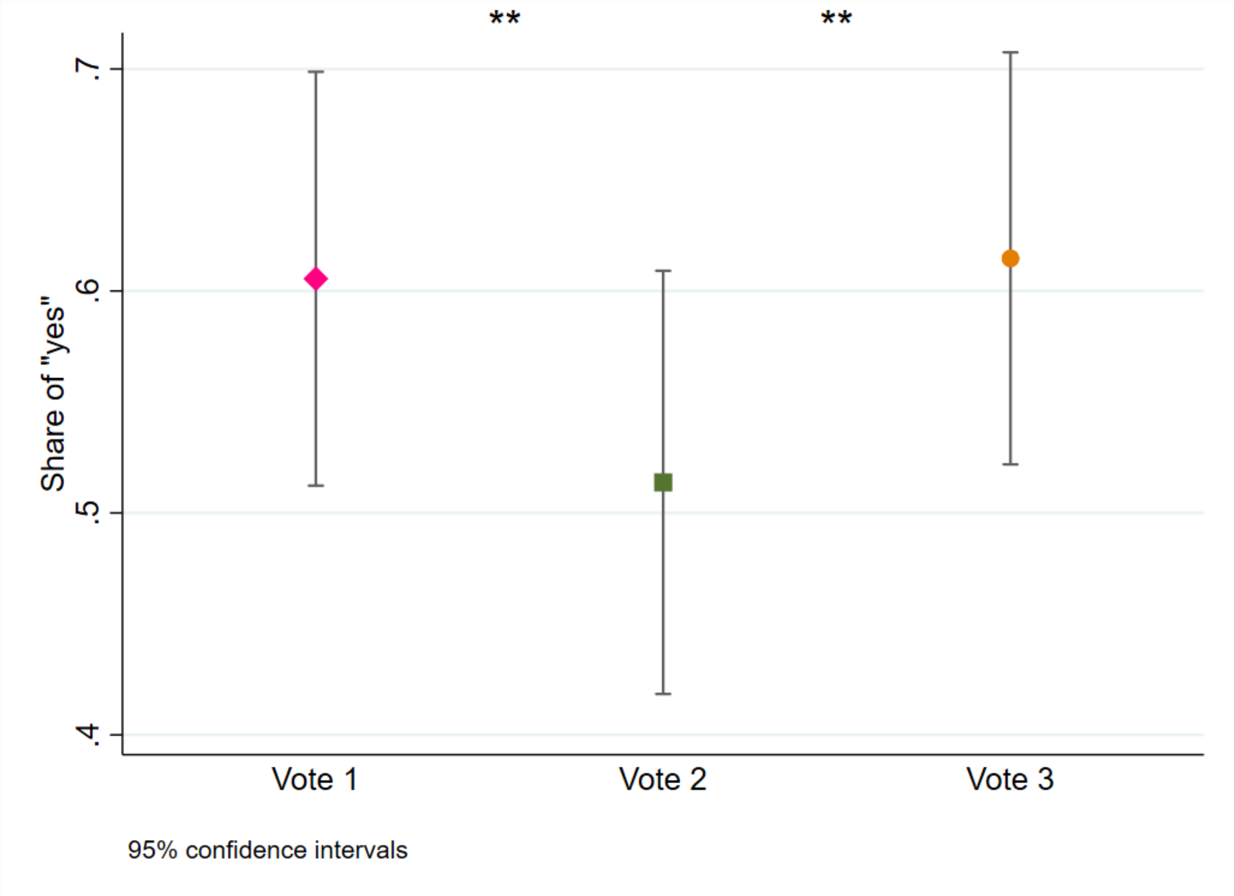
Notes: Share of participants' choice in the taxation treatment. Note that the dominant strategy is option C if the policy is not implemented and equal to the strategy yielding the social optimum if the policy is implemented.

implemented, corresponds to choosing option C. The socially optimal strategy depends on the type of player. If the player is assigned to player 1, 2, or 3, the socially optimal strategy is choosing option A; if the player is assigned to player 4, 5, or 6, the socially optimal strategy is choosing option B. If the public policy is implemented, the dominant strategy corresponds to the socially optimal one.

The results of Tables 2.2 and 2.3 suggest that most participants choose either their dominant strategy or the socially optimal one. However, we can see that a small proportion of participants do not behave as predicted. In Table 2.2, in Part 1, for players 1, 2, and 3, 6.4% of the participants chose option B, which was the least advantageous strategy for this type of player. When the policy is implemented in Part 2, this proportion stays constant. For players 4, 5, and 6, 17.86% of the participants chose option A in Stage 1, this proportion increases to 33.57% in Part 2.

In Table 2.3, we can observe that in Part 1, for players 1, 2, and 3, 13.33% of the participants chose option B, the proportion decreases in Part 2. For players 4, 5, and 6, 21.38% of the participants choose option A, and slightly decreases in Part 2. We observe that even when the policy is implemented, participants continue choosing option C, even though a strategy dominates option C because of the implementation of the tax. This result suggests that a small share of participants prefer choosing the option generating negative externalities and paying a tax.

Figure 2.7: Share of participants having voted for the implementation of the public policy



Notes: Stars represent the significance level for Exact McNemar significance probability. ***p $<$ 0.01, **p $<$ 0.05, p* $<$ 0.1. Grey lines correspond to 95% confidence intervals.

2.5.2 The acceptability of public policies

The impact of a policy trial

The following analysis is conducted based on the three parts of the experiment, taking into account the three votes. As a reminder, the first vote takes place at the beginning of the experiment, the second vote takes place after the five rounds of option choice without policy implementation, and the third vote takes place in Part 3, after the five rounds of option choice with policy implementation (after ten rounds from the beginning of the experiment).

Considering both treatments and the three votes, 57.8% of the participants voted favorably to implement the public policy. Figure 2.7 shows the share of participants having voted for the implementation of any public policy, focusing on each vote separately. In the initial vote (Part 1 of the experiment), 60.55% (s.d.= 0.49) of participants favored the implementation, indicating a consensus supporting public policies. Vote 2 slightly decreases in approval, with 51.37% (s.d.$= 0.50$) voting "yes", there is a significant difference between vote 1 and vote 2 (a McNemar test yields a p-value$= 0.04$). While the third vote experienced a resurgence in support at 61.47% (s.d.$= 0.49$), there is a significant difference between votes 2 and 3 (a McNemar test yields a p-value$= 0.02$). These results collectively suggest that a majority of participants endorse the adoption of public policies. If we focus on Table 2.4, we use logit regressions clustered at the group level in a panel data set, the results from regression (1) shows that the part of the experiment has an impact on the acceptability of public policies. This result confirms the result previously discussed, we observe that the probability of voting "yes" in vote 2 decreases compared to vote 1. We also observe that the probability of voting "yes" in vote 3 increases compared to vote 2. The difference between votes 1 and 2 suggests that experiencing the game decreases support for any public policy. Between votes 2 and 3, we observe an increase in support, suggesting that experiencing the policy trial positively impacts acceptability.

Figure 2.8 presents the share of participants who voted for the implementation of the public policy by treatment and by vote. If we focus on the taxation treatment, there is no significant difference between the votes. In the regulatory standards treatment, we observe a decrease in the acceptability of the implementation of the public policy in the second vote (compared to the first vote), however, this difference is not significant. We observe an increase in the acceptability in the third vote (compared to the second vote), this difference is significant (a McNemar test yields a p-value$= 0.034$, and an exact McNemar significance probability equal to 0.07). We observe that the acceptability is similar in vote 1 and vote 3. Table 2.4 presents the results of logit regressions clustered at the group level in a panel data set. In this table we confirm the results of the chi-squared tests; in regression (2), we observe that in the regulatory standards treatment, the probability of voting in favor of the regulatory standard increases compared to vote 2. On the contrary, in regression (3), we do not find any impact of being in period 1 or 3 compared to period 2, suggesting that the policy trial has no impact on the probability of voting "yes". From these results, we find that hypothesis 1 is partially verified. Understanding the different mechanisms and the benefits of implementing public policies through a policy trial seems to significantly impact the acceptability of public policies, specifically on regulatory standards. Our results align with the literature (Cherry et al., 2014, 2017 and Janusch et al., 2021), experience with policy trial increases the probability of

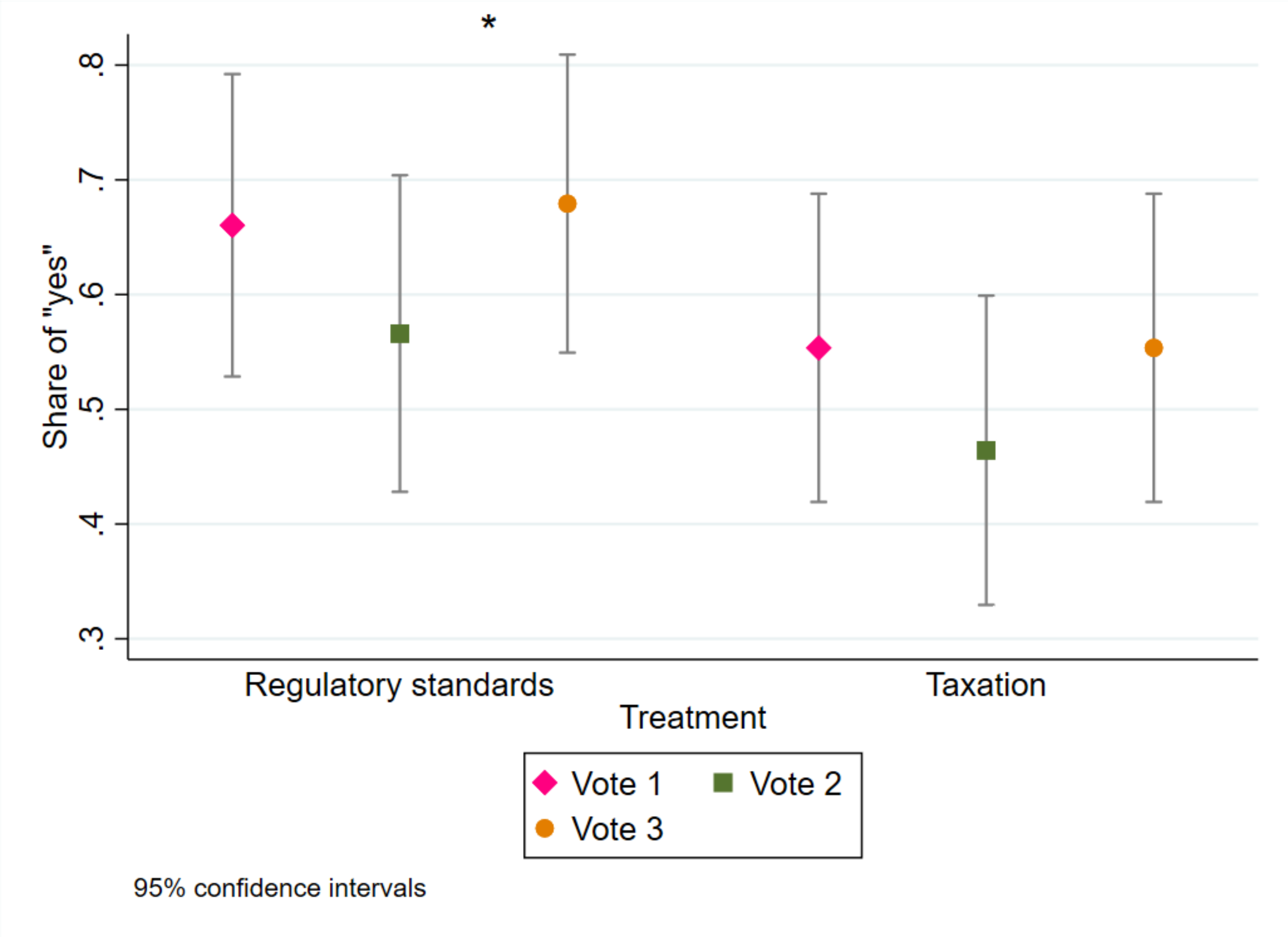
Table 2.4: Determinants of the acceptability of public policies

Dependent variable: Vote	(1) Global	(2) Regulatory standards	(3) Taxation
Tax treatment	-1.65		
	(1.11)		
Period = 1	1.09**	1.23	0.98
	(0.50)	(0.89)	(0.62)
Period = 3	1.20**	1.49*	0.98
	(0.52)	(0.90)	(0.68)
Option B is advantageous	1.19	1.34	0.65
	(0.95)	(1.68)	(0.96)
Age	-0.04	-0.09*	-0.01
	(0.03)	(0.05)	(0.03)
Female	-0.69	-1.56	0.28
	(0.96)	(1.29)	(1.38)
Student	1.56	0.08	4.19**
	(1.34)	(2.57)	(1.83)
In activity	-0.09	-1.14*	2.40
	(0.69)	(0.58)	(1.62)
# option C: Part 1	-0.66*	-1.53**	-0.07
	(0.34)	(0.69)	(0.52)
Others - option C: Part 1	0.08	-0.14	0.02
	(0.08)	(0.23)	(0.10)
# option C: Part 2			-0.44
			(0.54)
Others - option C: Part 2			-0.04
			(0.18)
Constant	2.25	10.11***	-3.33
	(2.50)	(3.69)	(3.60)
Number of clusters	20	10	10
Observations	327	159	168
Number of subjects	109	53	56

Robust standard errors clustered at the group level are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: We use logit regressions clustered at the group level in a panel data set with three periods, each period corresponds to each part of the experiment. The dependent variable is a binary variable equal to 1 for a yes vote and 0 for a no vote. Regression (1) comprises both treatments, regression (2) only uses observations from the regulatory standards treatment, and regression (3) only uses observations from the tax treatment. *Tax treatment* is a dummy variable = 1 when it is the tax treatment. *Period* is a categorical variable, equal to 1 if it corresponds to vote 1, equal to 2 if vote 2, and equal to 3 if vote 3, the reference category is vote 2. In the controls, we include a dummy variable *Option B is advantageous* = 1 when the participant was assigned to player 4, 5, or 6; it is equal to 0 when the participant was assigned to player 1, 2, or 3. *Female* is a dummy variable = 1 if the participant is a female. *Student* is a dummy variable = 1 if the participant is a student. *In activity* is a dummy variable = 1 if the participant works. We include as controls *# option C: Part 1 and Part 2*, representing the number of times the participant chose option C in Part 1 and Part 2, respectively. We include the control *Others - Option C: Part 1 and Part 2*, representing the sum of the number of participants having chosen option C in each round of the first and second parts of the experiment within each group, respectively.

Figure 2.8: Share of participants having voted for the implementation of the public policy by vote and by treatment



Notes: Stars represent the significance level for Exact McNemar significance probability. ***p < 0.01, **p < 0.05, p* < 0.1. Grey lines correspond to 95% confidence intervals.

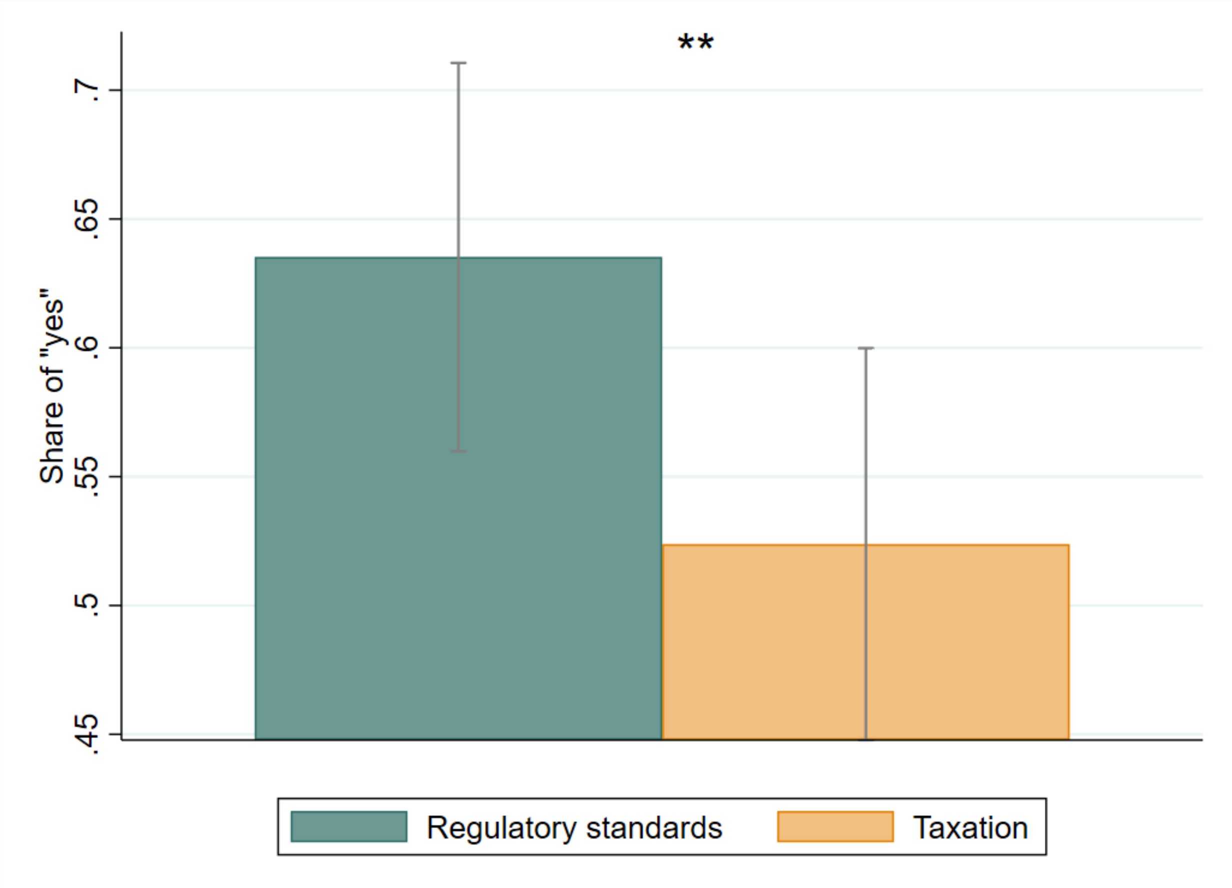
accepting the policy.

Result 1: There is an increase in the acceptability of regulatory standards after a regulatory standards policy trial. We do not find this effect after a taxation policy trial.

Support for instrument-specific policies

Focusing on votes in Figure 2.8, on average, the acceptability of taxes remains lower than that of regulatory standards for any of the votes. In Figure 2.9, we observe the share of participants having voted for the implementation of the public policy, by treatment. Overall, regulatory standards (63.52%) are more accepted than a

Figure 2.9: Share of participants having voted for the implementation of the public policy by treatment



Notes: Stars represent the significance level for the chi-squared test.
***p < 0.01, **p < 0.05, p* < 0.1. Grey lines correspond to 95% confidence intervals.

Table 2.5: Determinants of the acceptability of public policies by vote

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	**Vote 1**	**Vote 1**	**Vote 2**	**Vote 2**	**Vote 3**	**Vote 3**
Tax treatment	-0.45	-0.58	-0.41	-0.49	-0.54	-0.74*
	(0.44)	(0.51)	(0.42)	(0.49)	(0.35)	(0.40)
Option B is advantageous		0.49		0.61		0.14
		(0.44)		(0.42)		(0.44)
Age		-0.02		0.01		-0.03**
		(0.02)		(0.02)		(0.01)
Female		0.40		-0.51		-0.55
		(0.41)		(0.50)		(0.44)
Student		0.70		1.01		0.21
		(0.55)		(0.70)		(0.63)
In activity		0.14		0.18		-0.50
		(0.36)		(0.43)		(0.37)
# option C: Part 1				-0.29*		-0.31**
				(0.17)		(0.16)
Others - option C: Part 1				0.04		0.10**
				(0.04)		(0.04)
Constant	0.66**	0.49	0.27	-0.29	0.75**	2.32*
	(0.32)	(1.01)	(0.28)	(1.30)	(0.30)	(1.23)
Number of clusters	20	20	20	20	20	20
Observations	109	109	109	109	109	109
Pseudo R-squared	0.01	0.06	0.01	0.08	0.01	0.13

Robust standard errors clustered at the group level are in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Dependent variables are a binary variable equal to 1 for a yes vote and 0 for a no vote. For regressions (1) and (2) is the acceptability of taxes at vote 1; for regressions (3) and (4) is the acceptability at vote 2, and for regressions (5) and (6), is the acceptability at vote 3. We use logit regressions clustered at the group level. *Tax treatment* is a dummy variable = 1 when it is the tax treatment. In the controls, we include a dummy variable *Option B is advantageous* = 1 when the participant was assigned as player 4, 5, or 6; it is equal to 0 when the participant was assigned to player 1, 2, or 3. *Female* is a dummy variable = 1 if the participant is a female. *Student* is a dummy variable = 1 if the participant is a student. *In activity* is a dummy variable = 1 if the participant works. We include as a control *# option C: Part 1* representing the number of times the participant chose option C in Part 1. We include the control *Others - Option C: Part 1*, representing the sum of the number of participants having chosen option C in each round of the first part of the experiment within each group.

taxation policy (52.38%), this difference is significant (a Chi-squared test yields a p-value= 0.041). We conduct logit regressions clustered at the group level with each vote as a dependent variable, as presented in Table 2.5. We do not observe any effect on the probability of voting in favor of implementing a public policy depending on the treatment, except in vote 3 when adding the controls, there is a negative and marginally significant effect of being in the taxation treatment compared to the regulatory standards treatment. However, in table 2.4, in regression (1), we do not observe any impact of being in the taxation treatment compared to the regulatory standards on the probability of voting "yes" in favor of the public policy. As a result, hypothesis 2 is not supported.

Our findings deviate from those of Cherry et al. (2012), who report a preference for taxes over regulatory standards, and Cherry et al. (2017), who find no difference in preferences for taxes and regulatory standards. In contrast, our results align with Dechezleprêtre et al. (2022) that report higher support for bans on polluting vehicles over price mechanisms. They also align with Douenne and Fabre (2020), whose results indicate rejection of the carbon tax but majority support for stricter norms.

Result 2: Regulatory standards are more accepted than taxes.

Determinants of the acceptability of public policies

An analysis of the additional determinants influencing public policy acceptability is shown in Table 2.4. In regression (1), considering both treatments, we observe that the number of times the participant chooses option C in the first part of the experiment negatively impacts the probability of voting in favor of the policy. Focusing on instrument-specific determinants, we observe that the effect is still present in regression (2) (regulatory standards), however, the effect disappears in the taxation treatment. We also find that age and if the participant works have a negative impact on the acceptability of regulatory standards. Concerning regression (3), we only observe a positive impact on the acceptability of taxes if the participant is a student. Furthermore, in Table 2.5, we find that the number of times the other group members chose option C positively impacts the probability of voting in favor of the policy in vote 3. This result suggests that the more the participant suffers from negative externalities, the more she is inclined to support the public policy.

2.5.3 Does cultural worldviews impact the acceptability of public policies?

In this section, we study the impact of worldviews (individualistic-communitarian and hierarchical-egalitarian) on the acceptability of public policies. The average of the individualistic-communitarian variable is 20.14 (s.d.= 5.16).[17] The median is 21.

[17] Individualistic-communitarian and hierarchical-egalitarian worldviews are comprised between 6 and 36 .

The higher the score, the more individualistic worldviews the participant possesses. 54 participants (49.54%) had a score below the median, meaning that we can classify them as "communitarians", 8 participants (7.34%) possess a score equal to the median, meaning that they are not "individualists" nor "communitarians", and finally, 47 participants (43.12%) were "individualists" (score over 21).[18] Cronbach's alpha for individualism is equal to 0.71. The average of hierarchical-egalitarian is 14.62 (s.d.=6.25), the higher the score, the more hierarchical worldviews the participant possesses. The median is 14. 55 participants (48.33%) are classified as "egalitarians" (score below 14), 6 (5%) are not classified as "egalitarians" nor "hierarchicals" (score equal to 14), and finally, 48 participants (44.04%) are "hierarchicals". Cronbach's alpha for hierarchy is equal to 0.81.

Tables 2.6 and 2.7 show the impact of worldviews on each vote by the type of policy. We observe that cultural worldviews do not have the same impact on the probability of voting for the implementation of a public policy, depending on the treatment. If we focus on regulatory standards in Table 2.6, we observe that individualistic worldviews do not impact support. Hierarchical worldviews only have an impact on the probability of voting for the implementation in vote 1, but the effect disappears when adding the controls.

If we focus on the taxation policy, we find that hierarchical-egalitarian worldviews have a negative impact on the acceptability of taxes across the three votes (Table 2.7). Our results indicate that hierarchical-egalitarian worldviews affect redistributive instruments, consistent with the findings of Cherry et al. (2017) and Janusch et al. (2021). However, they differ in the impact of individualistic worldviews, for which we do not find any impact on support. Our analysis suggests that the effect of hierarchical-egalitarian worldviews on the acceptability of taxation policies remains stable across votes, indicating that neither policy experience nor exposure to the tax change the impact of worldviews. This result aligns with Cherry et al. (2017), contrary to Janusch et al. (2021). The similarity in our result with Cherry et al. (2017) may come from the equal tax redistribution in both experiments, contrary to Janusch et al. (2021) in which the redistribution had a different impact on subjects.

Result 3: Hierarchical worldviews decrease the acceptability of taxes. They do not impact the acceptability of regulatory standards. Individualistic worldviews have no effect.

[18] We used the same method to classify the participants as in Janusch et al. (2021), using the median.

Table 2.6: The impact of worldviews on the acceptability of regulatory standards

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	**Vote 1**	**Vote 1**	**Vote 2**	**Vote 2**	**Vote 3**	**Vote 3**
Individualistic-communitarian	0.94	1.00	0.66	1.06	0.05	0.45
	(0.87)	(0.85)	(0.51)	(0.73)	(0.73)	(1.04)
Hierarchical-egalitarian	-1.57*	-1.58	0.26	0.70	-0.68	-1.16
	(0.82)	(1.01)	(0.74)	(1.17)	(0.88)	(1.29)
Option B is advantageous		1.01		0.41		-0.39
		(0.73)		(0.85)		(0.83)
Age		-0.02		-0.04		-0.05**
		(0.03)		(0.03)		(0.02)
Female		-0.12		-0.83		-2.26***
		(0.94)		(0.66)		(0.75)
Student		0.21		-0.52		-0.49
		(1.06)		(0.96)		(1.04)
In activity		-0.65		-0.50		-1.25**
		(0.60)		(0.60)		(0.58)
# option C: Part 1				-0.71**		-0.88***
				(0.31)		(0.33)
Others - option C: Part 1				-0.02		-0.12
				(0.11)		(0.12)
Constant	1.04	1.52	-0.12	3.47**	1.03	9.15***
	(0.70)	(2.11)	(0.64)	(1.74)	(0.79)	(2.47)
Number of clusters	10	10	10	10	10	10
Observations	53	53	53	53	53	53
Pseudo R-squared	0.14	0.20	0.02	0.20	0.02	0.27

Robust standard errors clustered at the group level are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Dependent variables are a binary variable equal to 1 for a yes vote and 0 for a no vote. Columns (1) and (2) show the acceptability of taxes at vote 1; columns (3) and (4) the acceptability at vote 2, and columns (5) and (6) show the acceptability at vote 3. We use Logit regressions clustered at the group level. *Individualistic-communitarian* is a dummy variable = 1 if the participant is individualistic, and = 0 if communitarian. *Hierarchical-egalitarian* is a dummy variable = 1 if hierarchical and = 0 if egalitarian. We include the control *Others - Option C: Part 1* in regression (4), representing the mean of participants within the group having chosen option C in the first part of the experiment. We include a dummy variable *Option B is advantageous* = 1 when the participant was assigned to player 4, 5, or 6; it is equal to 0 when the participant was assigned to player 1, 2, or 3. We also include as a control textit option C: Part 1, which represents the number of times that the participant chose option C in Part 1.

Table 2.7: The impact of worldviews on the acceptability of taxation policies

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	**Vote 1**	**Vote 1**	**Vote 2**	**Vote 2**	**Vote 3**	**Vote 3**
Individualistic-communitarian	-0.33	-0.17	-0.63	-0.74	-0.68	-0.59
	(0.55)	(0.58)	(0.60)	(0.79)	(0.46)	(0.72)
Hierarchical-egalitarian	-1.31***	-1.15**	-1.54***	-1.71***	-1.65**	-1.50**
	(0.47)	(0.51)	(0.52)	(0.61)	(0.66)	(0.75)
Option B is advantageous		0.01		0.62		0.39
		(0.67)		(0.46)		(0.57)
Age		-0.01		0.06**		-0.02
		(0.02)		(0.03)		(0.03)
Female		-0.14		-0.35		-0.17
		(0.85)		(0.98)		(1.11)
Student		1.33		2.65*		0.80
		(0.90)		(1.41)		(1.54)
In activity		1.18		1.32		0.60
		(0.81)		(1.11)		(1.05)
# option C: Part 1				-0.01		-0.06
				(0.34)		(0.29)
# option C: Part 2						-0.04
						(0.30)
Others - option C: Part 1				0.01		0.13**
				(0.06)		(0.05)
Others - option C: Part 2						-0.01
						(0.09)
Constant	0.99*	0.05	0.81*	-3.26	1.31**	0.12
	(0.52)	(1.02)	(0.49)	(2.89)	(0.55)	(2.43)
# of clusters	10	10	10	10	10	10
Observations	56	56	56	56	56	56
Pseudo R-squared	0.01	0.12	0.11	0.20	0.13	0.22

Robust standard errors clustered at the level of each group are in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Dependent variables are a binary variable equal to 1 for a yes vote and 0 for a no vote. For regressions (1) and (2) is the acceptability of taxes at vote 1; for regressions (3) and (4) is at vote 2, and for regressions (5) and (6) is at vote 3. We use logit regressions clustered at the group level. *Individualistic-communitarian* is a dummy variable = 1 if the participant is individualistic, and = 0 if communitarian. *Hierarchical-egalitarian* is a dummy variable = 1 if hierarchical and = 0 if egalitarian. We include the control *Others - Option C: Part 1* in regression (4), which represents the mean of participants within the group having chosen option C in the first part of the experiment. We include *Others - option C: Part 2* in regression (6), which represents the mean of participants having chosen option C in Part 2 of the experiment. We include a dummy variable *Option B is advantageous* = 1 when the participant was assigned as player 4, 5, or 6; it is equal to 0 when the participant was assigned to player 1, 2, or 3. We also include as a control two variables *# option C: Part 1 and Part 2*, representing the number of times the participant chose option C in Part 1 and Part 2, respectively.

2.5.4 What are the determinants of option choice?

We seek to study the determinants of choosing a specific option in the game. In this subsection, statistics will be based on the 15 rounds of option choice of the experiment. However, we do not include 445 observations that correspond to the periods in the regulatory standards treatment when the policy is implemented (five rounds in Part 2 for all the participants in the regulatory standards treatment, and the last 5 rounds in Part 3 for 36 participants for which the regulatory standards are implemented in Part 3).

Table 2.8 displays the results of a multinomial logit regression analysis clustered at the group level, in which options A, B, and C serve as the dependent variable, with option C designated as the reference category. We employ panel data for this analysis, treating each round of the experiment (15 rounds) as a distinct period. We include the dummy variable tax treatment, equal to 1 if the choice was taken in the taxation treatment. We find no treatment effect in the probability of choosing options A or B compared to option C. *Option B is advantageous* is a dummy variable equal to 1 when the participant is assigned to player 4, 5, or 6. If the participant is assigned to player 4, 5, or 6, the probability of her choosing option A decreases compared to option C. However, the probability of choosing option B compared to option C increases, which is an expected result since players 4, 5, or 6 are better off choosing option B than option A. We do not find either a temporal effect or a learning effect, being at later rounds in the game does not influence the decision of choosing option A or option B compared to option C. Concerning cultural worldviews, we do not find any impact of individualistic-communitarian or hierarchical-egalitarian worldviews in the option choice.

We include the dummy variable *Policy implemented*, which represents the impact of implementing a policy. Since we include the rounds when the tax policy is implemented (and not those when regulatory standards are implemented), this variable shows only the effect of taxes on option choice. When the tax is implemented, the probability of choosing options A or B increases compared to option C. Taxes create a disincentive for choosing the option that generates negative externalities. Within the environmental framework, this implies that taxes are efficient for decreasing pollution since it is in the interest of the individuals to choose another non-polluting option in order to avoid the tax. In the transportation mode choice framework, we could say that there is an increase in the probability of preferring an electric vehicle (option A) or public transportation (option B) over a conventional vehicle (option

Table 2.8: Determinants of option choice

Dependent variable: option choice	*Option A*	*Option B*
Tax treatment	0.45	0.04
	(0.37)	(0.42)
Policy implemented	1.87***	1.80***
	(0.60)	(0.55)
Option B is advantageous	-1.50***	2.72***
	(0.32)	(0.47)
Period	-0.04	0.03
	(0.03)	(0.02)
Hierarchical-egalitarian	-0.00	-0.61
	(0.40)	(0.53)
Individualistic-communitarian	0.43	-0.39
	(0.31)	(0.59)
Age	0.03*	0.02
	(0.02)	(0.02)
Female	0.76**	0.90*
	(0.31)	(0.47)
In activity	-0.27	0.06
	(0.30)	(0.51)
Option C in previous round	-1.86***	-1.52***
	(0.38)	(0.29)
Others - option C in previous round	-0.22**	-0.17
	(0.11)	(0.12)
Constant	-0.96	-2.96***
	(0.69)	(0.65)

Robust standard errors clustered at the group level are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Option C is the reference category. Each category and dummy variables have to be compared to the reference. We use a multinomial logit regression. The periods in the regulatory standards when the policy was implemented were not considered. The dependent variable is the option choice (categorical variable), it is equal to 1 if the participant chooses option A, equal to 2 if option B, and equal to 3 if option C. Option B is advantageous, is a dummy variable = 1 when the participant was assigned as player 4, 5, or 6. Policy implemented is a dummy variable = 1 if the policy was implemented in the round. Option C in previous period is a dummy variable = 1 if the participant chose option C in the previous round. # of others - option C in the previous round represents the number of group members (excluding the participant) that chose option C in the previous round. Period is a variable that captures any learning effect of the game.

C) when taxes are implemented.

We find that if the participant chose option C in the previous round, the more likely is that she will continue choosing option C, compared to option A or B. We also include the variable *Others - option C in the previous round*, representing the number of members within a group who chose option C in the previous round. It shows that the more participants chose option C in the previous round, the lower the probability of choosing option A compared to option C, however, the effect is not significant for option B. This result suggests a social norm effect, where the participants follow the majority's choice. It can also suggest a vindictive effect, where the participants that took a prosocial choice (by not choosing option C) were incentivized to choose the option generating a negative externality in the following rounds since the other participants did the same.

2.6 Discussion and conclusion

We use a laboratory experiment to study different public policies' acceptability to understand why they may fail after implementation. We compare taxes with equal redistribution and regulatory standards. We also look at the impact of cultural worldviews on acceptability, and finally, we study whether a policy trial increases acceptability.

Our analysis reveals that 57.8% of participants voted in favor of the implementation of the public policy. In practice, rejection rates are often lower, a rejection rate of 40% or more would likely make it difficult to implement such public policies due to the significant level of opposition. The high rejection rate compared to what is seen in practice might be explained by the fact that some individuals who expressed opposition to implementing the public policy in our experiment may have been unsure or indifferent towards the policy and were expressing their uncertainty or lack of strong preference by opposing the policy.

The findings of this study indicate that individuals' support for public policies is increased by their experience with a policy trial, whereas experiencing the game before the implementation of the public policy decreases support. The results suggest that exposure to a policy trial can increase support for public policies by making the social benefits more evident to individuals. Focusing on the different types of instruments, we find that this effect is not observed for taxation policies, but it is for regulatory standards, which are generally more accepted than taxes. The difference in the results between instruments might come from the challenge of changing individuals' preferences when there is strong policy aversion towards a specific instrument. The result highlights that even after pedagogical efforts to increase understanding of the benefits of taxation, the participants are still reticent to support it. In contrast, pedagogical efforts do have an impact on the acceptability of regulatory standards since rejection is less important than for taxes.

Furthermore, we see from the cultural worldviews' results that hierarchical-egalitarian worldviews only impact taxes' acceptability. The results affirm the role of cultural dimensions in the rejection of taxation policies, reinforcing the notion that differences in the acceptability of public policies could stem from cultural variations. Although our sample is not strictly representative of the french population, our result highlights French people's behavior, which may explain why we find contrasting results with the experimental literature. For instance, Cherry et al. (2012) finds higher support for taxes than for bans, and Cherry et al. (2017) finds no difference in acceptability between policies. In line with our results, Douenne and Fabre (2020, 2022) evidenced that French people largely reject a carbon tax and dividend policy, even though they appear aware and concerned about climate change. This is in contrast with Stockholm's implementation of a congestion charges trial, which led to increased acceptability of the fees. It is necessary to understand precisely which type of policies are more accepted according to the region's culture where they are aimed to avoid large rejection. If we refer to the transportation mode choice framework and the different cases of policy instruments, we can infer that the choice of implementing bans in Paris could be a more effective approach for public acceptability compared to the implementation of a toll as seen in London. Acceptability differs depending on the cultural context of the region, for instance, Dechezleprêtre et al. (2022) finds that France is among the countries that support the lowest policies; meanwhile, the United Kingdom stands out as having overall higher support.

In order to prevent potential opposition, we strongly suggest that policymakers take into consideration the cultural attributes of the targeted region before instituting any public policy. The acceptance and implementation of public policies can considerably vary from one nation to another, potentially leading to a reduction in the intended efficacy of a policy. Thus, exploring the influence of public participation in decision-making processes can be beneficial in enhancing their involvement and acceptance of policies. Utilizing mechanisms such as referendums, collective deliberative institutions, and enabling individuals to propose policies could significantly improve public understanding and acceptance of policies.

In our investigation, we chose to decontextualize the experiment. However, replicating this study with a comprehensive contextualization around the subject of transportation might yield noteworthy results. Such an approach could allow us to control for variables like respondents' mobility habits or their environmental attitudes towards the acceptability and choice of policies. Yet, it's crucial to note that using lab experiment methodology to study respondents' transportation mode choices could result in a misrepresentation, given its divergence from real-world conditions. The Discrete Choice Experiment methodology, while adept at mimicking "real world" conditions, may not accurately capture political or social behaviors. Hence, this chapter provides a complementary and supplementary methodological approach to the one used in the preceding chapter.

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.1 Heterogeneity of the players

Figure A1: Player 2 payoffs

Player 2

	Option A	Option B	Option C
Earning	200 ECU	90 ECU	200 ECU
Cost	100 ECU	20 ECU	50 ECU
Loss	0 ECU	0 ECU	15 ECU

Initial endowment in each round: 100 ECU

Figure A2: Player 3 payoffs

Player 3

	Option A	Option B	Option C
Earning	200 ECU	100 ECU	200 ECU
Cost	100 ECU	20 ECU	50 ECU
Loss	0 ECU	0 ECU	15 ECU

Initial endowment in each round: 100 ECU

Figure A3: Player 4 payoffs

Player 4

	Option A	Option B	Option C
Earning	200 ECU	125 ECU	200 ECU
Cost	100 ECU	20 ECU	50 ECU
Loss	0 ECU	0 ECU	15 ECU

Initial endowment in each round: 100 ECU

Figure A4: Player 5 payoffs

Player 5

	Option A	Option B	Option C
Earning	200 ECU	135 ECU	200 ECU
Cost	100 ECU	20 ECU	50 ECU
Loss	0 ECU	0 ECU	15 ECU

Initial endowment in each round: 100 ECU

Figure A5: Player 6 payoffs

Player 6

	Option A	Option B	Option C
Earning	200 ECU	145 ECU	200 ECU
Cost	100 ECU	20 ECU	50 ECU
Loss	0 ECU	0 ECU	15 ECU

Initial endowment in each round: 100 ECU

.2 Theoretical model

.2.1 The model

We employ a negative externalities theoretical model where N heterogeneous individuals can choose one of three options: A, B, or C. Each option yields a gain and has a cost. Moreover, option C generates a negative externality and when an individual chooses this option, it imposes an external cost to all the individuals in the economy (including himself).

Let's assume that two strategies (two options) always dominate one strategy (one option). The dominated strategy, according to the preferences of the individual, can be option A or B. This assumption reduces the range of possibilities for the individual to two options. In the following theoretical model, the economy is composed of N individuals. We only consider two different options; we exclude the dominated option. We denote x_i, a variable equal to 1 if the individual chooses option C and equal to 0 if not. w_0 represents the salary, g_{ik} corresponds to the gain of individual $i = 1, ..., N$, yielded from choosing option $k = A, B$. c_{ik} is the cost of individual $i = 1, ..., N$, from choosing option $k = A, B$. g_C denotes the gain from choosing option C and c_C is the cost. E denotes the externality produced from choosing option C.

Nash equilibrium

The following maximization program gives the individual's problem with strategic interactions at the Equilibrium. This program does not take into account the supplementary costs of choosing option C:

$$\max_{x_i} U(x_i) = x_i \times (w_o + g_C - c_C - E) + (1 - x_i) \times (w_0 + g_{ik} - c_{ik}) - \sum_{j \neq i}^{N} x_j E \quad (1)$$

The solution to the individual's problem, denoted x_i^*, is defined by:

$$x_i^* = \begin{cases} 1 \text{ if } g_C - g_{ik} + c_{ik} - c_C - E \geq 0 \\ 0 \text{ otherwise.} \end{cases} \quad (2)$$

The left side of the above inequality represents the benefit of individual i of choosing option C relative to option k. If this benefit is positive, the individual should choose option C over option k. The Nash Equilibrium is given by the simultaneous solution of the N individual's problem.

Social optimum

We assume a utilitarian central planner that maximizes a social welfare function represented by the sum of utilities:

$$\max_{x_i,\ldots,x_N} W = \sum_{i=1}^{N} x_i \times (w_0 + g_C - c_C - E) + \sum_{i=1}^{N} (1 - x_i) \times (w_0 + g_{ik} - c_{ik}) - N \sum_{j \neq i}^{N} x_j E \quad (3)$$

The simultaneous solutions to the social planner's maximization problem, denoted x_i^{sp}, is defined by:

$$\begin{aligned}
x_1^{sp} &= \begin{cases} 1 \text{ if } g_C - g_{ik} + c_{ik} - c_C - E \geq (N-1)E \\ 0 \text{ otherwise.} \end{cases} \\
&\vdots \\
x_i^{sp} &= \begin{cases} 1 \text{ if } g_C - g_{ik} + c_{ik} - c_C - E \geq (N-1)E \\ 0 \text{ otherwise.} \end{cases} \\
&\vdots \\
x_N^{sp} &= \begin{cases} 1 \text{ if } g_C - g_{ik} + c_{ik} - c_C - E \geq (N-1)E \\ 0 \text{ otherwise.} \end{cases}
\end{aligned} \quad (4)$$

The left side of the above inequalities represents the benefit of choosing option C over option k. The right side of the equation represents their impact on the other individuals, it represents the marginal external cost of choosing option C. The condition states that the optimal choice of options is one in which for all individuals having chosen option C, the benefit is higher than the cost imposed on other individuals.

The difference between the individual's choice condition and the social planner's is given by $(N-1)E$, the cost imposed on the other individuals of the economy. If one participant chooses option C, then there is an external cost imposed on all the other individuals.

Pigouvian tax

In order to internalize the negative externality produced by choosing option C, we propose a Pigouvian tax, which is a market-based instrument. A Pigouvian tax allows us to completely consider the external costs of the externality imposed on the other individuals if individual i chooses option C. The Pigouvian tax is designed to equal the external marginal cost making the private cost of the good equal to the social cost.

From equations 2 and 4, we can deduce the Marginal External Cost (MEC), which is equal to the Pigouvian tax:

$$MEC = (N-1)E$$

Decentralized solution

Let's demonstrate that when the Pigouvian tax is equal to $t = (N-1)E$, the decentralized solution yields the socially optimal solution.

$$\begin{gathered}\max_{x_i} U(x_i) = x_i \times (w_0 + g_C - c_C - E - t) + (1 - x_i) \times (w_0 + g_{ik} - c_{ik}) - \sum_{j \neq i}^{N} x_j E \\ s.t. \;\; t = (N-1)E\end{gathered} \tag{5}$$

Substituting the condition in the maximization function, we obtain:

$$\max_{x_i} U(x_i) = x_i \times (w_0 + g_C - c_C - E - (N-1)E + (1 - x_i) \times (w_0 + g_{ik} - c_{ik}) - \sum_{j \neq i}^{N} x_j E \tag{6}$$

The solution to the decentralized individual's problem, denoted x_i^d, is defined by:

$$x_i^d = \begin{cases} 1 \text{ if } g_C - g_{ik} + c_{ik} - c_C - E \geq (N-1)E \\ 0 \text{ otherwise.} \end{cases} \tag{7}$$

The above condition states that the decentralized solution with the Pigouvian tax is the one where the benefit of choosing option C over option k must be greater than the external cost produced by choosing option C. It yields the same solution as the social optimum.

.2.2 Experimental application

The experiment uses $N = 6$, $g_A = g_C = 200$, $g_{1B} = 80$, $g_{2B} = 90$, $g_{3B} = 100$, $g_{4B} = 125$, $g_{5B} = 135$, $g_{6B} = 145$, $c_A = 100$, $c_B = 20$, $c_C = 50$, and $E = 15$ as parameters of the negative externalities game.

At the Nash equilibrium, the inequality:

$$g_C - g_{ik} + c_{ik} - c_C - E \geq 0 \tag{8}$$

is verified for any type of player.

Considering players 1, 2, or 3, the dominated strategy is option B. The participant chooses between option A and option C. We substitute in equation 8 the parameters of the game:

$$200 - 200 + 100 - 50 - 15 > 0$$

The inequality above is verified.

Considering players 4, 5, or 6, the dominated strategy is option A. The participant chooses between options B and C:

$$200 - g_{iB} + c_{iB} - 50 - 15 > 0$$

with $i = 4, 5, 6$.

The above condition is verified for any player 4, 5, or 6. Therefore the equilibrium in our experimental framework is for every participant to choose option C.

At the social optimum, the following inequality is not verified for any of the individuals:

$$g_C - g_{ik} + c_{ik} - c_C - E \geq (N-1)E$$

Let's consider players 1, 2, or 3, for which the dominated strategy is option B.

$$200 - 200 + 100 - 50 - 15 < 75$$

Let's consider players 4, 5, or 6, for which the dominated strategy is option A.

$$200 - g_{iB} + c_{iB} - 50 - 15 < 75$$

Therefore, the social optimum in our experiment is given by players 1, 2, and 3, choosing option A, and players 4, 5, and 6, choosing option B.

Under our experimental framework, the marginal external cost gives the Pigouvian tax:

$$t = (N - 1)E = 5 \times 15 = 75$$

.

The individual chooses option C with the Pigouvian tax if the following condition is verified following equation 7:

$$g_C - g_{ik} + c_{ik} - c_C - E \geq (N - 1)E$$

We replace the parameters with their values, and for any type of individual or option, the following is not verified:

$$200 - g_{ik} + c_{ik} - 15 \geq 75$$

.3 Robustness checks

We run robustness checks eliminating 47 participants that answered incorrectly at least one question from the comprehension checks. We run the analysis with 73 participants, 38 in the regulatory standards treatment and 35 in the taxation treatment.

There is a significant difference between vote 1 and vote 2 (Exact McNemar significance probability yields a p-value= 0.02) and between vote 2 and vote 3 (Exact McNemar significance probability yields a p-value= 0.04). Concerning the taxation treatment, there is no significant difference between votes. Focusing on the regulatory standards treatment, there is only a significant difference between vote 2 and vote 3 (Exact McNemar significance probability yields a p-value= 0.06). The difference between treatments disappears, we think that it might be due to the suppression of a large part of the observations.

Table C1: Robustness checks: Determinants of the acceptability of public policies

Dependent variable: Vote	(1) Global	(2) Regulatory standards	(3) Taxation
Treatment	-0.33		
	(1.53)		
Period = 1	1.76***	2.27*	1.39*
	(0.68)	(1.35)	(0.76)
Period = 3	1.55**	2.27**	1.01
	(0.69)	(1.09)	(0.88)
Option B is advantageous	0.47	1.76	-0.52
	(1.35)	(3.62)	(1.26)
Age	-0.06	-0.06	-0.09
	(0.05)	(0.10)	(0.06)
Female	-0.45	-2.93	0.79
	(1.12)	(2.46)	(1.09)
Student	1.72	1.64	2.60
	(1.87)	(4.39)	(2.20)
In activity	1.17	-0.12	3.10
	(1.02)	(1.91)	(2.54)
# option C: Part 1	-1.11***	-2.08*	-0.43
	(0.43)	(1.17)	(0.52)
Others - option C: Part 1	0.15	-0.32	0.29
	(0.15)	(0.73)	(0.21)
# option C: Part 2			0.69
			(0.66)
Others - option C: Part 2			0.09
			(0.26)
Constant	2.42	11.34**	-2.38
	(3.55)	(5.12)	(5.78)
Number of clusters	20	10	10
Observations	219	114	105
Number of subjects	73	38	35

Robust standard errors clustered at the group level are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: We use logit regressions clustered at the group level in a panel data set with three periods, each period corresponds to each part of the experiment. The dependent variable is a binary variable equal to 1 for a yes vote and 0 for a no vote. Regression (1) comprises both treatments, regression (2) only uses observations from the regulatory standards treatment, and regression (3) only uses observations from the tax treatment. *Tax treatment* is a dummy variable = 1 when it is the tax treatment. *Period* is a categorical variable, equal to 1 if it corresponds to vote 1, equal to 2 if vote 2, and equal to 3 if vote 3, the reference category is vote 2. In the controls, we include a dummy variable *Option B is advantageous* = 1 when the participant was assigned to player 4, 5, or 6; it is equal to 0 when the participant was assigned to player 1, 2, or 3. *Female* is a dummy variable = 1 if the participant is a female. *Student* is a dummy variable = 1 if the participant is a student. *In activity* is a dummy variable = 1 if the participant works. We include as controls *# option C: Part 1 and Part 2*, representing the number of times the participant chose option C in Part 1 and Part 2, respectively. We include the control *Others - Option C: Part 1 and Part 2*, representing the sum of the number of participants having chosen option C in each round of the first and second parts of the experiment within each group, respectively.

Table C2: Robustness checks: determinants of the acceptability of public policies by vote

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	**Vote 1**	**Vote 1**	**Vote 2**	**Vote 2**	**Vote 3**	**Vote 3**
Tax treatment	0.13	0.01	0.18	0.12	-0.00	-0.36
	(0.52)	(0.58)	(0.58)	(0.63)	(0.51)	(0.57)
Option B is advantageous		0.20		0.25		-0.34
		(0.52)		(0.54)		(0.59)
Age		-0.01		0.00		-0.05*
		(0.02)		(0.02)		(0.02)
Female		0.65		-0.37		-0.62
		(0.43)		(0.56)		(0.50)
Student		0.81		0.66		0.23
		(0.72)		(0.70)		(0.94)
In activity		0.81**		0.59		-0.49
		(0.39)		(0.41)		(0.48)
# option C: Part 1				-0.33**		-0.47***
				(0.16)		(0.17)
Others - option C: Part 1				0.04		0.06
				(0.05)		(0.07)
Constant	0.65**	0.03	0.11	0.08	0.65*	3.69**
	(0.33)	(1.13)	(0.38)	(1.60)	(0.38)	(1.85)
Number of clusters	20	20	20	20	20	20
Observations	73	73	73	73	73	73
Pseudo R-squared	0.00	0.07	0.00	0.08	0.00	0.17

Robust standard errors clustered at the group level are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Dependent variables are a binary variable equal to 1 for a yes vote and 0 for a no vote. For regressions (1) and (2) is the acceptability of taxes at vote 1; for regressions (3) and (4) is the acceptability at vote 2, and for regressions (5) and (6), is the acceptability at vote 3. We use logit regressions clustered at the group level. *Tax treatment* is a dummy variable = 1 when it is the tax treatment. In the controls, we include a dummy variable *Option B is advantageous* = 1 when the participant was assigned as player 4, 5, or 6; it is equal to 0 when the participant was assigned to player 1, 2, or 3. *Female* is a dummy variable = 1 if the participant is a female. *Student* is a dummy variable = 1 if the participant is a student. *In activity* is a dummy variable = 1 if the participant works. We include as a control *# option C: Part 1* representing the number of times the participant chose option C in Part 1. We include the control *Others - Option C: Part 1*, representing the sum of the number of participants having chosen option C in each round of the first part of the experiment within each group.

Table C3: Robustness checks: The impact of worldviews on the acceptability of regulatory standards

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	**Vote 1**	**Vote 1**	**Vote 2**	**Vote 2**	**Vote 3**	**Vote 3**
Individualistic-communitarian	0.59	0.38	0.26	0.50	0.10	0.40
	(1.00)	(1.07)	(0.44)	(0.66)	(0.54)	(0.90)
Hierarchical-egalitarian	-1.35*	-1.39	0.08	0.08	-0.89	-1.26
	(0.80)	(1.02)	(0.75)	(1.16)	(0.92)	(1.29)
Option B is advantageous		1.14		0.08		-0.56
		(0.75)		(1.11)		(0.91)
Age		0.01		-0.02		-0.04
		(0.03)		(0.03)		(0.03)
Female		-0.28		-0.96		-1.84***
		(0.74)		(0.76)		(0.68)
Student		0.96		-0.46		-0.20
		(1.17)		(0.99)		(1.13)
In activity		0.06		0.04		-0.84*
		(0.50)		(0.48)		(0.45)
# option C: Part 1				-0.61**		-0.69**
				(0.24)		(0.28)
Others - option C: Part 1				-0.09		-0.15
				(0.14)		(0.16)
Constant	1.02	-0.02	-0.04	3.70	0.99	7.51***
	(0.77)	(1.58)	(0.75)	(2.63)	(0.89)	(2.45)
Number of clusters	10	10	10	10	10	10
Observations	38	38	38	38	38	38
Pseudo R-squared	0.09	0.14	0.00	0.15	0.04	0.21

Robust standard errors clustered at the group level are in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Dependent variables are a binary variable equal to 1 for a yes vote and 0 for a no vote. For columns (1) and (2) is the acceptability of taxes at vote 1; for columns (3) and (4) is the acceptability at vote 2, and for columns (5) and (6) is the acceptability at vote 3. We use Logit regressions clustered at the group level. *Individualistic-communitarian* is a dummy variable = 1 if the participant is individualistic, and = 0 if communitarian. *Hierarchical-egalitarian* is a dummy variable = 1 if hierarchical and = 0 if egalitarian. We include the control *Others - Option C: Part 1* in regression (4), representing the mean of participants within the group having chosen option C in the first part of the experiment. We include a dummy variable *Option B is advantageous* = 1 when the participant was assigned to player 4, 5, or 6; it is equal to 0 when the participant was assigned to player 1, 2, or 3. We also include as a control textit# option C: Part 1, which represents the number of times that the participant chose option C in Part 1.

Table C4: Robustness checks: The impact of worldviews on the acceptability of taxation policies

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	**Vote 1**	**Vote 1**	**Vote 2**	**Vote 2**	**Vote 3**	**Vote 3**
Individualistic-communitarian	-0.20	-1.11	-1.24*	-2.68***	-0.59	-0.12
	(0.84)	(1.17)	(0.69)	(0.96)	(0.57)	(0.93)
Hierarchical-egalitarian	-1.88***	-2.31*	-1.96**	-2.62**	-1.56*	-0.58
	(0.64)	(1.30)	(0.78)	(1.06)	(0.81)	(1.23)
Option B is advantageous		-1.41		-0.18		-0.60
		(0.94)		(0.79)		(1.02)
Age		-0.03		0.05*		-0.11*
		(0.04)		(0.03)		(0.06)
Female		1.02		-0.09		-0.28
		(1.06)		(0.94)		(0.98)
Student		2.26		3.15*		0.59
		(1.96)		(1.69)		(1.73)
In activity		3.91**		4.12**		0.63
		(1.65)		(1.69)		(1.77)
# option C: Part 1				0.00		-0.38
				(0.33)		(0.33)
# option C: Part 2						0.92
						(0.64)
Others - option C: Part 1				0.13		0.23
				(0.11)		(0.19)
Others - option C: Part 2						-0.04
						(0.19)
Constant	1.81**	0.88	1.62**	-3.58	1.62**	2.59
	(0.76)	(2.00)	(0.71)	(3.20)	(0.68)	(3.33)
Number of clusters	10	10	10	10	10	10
Observations	35	35	35	35	35	35
Pseudo R-squared	0.14	0.35	0.18	0.33	0.11	0.32

Robust standard errors clustered at group level are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Dependent variables are a binary variable equal to 1 for a yes vote and 0 for a no vote. For regressions (1) and (2) is the acceptability of taxes at vote 1; for regressions (3) and (4) is at vote 2, and for regressions (5) and (6) is at vote 3. We use logit regressions clustered at the group level. *Individualistic-communitarian* is a dummy variable = 1 if the participant is individualistic, and = 0 if communitarian. *Hierarchical-egalitarian* is a dummy variable = 1 if hierarchical and = 0 if egalitarian. We include the control *Others - Option C: Part 1* in regression (4), representing the mean of participants within the group having chosen option C in the first part of the experiment. We include *Others - option C: Part 2* in regression (6), representing the mean of participants having chosen option C in Part 2 of the experiment. We include a dummy variable *Option B is advantageous* = 1 when the participant was assigned to player 4, 5, or 6; it is equal to 0 when the participant was assigned to player 1, 2, or 3. We also include as a control two variables *# option C: Part 1 and Part 2*, representing the number of times the participant chose option C in Part 1 and Part 2, respectively.

Table C5: Robustness checks: determinants of option choice

Dependent variable: option choice	*Option A*	*Option B*
Tax treatment	0.106	-0.260
	(0.399)	(0.619)
Policy implemented	2.340***	2.817***
	(0.722)	(0.744)
Option B is advantageous	-2.097***	4.028***
	(0.397)	(0.781)
Period	-0.015	0.008
	(0.034)	(0.027)
Hierarchical-egalitarian	-0.194	-0.608
	(0.322)	(0.567)
Individualistic-communitarian	-0.073	-0.653
	(0.377)	(0.732)
Age	0.010	0.035
	(0.015)	(0.024)
Female	0.160	1.202**
	(0.246)	(0.513)
In activity	0.029	0.106
	(0.356)	(0.667)
Option C in previous round	-2.098***	-1.634***
	(0.390)	(0.349)
Others - option C in previous round	-0.219*	-0.181
	(0.124)	(0.195)
Constant	0.443	-4.357***
	(0.654)	(1.154)

Robust standard errors clustered at the group level are in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Option C is the reference category. Each category and dummy variables have to be compared to the reference. We use a multinomial logit regression. The periods in the regulatory standards when the policy was implemented are not considered. The dependent variable is the option choice (categorical variable), it is equal to 1 if the participant chooses option A, equal to 2 if option B, and equal to 3 if option C. Option B is advantageous is a dummy variable = 1 when the participant was assigned to player 4, 5, or 6. Policy implemented is a dummy variable = 1 if the tax policy was implemented in the round. Option C in previous period is a dummy variable = 1 if the participant chose option C in the previous round. # of others - option C in the previous round represents the number of group members (excluding the participant) that chose option C in the previous round. Period is a variable that captures any learning effect of the game.

.4 Screenshots of the experiment

Figure B1: Screenshot of the feedback page of option choice

Résultats

Vous avez choisi l'option Option C. Parmi les six membres de votre groupe 2 ont choisi l'option A; 2 ont choisi l'option B; et 2 ont choisi l'option C, vous perdez donc 30 ECUs.

Votre paiement pour cette période 1 correspond à 220 points ECUS.

100 + 200 - 50 - (2 × 15) = 220 points ECUs

Détail du calcul:

100 correspond à la dotation initiale.

200 correspond à votre gain lié à votre choix.

50 correspond au coût de l'option.

2 × 15 correspond au dégât généré par les participants ayant choisi l'option C.

Suivant

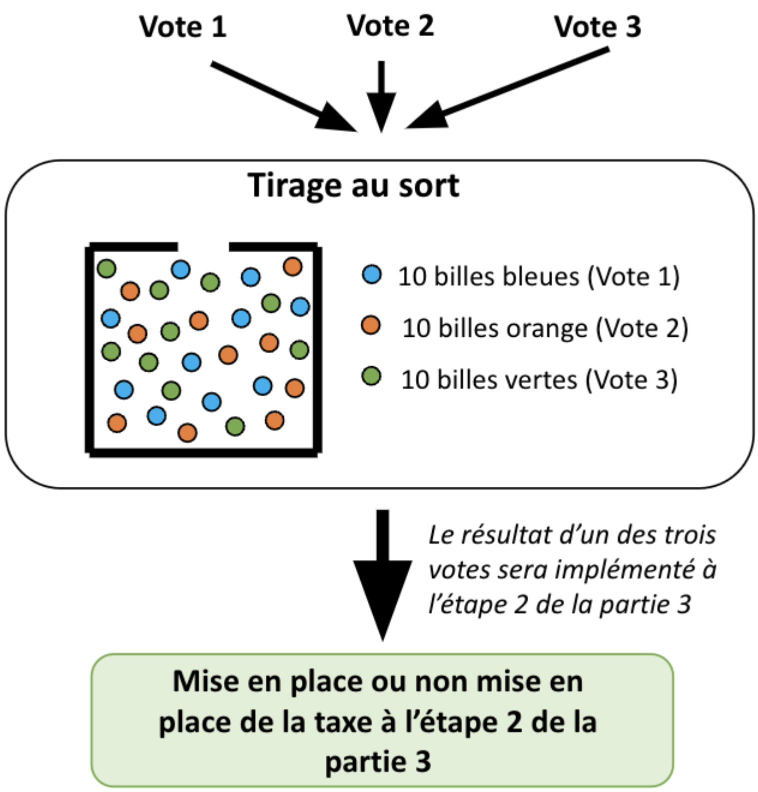
Figure B2: Screenshot of the vote page

L'expérience commence à partir de maintenant.

Partie 1

Etape 1 (vote)

Rappel : ce vote ne pourra être appliqué qu'à la partie 3.



Vous devez voter pour ou contre la mise en place de la taxe.

Les membres de votre groupe devront aussi voter pour ou contre la mise en place de la taxe.

Rappel : ce vote ne pourrait être appliqué qu'à la partie 3.

En quoi consiste la mise en place de la taxe?

S'il y a mise en place de la taxe les individus qui auront choisi **l'option C** devront payer une *taxe* de **75 ECUs.**

Les ECUs collectés en tant que taxe seront **redistribués** parmi les six membres du groupe de façon équitable.

Si seulement un membre (vous ou quelqu'un d'autre) de votre groupe a choisi l'option C, vous allez avoir une perte de 15 ECUs, mais vous allez recevoir 75/6= 12,5 ECUs supplémentaires.

Si deux membres (vous inclus) de votre groupe ont choisi l'option C, alors vous allez avoir une perte de 30 ECUs. Chaque membre du groupe qui aura choisi l'option C devra payer 75 ECUs de taxe, le total des taxes collectées s'élève à 75 × 2 = 150 ECUs. Vous allez donc recevoir grâce à la redistribution de la taxe 150/6 = 25 ECUs, et ainsi de suite.

Veuillez voter pour ou contre la mise en place de la taxe à la Partie 3 :

- ◯ Pour : Oui, je souhaite la mise en place d'une taxe de 75 ECUs qui devra être payée par chaque membre du groupe qui choisit l'option C.
- ◯ Contre : Non, je ne souhaite pas la mise en place d'une taxe de 75 ECUs.

Suivant

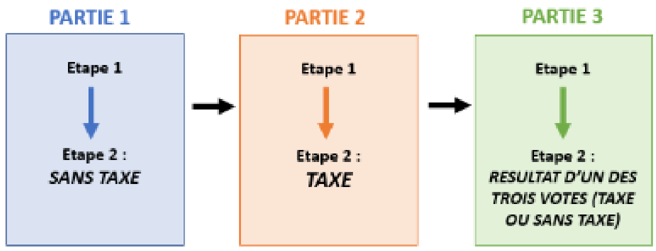
Figure B3: Screenshot of the option choice page

PARTIE 1

Etape 2

Il n'y a pas de mise en place de la taxe à cette partie !

Rappel :



Cette étape comporte **5 périodes**.

A chaque période vous et les autres membres du groupe devez décider de façon individuelle **l'option que vous préférez entre l'option A, B et C**.

Au début de chaque période, vous, ainsi que les cinq autres membres de votre groupe, disposez chacun d'une dotation de 100 ECUs.

Chaque membre du groupe ayant choisi l'option C imposera une perte de 15 ECUs à chaque membre du groupe. Plus il y a de membres de votre groupe qui choisissent l'option C, plus les pertes sont importantes.

Vous êtes à la période 1. Il reste 4 périodes.

Veuillez vous référer au tableau suivant afin de prendre votre choix:

Joueur 6

	Option A	**Option B**	**Option C**
Gain	200 ECUs	145 ECUs	200 ECUs
Coût	100 ECUs	20 ECUs	50 ECUs
Perte	0 ECUs	0 ECUs	15 ECUs

Dotation initiale à chaque tour : 100 ECUs

Nombre de personnes de votre groupe ayant pris l'option C :	**Vous perdez:**
1	**15 ECUs**
2	**30 ECUs**
3	**45 ECUs**
4	**60 ECUs**
5	**75 ECUs**
6	**90 ECUs**

.5 Cultural worldviews survey

The following survey was presented in French. We modified questions 9 and 11 in order to make the questions more relevant to french culture. This survey was taken from Kahan et al. (2011).

People in our society often disagree about how far to let individuals go in making decisions for themselves. How strongly you agree or disagree with each of these statements? [strongly disagree, moderately disagree, slightly disagree, slightly agree, moderately agree, strongly agree]

1. The government interferes far too much in our everyday lives.

2. Sometimes government needs to make laws that keep people from hurting themselves.

3. It's not the government's business to try to protect people from themselves.

4. The government should stop telling people how to live their lives.

5. The government should do more to advance society's goals, even if that means limiting the freedom and choices of individuals.

6. Government should put limits on the choices individuals can make so they don't get in the way of what's good for society.

People in our society often disagree about issues of equality and discrimination. How strongly you agree or disagree with each of these statements? [strongly disagree, moderately disagree, slightly disagree, slightly agree, moderately agree, strongly agree]

7. We have gone too far in pushing equal rights in this country.

8. Our society would be better off if the distribution of wealth was more equal.

9. We need to dramatically reduce inequalities between the rich and the poor, and men and women.

10. Discrimination against minorities is still a very serious problem in our society.

11. It seems that minority groups don't want equal rights, they want special rights just for them.

12. Society as a whole has become too soft and feminine.

.6 Tax treatment instructions

The following instructions were originally in french.

Hello and welcome!

Thank you for participating in this experiment!

You are participating in an experiment where you can earn money based on your choices and the choices of other players. Your earnings will also depend on various events. Each participant will make their decisions individually in front of their computer.

We ask you to please read the instructions carefully. These instructions will help you understand the experiment.

Responses to this experiment are important to us and will be completely anonymous and confidential.

During this experiment, you will have to make several decisions. Your earnings will depend on your decisions as well as the decisions of other participants.

At the end of the experiment, one of your decisions will be randomly selected and will determine your payment. As a thank you for your participation, you will receive 7 euros, in addition to the earnings from the experiment. The total payment of your earnings in euros will be made in cash and privately at the end of the experiment. The earnings are expressed in ECUs.

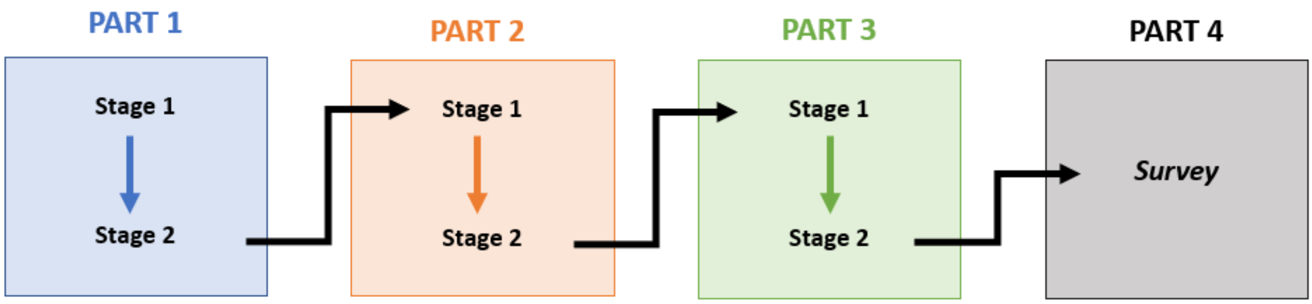
The conversion rate of ECUs to euros is 1 ECU = 0.05 euros.

You can ask questions at any time during the experiment. To do so, raise your hand and an experimenter will come to you to respond privately. During the experiment, all communication between participants is prohibited. Please read the instructions carefully.

The computer will randomly form groups of **6 participants**. The composition of the groups **will remain unchanged** throughout the experiment. You cannot identify the other members of your group and they cannot identify you.

The experiment consists of **four parts**, and you must answer all parts. The first three parts each consist of two stages in which you will have to make decisions. The fourth part of the experiment is a questionnaire.

The composition of the experiment can be summarized with the following image:



For parts 1, 2, and 3:

Stage 1

Stage 1 corresponds to a vote.

The votes are ***important***.

You must vote for or against the implementation of a tax. **All members of your group must also vote.**

We will explain later in the instructions what the tax consists of.

Stage 2

In stage 2, you have a choice to make between three options.

Stage 2 consists of *5 rounds*.

At the beginning of each round, we will give you an endowment of **100 ECUs** and ask you to choose the option you prefer among options A, B, and C.

Each option will earn you a **different gain** and each option has a **different usage cost**.

How do losses work?

If you choose option C, you incur a **loss of 15 ECUs**, and you **impose a loss of 15 ECUs on each participant** in your group, even if they did not choose option C.

Likewise, if another member of your group chose option C, you also incur a loss of 15 ECUs.

Thus, if two members of your group chose option C, each of you incurs a loss of 30 ECUs.

The more members of your group who choose option C, the greater the losses.

Number of members of your group who chose option C:	You lose:
1	15 ECU
2	30 ECU
3	45 ECU
4	60 ECU
5	75 ECU
6	90 ECU

Example: Suppose you have chosen option A and three members of your group have chosen option C.

Your payment will therefore be:

$$100 + 200 - 100 - (15 \times 3) = 155ECU$$

100 corresponds to your initial endowment, 200 corresponds to your earnings, 100 corresponds to the cost of using the chosen option, and 15×3 corresponds to the loss imposed by the 3 members of your group who chose option C. After each round, your payment will be displayed on your screen for the relevant round.

What does the implementation of the tax consist of?

If the tax is implemented, individuals who have chosen **option C** will have to pay an additional *tax* of **75 ECUs.**

The ECUs collected as tax will be redistributed equitably among the six members of the group.

For each round, if only one member of your group has chosen option C, you will have a loss of 15 ECUs, but you will receive an additional $75/6 = 12.5$ ECUs through tax redistribution.

For each round, if two members of your group have chosen option C, then you will each have a loss of 30 ECUs. Each member of the group who has chosen option C will have to pay 75 ECUs in tax, the total amount of collected taxes will be 150 ECUs. You will therefore receive $150/6 = 25$ ECUs through tax redistribution, and so on.

The following table represents the redistribution of the tax:

Number of members of your group who chose option C:	You lose:	Thanks to the redistribution you earn:
1	15 ECU	75/6= 12.5 ECU
2	30 ECU	150/6= 25 ECU
3	45 ECU	225/6= 37.5 ECU
4	60 ECU	300/6= 50 ECU
5	75 ECU	375/6= 62.5 ECU
6	90 ECU	450/6= 75 ECU

If you have chosen option C, you will pay 75 ECU

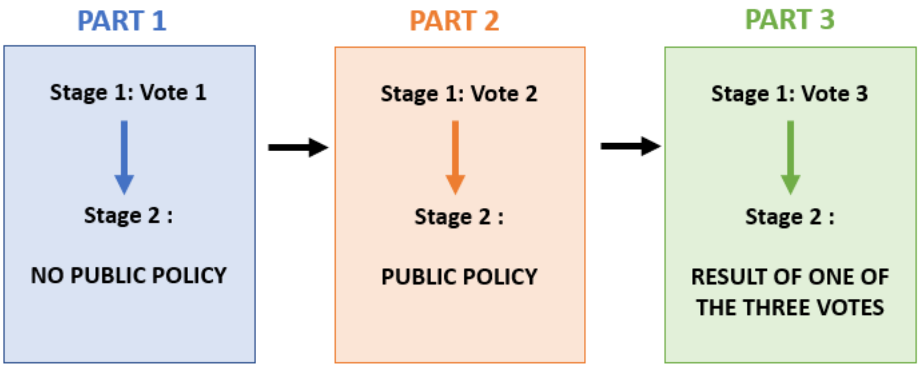
The amount of the redistribution corresponds to: (tax * Number of members of your group who chose option C) / 6

Attention, regardless of the result of the vote in Part 1, the tax **will not be** implemented.

In **Part 2**, regardless of the result of the vote, the tax **will be** implemented *independently* of the result of the Part 2 vote.

In **Part 3**, the result of the **vote** of one of the three parts will be drawn at random and implemented. **Therefore, it is possible that in Part 3, the tax may or may not be implemented.**

Thus, the votes of the three parts will only have an impact on Part 3.



How will the chosen vote be determined?

The vote will be determined by drawing a **marble** at random.

We will set up an urn in front of you, consisting of 30 marbles:

- 10 green marbles
- 10 orange marbles
- 10 blue marbles

If a **blue marble** is drawn, then the result of the vote in **part 1** will be implemented.

If an **orange marble** is drawn, then the result of the vote in **part 2** will be implemented.

If a **green marble** is drawn, then the result of the vote in **part 3** will be implemented.

Each of the three votes has **an equal probability** of being implemented, which is 1 in 3.

If there is a tie (3 yes and 3 no) in the vote drawn at random, we will roll a die to break the tie. If the number is even, then the tax will be implemented. If the number is odd, then the tax will not be implemented.

You will know the results of the different votes in your group after the vote in part 3.

Chapter 3

Integrating Behavioral Economics Insights into Transport Demand Modelling: A Revised Approach to Decarbonization Policy Analysis

3.1 Introduction

In numerous European energy transition scenarios, the electrification of the transport sector is seen as a unanimous solution for reducing the European Union's reliance on fossil fuels and the transport sector's CO2 emissions. By doing so, this policy not only meets energy security concerns by lessening dependence on fossil fuels, but also aligns with the aim to restrict global temperature increases to below 2°C.

The National Low Carbon Strategy (Stratégie Nationale Bas Carbone - SNBC), instituted in line with the Paris Agreement (2016), sets an ambitious goal to achieve a 40% reduction in greenhouse gas (GHG) emissions from land transport by 2030, compared to 1990 levels, and carbon neutrality by 2050[1]. To evaluate diverse public policies promoting transport decarbonization and to explore scenarios for achieving CO2 emission targets as set by the SNBC, IFP Energies Nouvelles, a research institute, developed the DRIVERS fleet model (DiscRete choIce modeling for low-carbon VEhicles fleet scenaRioS). This integrated transport simulation model focuses on the demand side dynamics of the private vehicle market in France and Europe up to 2050, projecting distinct vehicle sales scenarios, mainly electric and thermal, identifying potential strategies for low-carbon mobility, and evaluating the impacts on polluting emissions from the transport sector.

The DRIVERS model projects vehicle stocks and distances travelled up to 2050, and breaks down demand by vehicle type and technology. Once vehicle demand is determined, the model calculates the energy consumption and pollutant emissions of the fleet's vehicles, based on real driving conditions calculated by the IFP Energies Nouvelles research institute. Future purchasing behaviors are modeled based on discrete choice models literature, which aims to explain economic agents' choices when faced with multiple alternatives. These models are widely used in transport demand literature, with the Mobility model (MoMo) used by the International Energy Agency (I.E.A.) for its transport demand projections. Although discrete choice models accurately reflect the purchasing behavior and diffusion of traditional vehicles, the predictions for low-carbon vehicles in the DRIVERS model are less reliable due to factors other than cost comparison, such as environmental awareness.

To improve this model, we incorporate insights from a behavioral economics study used in the Chapter 1 of this thesis. The integration of a behavioral dimension into

[1] Ministère de la Transition écologique, "Stratégie nationale bas-carbone (SNBC)," [Online]. Available: https://www.ecologie.gouv.fr/strategie-nationale-bas-carbone-snbc.

discrete choice models is a unique approach in this chapter. The aim is to make the purchasing behavior for low-carbon vehicles dependent on several unique explanatory factors. By enhancing the empirical foundations of the DRIVERS model to better explain the initiation and deployment of low-carbon vehicles, this chapter contributes to the refinement of an existing transport demand model. Our findings suggest that the modified DRIVERS model, incorporating behavioral economics insights, predicts fewer early electric vehicle sales and longer dominance of thermal vehicles in the market. This modification, therefore, highlights the need for specific public policies, such as vehicle bans, to close the gap between predicted vehicle emissions and targets set by the French state. These results represent the opportunity to interact the dimensions of public acceptability discussed in Chapter 2 of this thesis with indicators about environmental policy effectiveness seen through the results of this study.

This chapter is structured as follows: Section 3.2 gives a brief overview of the discrete choice experiment study used for it's behavioral insights, section 3.3 gives an overview of the process through which the DRIVERS model gives vehicle projections, following that section 3.4 details the theory behind the DRIVERS model's discrete choice estimation and its modification. Then, section 3.5 explains how the results from the behavioral economics study used in this chapter were adjusted to fit with the DRIVERS modeling paradigm then implemented in the model. Section 3.6 shows the scenarios through which the DRIVERS model makes it's predictions. Section 3.7 presents the effects of the modifications on the vehicle sales/stocks and emissions predictions of the DRIVERS model. Finally, section 3.8 discusses the implications of these results and formulates policy recommendations, and section 3.9 gives a conclusion.

3.2 The Discrete Choice Experiment Study

This section describes the study seen in chapter 1, and how it can be used for it's behavioral economics insights to be imported inside the DRIVERS modelling method. Discrete choice experiments (DCEs) offer valuable insights into decision-making processes by presenting participants with a series of choices and allowing them to select their preferred option. In this specific study, we conducted two separate DCEs, focusing on small city-type vehicles and medium-sized vehicles respectively. The data comes from an online survey that was distributed in France in 2021, to a sample representative of the french population.

We characterized each vehicle through six key attributes: purchase price, annual fuel cost, annual maintenance cost, vehicle range (in kilometers), emissions amount depicted through an environmental label, and the future projection of the level of fast-charging infrastructure. The levels of these attributes were crafted based on expert recommendations and the average value of a reference vehicle (RV) of the same technology and size.

The choice experiment attempted to capture the complexity of purchasing decisions by incorporating current market conditions and future uncertainties. The variations in purchase price were designed to mirror French public policies such as environmental bonuses and penalties. Purchase price values for battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) were presented as: -30%, -15%, and status quo (SQ), whereas conventional vehicles (CV) were presented as SQ, +15%, and +30%. The annual fuel cost, annual maintenance cost, and vehicle range offered three value options: -30%, SQ, and +30%.

We chose to represent vehicle emissions through an environmental label, ranging from A (lowest greenhouse gas emissions) to E (highest emissions). This only considered emissions from vehicle usage, not the manufacturing or recycling stages.

We made a key assumption that public charging for electric vehicles would only occur at fast-charging stations due to the significant difference in charging time compared to regular charging infrastructure. We thus introduced the future level of fast-charging infrastructure as an attribute, acknowledging that this could be subject to fluctuations based on private or public investment and the popularity of electric vehicles.

Respondents were presented with a projected scenario on the future availability of fast-charging infrastructure, with some scenarios offering certainty, and others including risk with two equally probable outcomes.

Each participant was presented with eight choice tasks, each featuring three different vehicle technologies: a conventional diesel/gas car, a plug-in hybrid car, and a battery electric car. Participants were asked to select their most preferred vehicle based on the detailed attribute information provided.

The results from chapter 1 showed a difference in preferences for vehicle attributes between small and medium vehicle users. They also demonstrated that vehicle users prioritise immediate costs over costs incurred from the usage of the vehicle, such as fuel or maintenance costs. These are very interesting results that differ from the traditional way of thinking that vehicle users just choose the vehicle presented to them with the lowest cost of ownership, and provide a great opportunity to increase the realism of the DRIVERS model's projections.

3.3 Presentation of the DRIVERS model

All the information on the DRIVERS model presented in this chapter is based off of the E4T study realised by the ADEME in collaboration with IFP Energies Nouvelles Chèze et al. (2023). This model enables the study of the dynamics of the private vehicle market up to 2050 in France and Europe. The DRIVERS model aims to firstly, establish different vehicle sales scenarios, mainly electric and thermal, then identify the conditions and actions of a wide range of instruments and public policies to be implemented to develop low-carbon mobility, including electric mobility, and finally to evaluate the impacts of these policies on polluting emissions (CO2, CO, NOx, PM10) from the transport sector. The model focuses on individual behavior in that it simulates changes in consumer behavior in response to a change in economic conditions. DRIVERS incorporates: an econometric travel demand model, which projects the stock of vehicles and distances traveled to 2050; and a discrete choice model, allowing the breakdown of demand by vehicle type (small, medium, large) and by technology: Diesel, Gasoline, Compressed Natural Gas (CNG), Hybrid Electric Vehicle (HEV) Diesel, HEV Gasoline, Plug-In Hybrid Electric Vehicle (PHEV) Diesel, PHEV Gasoline, Battery Electric Vehicle (BEV), Hydrogen. From the vehicle demand, the unit energy consumption of the different vehicles that compose it and their pollutant emissions are then deduced. The latter are based on values calculated by IFP Energies Nouvelles from real driving conditions. IFP Energies Nouvelles has simulation models for conventional, electric and hybrid vehicles that allow the measurement and evaluation of the energy consumption of vehicles according to their conditions of use.

The DRIVERS model uses a set of contextual and public policy scenarios in order to analyse the effect of: a growth in vehicle energy performance, a growth in vehicle demand, and the increasing decarbonisation of the energy consumed by vehicles. The results of the DRIVERS model are analyzed mainly in terms of i) the level of sales of electric and thermal vehicles and ii) polluting emissions. The impact of public policies on these two criteria is evaluated on a set of 64 scenarios. These scenarios are built according to a tree logic where all the dimensions of each branch are crossed in order to evaluate the combined effects of these different policies (see also Section 3.6).

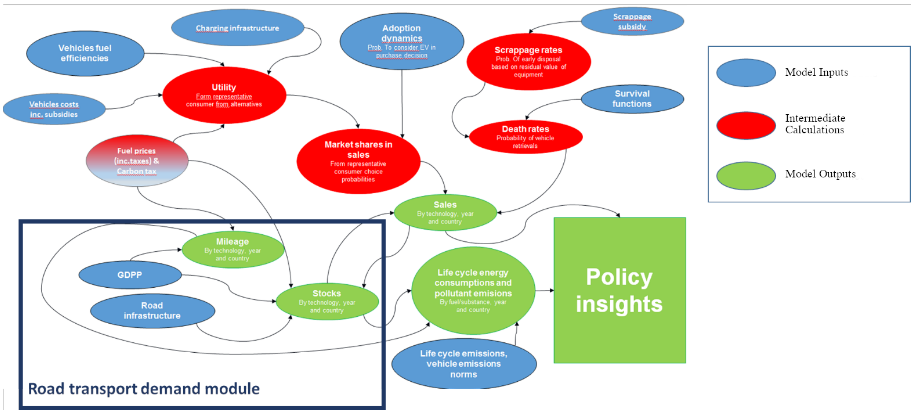
Each step of DRIVERS's forecasting is presented in this section. We start by presenting the theoretical foundations for the different simulations provided by the DRIVERS model such as the projections of vehicle demand and the assignment of this demand to different vehicle technologies. Then we detail the different contextual and public scenarios used as inputs into the model.

We now provide a description of the DRIVERS model structure, developed to project road transport demand and determine sales by vehicle type in the future.

3.3.1 The DRIVERS Model

The DRIVERS model consists of two modules (See Figure 3.1)

Figure 3.1: DRIVERS model architecture



The first, presented inside the square in figure 3.1, allows to make projections on the demand for road transport, by year and by country, up until 2050. This demand is expressed either in the total number of vehicles, without distinction as to type of vehicle or technology, or in the total number of kilometers travelled. For detailed information about how projections on vehicle demand and vehicle stock are realised please refer to the Appendix A section.

The second module, presented outside the square in 3.1, consists of a discrete choice model (see for example Train (2009)) that allows the allocation of new sales between the different types of vehicles, according to vehicle size, then vehicle according the motor technology. Beforehand, new sales were obtained by subtracting from the total demand for the "projected" vehicle stock in year t the remaining stock of vehicles once the scrapped vehicles had been removed. This type of modelling is commonly used in the road transport literature [2]. The Structure of DRIVERS is based on the work of De Ceuster, G., van Herbruggen, B., Ivanova, O., Carlier, K., Martino, A., Fiorello, D. (2007) on the TREMOVE model.

Once the total number of new sales is calculated per year, we now need to determine the allocation of these sales according to vehicle type and propulsion technology. Future demand for new electric or internal combustion vehicles cannot be modeled by "drawing the line under it " and extrapolating, i.e. simply assuming that future purchasing behavior will be the same as in the past.

To model these future purchasing behavior, we choose to rely on the literature of discrete choice models (Train, 2009). This literature focuses on explaining the choice of economic agents when faced with a multi-nomial choice, i.e. a choice with several alternatives. The use of these models to represent goods transport or mobility behavior is particularly justified in the sense that these goods (means of transport or mobility) are not requested for themselves, but rather to meet a demand for a service : go from point A to point B. In order to travel for a given journey, an individual has a choice of several options/modalities. The preferred mode of travel (by foot, bike, car, public transport, etc.) will be the one that will give the most satisfaction amongst all the alternatives available, given preferences and budgetary constraints. The changes brought to the DRIVERS model in this chapter are solely located in the "Utility" bubble displayed in figure 3.1.

A discrete choice model

Here we assume that the decision to purchase a new vehicle is based on a comparison of the levels of satisfaction provided by each type of vehicle available (internal

[2]The interested reader can consult the following reference works: Ben-Akiva and Lerman (1985), Hensher et al. (2005), Train (1993), Koppelman and Bhat (2006)

combustion or electric). The vehicle purchased will be the vehicle that provides the economic agent with the greatest satisfaction, measured by a utility function, in view of its intended use.

The discrete choice model used here is a nested multi-nomial logit model in which the company will make a car purchase decision based on the vehicle size $S = \{Small, Medium, Large\}$ desired before determining the type of propulsion technology of set $K = \{Diesel, Gasoline, CNG, HEV, PHEV, BEV, Hydrogen\}$ best suited to them. This choice is made by comparing the respective costs of the different vehicles, available for sale, but also depends on their technical characteristics.

Following Lancaster (1966), and in order to compare the satisfaction levels of each vehicle type, we express them as a utility function whose arguments depends on their respective technical and economic characteristics. These are expressed by year t and by technology $j \epsilon K$ for a given country c. Thus from exogenous series of energy prices, taxes, subsidies, but also from the energy efficiency of vehicles and their respective investments costs, we can approximate the utility (or satisfaction) drawn from the purchase of a given vehicle j.

We assume that the ownership of a vehicle j, with a period of ownership τ, provides consumers in a country c at time t with a level of utility $U_{j,c,t}$. This utility may be expressed, for each date t, as a linear combination of a number of corresponding attributes :
i) the annualized cost of the initial (possibly subsidized) investment in the purchase of vehicle j,
ii) its user costs (energy, and/or fuel prices, including taxes),
iii) its maintenance and operating costs. At each date t, the level of utility $U_{j,c,t}$, resulting from the possession of a vehicle j, of age τ, by a consumer located in a country c, can therefore be expressed as follows :

$$\begin{aligned} U_{j,c,t} = {} & \mu^{FC} \sum_{\tau=t}^{t+15} df(\tau - t) FC_{j,c,t,\tau} + \mu^{OC} \sum_{\tau=t}^{t+15} df(\tau - t) OC_{j,c,t,\tau} \\ & + \mu^{CI} \sum_{\tau=t}^{t+15} df(\tau - t)(2 - CI_{j,c,t,\tau}) \end{aligned} \tag{3.1}$$

Where μ_{FC}, μ_{OC} and μ_{CI} represent the weighting coefficients of the utility function terms corresponding respectively to Fuel Cost (FC), Other Cost (OC) and Charging Infrastructure (CI).

Due to their complexity the equations for Fuel Costs and Other Costs will be decomposed before being detailed below.

FUEL COSTS

We can see from Equation (3.2) that the Fuel Costs (FC) incentive consists of the discounted sum of all cost factors associated to vehicle fuel efficiency for short and long distance travel, for the technology j, from country c, discounted with rate ρ, at time t.

$$FC_{j,c,t} = \frac{\sum_{\tau_r=0}^{T} \left[MA_{j,c,t}(Short_{j,c,t} + Long_{j,c,t}) \right] (1+\rho)^{-\tau}}{\sum_{\tau_r=0}^{\tau} (MA_{j,c,t}) (1+\rho)^{-\tau}} \tag{3.2}$$

Where MA represents the vehicle's yearly mileage, Short comprises of short distance fuel consumption and emissions, while Long represents the same but for long distance travel, ρ represents the discount rate.

$$\begin{aligned} Short_{j,c,t} = SDS_m * \frac{SDEF_m}{100} (FC_m + FT_m + (1 - BS) * LH * CE * CP) \\ + SDS_a * \frac{SDEF_a}{100} (FC_a + FT_a + (1 - BS) * LH * CE * CP) \end{aligned} \tag{3.3}$$

Where SDS represents the vehicle's total share of short distance travel, $SDEF$ is the vehicle's fuel efficiency for short distance travel, FC is the cost of fuel, m accounts for the main motor of the vehicle and a for the alternative one (for hybrid-vehicles), FT is the amount of taxes on fuel, BS is the share of biofuel inside the fuel, LH is the energy content of the fuel, CE is the vehicle's CO2 emmissions, CP is the carbon price.

$$
\begin{aligned}
Long_{j,c,t} = {} & LDS_m * \frac{LDEF_m}{100}\left(FC_m + FT_m + (1 - BS) * LH * CE * CP\right) \\
& + LDS_a * \frac{LDEF_a}{100}\left(FC_a + FT_a\right)
\end{aligned} \tag{3.4}
$$

Where LDS represents the vehicle's total share of long distance travel, $LDEF$ is the vehicle's fuel efficiency for long distance travel.

This equation allows for the interaction of key policy instruments such as Fuel, FT, and Carbon (CP) taxes ,with energy prices fluctuations through fuel costs (FC). These are then weighted according to technological advancements such as vehicle fuel efficiency ($SDEF$ and $LDEF$), the yearly vehicle mileage (MA) and the amount of carbon neutral resources in the fuel (BS). We take into account the variation of these factors for the motor used, main (m) or alternative (a), and the share of long(LDS) and short (SDS) distance travelled.

OTHER COSTS

Other Costs (OC) computes the annualized fixed cost of possessing a vehicle for the referenced utility function. This equation represents the discounted sum of fixed costs over the horizon divided by the discounted sum of mileages over the horizon.

$$
OC_{j,c,t} = \frac{\sum_{\tau=0}^{T}\left(Front_{j,c,t} + Loan_{j,c,t} + MI_{j,c,t} * (1+\rho)^{-\tau}\right)}{\sum_{\tau_r=0}^{\tau}(MA_{j,c,t}) * (1+\rho)^{-\tau}} \tag{3.5}
$$

The first term (Front) is the the cash-flow of initial up-front payment of the car (only for the first year has a non-nul value), the second term is the cashflows due to the investment over loan (filled with constant annuities as long as they are reimbursed; 0 afterwards) and finally MI represents the maintenance and insurance costs (MI). The denominator is the sum of annual mileages.

$$
Front_{j,c,t} = OF_{j,c,t}(CC_{j,c,t} - SI_{j,c,t} - SB_{j,c,t}) \tag{3.6}
$$

Where OF is the amount of cash provided up front by the consumer, CC is the car purchasing cost, SI is the subsidies given for the purchase of a new vehicle, whereas SB is the bonus for the purchase of electric vehicles.

$$Loan_{j,c,t} = \sum_{\tau_r=0}^{DH} \left[(1 - OF_r)(CC_{j,c,t} - SI_{j,c,t} - SB_{j,c,t})(\frac{r}{1-(1+r)^{-DH}}) \right] \quad (3.7)$$

Where r is the interest rate, DH is the duration of the loan.

$$MI_{j,c,t} = CC_{j,c,t} * IC_{j,c,t} + MC_{j,c,t} * MA_{j,c,t} \quad (3.8)$$

Where MC is the car maintenance cost, IC is the insurance cost,

3.3.2 The Multi-nomial Logit Models

The discrete, multi-nomial logit models are based on the following three assumptions : i) consumers know (although with some degree of uncertainty) the cardinal utility U, with a scale parameter noted μ, of each of the alternatives j at the date t; ii) they prefer the alternative with the highest utility iii) the probability of choosing an alternative j depends of course on its utility, but also the utility of the other alternatives.

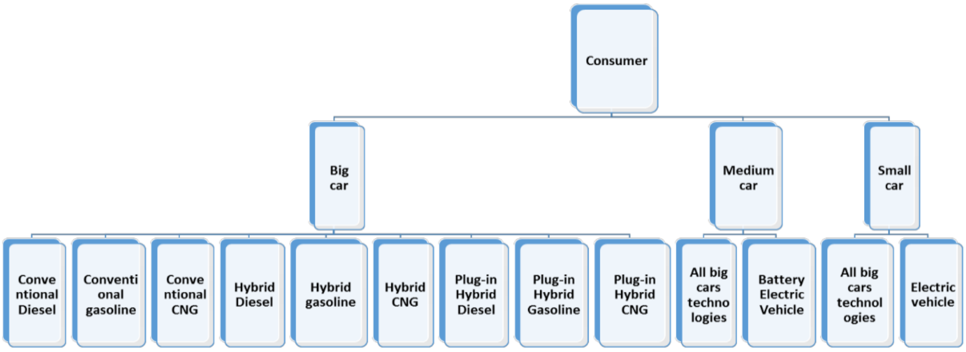
It can be shown (see Train (2009) for a formal demonstration) that with a layered logit model, the probability of choosing the alternative j from the set K of possible choices, can be written as follows.:

$$Pr_{j,c,t} = \frac{e^{\mu U_{j,c,t}}}{\sum_{k \epsilon K} e^{\mu U_{k,c,t}}} \quad (3.9)$$

According to expression (3.9), this probability depends on the utility of the alternative j related to the sum of the utility of all possible alternatives.

When modeling the purchasing behavior of a new vehicle, we need to take into account the fact that the choice of the type of propulsion technology (diesel, gasoline, CNG, HEV diesel, HEV gasoline, PHEV, BEV, Hydrogen) by a consumer is not independent of the type of vehicle (Small, Medium, Large) they wish to buy and the purpose for which they expect to use it. A buyer will first define the type of vehicle they are interested in before choosing their mode of propulsion. Hence we use a Nested Multinomial Logit Model.

Figure 3.2: The Nest Structure of DRIVERS



All types $S = \{S_B, S_M, S_S\}$ of vehicle sizes: small (S_S), medium (S_M) and big (S_B), correspond to the first node (nest) of our nested model.
Using Train (2009)'s Nested Logit model specification, the probability of choosing technology j is now given by the following equation:

$$P_S(j) = P_S(S_K)P_{S_K}(j) \tag{3.10}$$

Where :
- $P_S(S_K)$ corresponds to the probability of choosing the nest S_K
- $P_SK(j)$ corresponds to the conditional probability of choosing technology j (Diesel, Gasoline, CNG, HEV Diesel, HEV Gasoline, HEV CNG, BEV, Hydrogen) given the chosen vehicle size S_K.
The conditional probability follows a multinomial logit specification with a scale parameter σ_{S_K} :

$$P_{S_K}(j) = \frac{e^{\sigma_k U_j}}{e^{IV_k}} \tag{3.11}$$

Where $IV_k = ln \sum_{i \epsilon S_k} e^{\sigma_k U_i}$ is the inclusive value of the nest S_K.
The choice between nest (vehicle size types) is also described using a multinomial

logic specification, this time with a scale parameter noted μ.

$$P_S(S_K) = \frac{e^{\mu U'_{S_K}}}{\sum_{l=1}^{|S|} e^{\mu U'_{S_l}}}, U'_{S_K} = \frac{1}{\sigma_K} IV_K \tag{3.12}$$

Here, U'_{S_K} represents the utility obtained by the consumers following the choice of the second nest S_K. The IV parameter is essential for the calibration of the model in order to predict more accurately sales per vehicle and technology type.

Following the estimation of the Nested Logit model, the DRIVERS model uses a module to represent how vehicle users respond to new upcoming vehicle technologies. This module incorporates a Diffusion-Adoption Model, specifically the Bass model (Bass F., 1969), to better understand consumer behavior towards new technologies, especially electric vehicles. The Bass model classifies consumers into 'adopters' and 'followers', detailing their propensity to adopt new technology. The model's equations show how quickly a technology is adopted. This module was not modified and is not the main focus of this study, for details about the Bass model please refer to the Appendix B section.

3.4 Sequential Estimation

Building upon the original DRIVES framework discussed previously, we now delve deeper into the theory behind the amendments we have incorporated into our model. The nested logit model estimation can be accomplished through various methods, with the most commonly utilized ones being the full information maximum likelihood method (FIML) and the sequential method (Brownstone and Small, 1989). The FIML method simultaneously estimates all the model's parameters by maximizing the log-likelihood function. This method assumes complete and perfect information about the underlying data generating process, using all available information to estimate the model's parameters, which can lead to more efficient and consistent estimates when compared to other methods, especially in complex statistical models. However the simultaneous estimation of all parameters prevents us from updating DRIVERS with estimation results from a different model.

Here, we have adopted the sequential estimation method which allows us to leverage vehicle preference data derived from a Conditional Logit model to inform the parameters of our Nested Logit Model. As according to Nagakura and Kobayashi (2009), the sequential logit model is a sequence of independent multinomial logit model that provides slightly weaker estimates than it's nested logit counterpart. However this model specification is the only one that fits with our analysis. Our reference for vehicle preferences is based on estimates from a Discrete Choice Experiment which is detailed in the Chapter 1 of this thesis and revisited in section 3.2. For a more thorough understanding of the estimation procedure, we refer to Brownstone and Small's explanation (Brownstone and Small, 1989).

As previously indicated by equation 3.13, the probability of selecting a particular vehicle technology is a function of two factors - the probability of opting for that technology given the selection of an appropriate nest and the probability of picking that nest among all available options.

$$P_S(j) = P_S(S_K)P_{S_K}(j) \tag{3.13}$$

The probability of choosing an alternative technology j attached to vehicle size S_K is provided as follows:

$$P_{S_K}(j) = \frac{e^(U_{jS_K}/\sigma_{S_K})}{\sum_{k\in S_K} e^(U_{kS_K}/\sigma_{S_K})} \tag{3.14}$$

The probability of choosing a vehicle size S_K is provided as follows:

$$P_S(S_K) = \frac{e^{\mu U'_{S_K}}}{\sum_{l=1}^{|S|} e^{\mu U'_{S_l}}}, \tag{3.15}$$

In the equations above, U_{jS_K} denotes the utility derived from a specific technology j for vehicle size S_K, whereas σ_{S_K} is a scale parameter. The inclusive value of vehicle size S_K can be expressed as:

$$IV_K = \log \sum_{j\in S_K} \exp(U_{jS_K}/\sigma_{S_K}) \tag{3.16}$$

The log-likelihood function of expression 3.13 is then defined as follows:

$$L = \sum_{n} \log P_{S_K}(j_n) + \sum_{n} \log P_S(S_{K_n}) \tag{3.17}$$

Here, j_n represents the choice made by the nth individual in the sample, and S_{K_n} is the respective vehicle size.

Which can be split into two components:

$$L = L_1 + L_2 \tag{3.18}$$

To streamline the estimation process, we make the assumption that the scale parameters for each vehicle size are equivalent, i.e., $\sigma_S = \sigma_M = \sigma_B$.

An interesting point to note from equations (3.14) and (3.10) is that the scale parameter σ_{S_K} appears in the log-likelihood function L only through the ratios $\frac{U_{jS_K}}{\sigma_{S_K}}$. The sequential estimator utilizes this by initially estimating $\frac{U_{jS_K}}{\sigma_{S_K}}$ through the maximization of L_1 in the first stage. This estimate is then employed to compute IV_K, and σ_{S_K} is subsequently estimated by maximizing L_2 in the second stage. The convenience of the sequential estimation lies in the fact that both L_1 and L_2 follow the structure of logit log-likelihoods.

However in our case, since as mentioned previously in section 3.2 describing the data from the behavioral study, the respondents were randomly assigned to the different samples representing the different vehicle sizes. Therefore we never obtained the probability for vehicle users to choose a specific vehicle size, which mean that we can't estimate L_2 in equation (3.18). Thus we make the assumption that the probability for vehicle users to choose a vehicle size was already correctly specified in the original DRIVERS model and only make modifications to the probabilities of choosing a vehicle technology given that the vehicle size has already been chosen, represented as L_1 in equation (3.18).

Hence we have detailed the theoretical foundations for the implementation of modifications to the DRIVERS model that will be described in the following sections.

3.5 Incorporating Behavioral Economics into the DRIVERS Model

This section explains how we incorporated the findings from the behavioral economics study, discussed in the section 3.2, into the DRIVERS model. We aimed to refine this model's representation of consumer preferences for different vehicle sizes and technologies, by integrating insights derived from the estimates obtained in the behavioral study.

3.5.1 Estimating a New Model for Small and Medium Vehicles

We first estimated a new model specific to small and medium vehicles (please see Tables 3.1 and 3.2 for the detailed estimates) derived from the same dataset. [3] This model centered on factors contributing to the Total Cost of Ownership (TCO) and the limitations of the current recharging infrastructure. We've also included the original model used in the study in figure 3.3 for the purpose of comparison. In accordance with the DRIVERS model framework, which uses a single representative individual to predict vehicle preferences, we employed a Conditional Logit model. This model differs from the more complex Random Parameter Logit model used originally in the study, which accommodates varying respondent preferences (McFadden and Train, 2000; Train, 2009), and is more aligned with the DRIVERS' approach.

To achieve this, all attributes were expressed in terms of disutility, thus mimicking the decision-making process of a representative individual in the DRIVERS model. In addition, in order to ease the integration of results, we changed the infrastructure attribute to a continuous variable instead of a categorical variable that is used in figure 3.3. Notably, we separated the risk from the recharging infrastructure attribute amount and instead estimated separate terms for the presence of risk, the mean station count, and an interaction between the two. Though not part of the TCO analysis in the DRIVERS model, attributes like vehicle range and emissions

[3] All logit models and post-estimation procedures with this dataset used the Apollo R package by Hess and Palma (2019).

were included in the Discrete Choice Experiment model. Omitting these would overestimate other attributes, 1) the infrastructure quantity attribute, since the lower the vehicle range, the more vital the available infrastructure, and 2) the fuel cost attribute, as vehicles with lower fuel costs tend to emit less pollution. This adaptation provided a solid foundation for updating the utility coefficients within the DRIVERS model.

When comparing the results between figure 3.3 and table 3.1 and 3.2 we can see that the sign and significance of attributes is mostly the same for all except for the environmental label in the small vehicle sample, measuring the preference for "greener" vehicles. We can assign this to heterogeneity in preferences for this attribute, which is why the mixed logit model found that environmental label and it's heterogeneity coefficient were both significant. Even though the recharging infrastructure attribute was expressed differently in tables 3.1 and 3.2 it shows the same sign and significance as the original model. However neither the term that captures the presence of risk in this attribute nor it's interaction term with the level of infrastructure were found to be significant in either sample. The fact that the inclusion of risk didn't have any effect on the vehicle purpose decision is unfortunate but it greatly eases our inclusion of these results into the DRIVERS model. We can thus include the effect that the mean infrastructure level, the purchase, the fuel and maintenance costs have on utility levels in the DRIVERS model. The estimates of the attributes vehicle range and environmental label can not be imported into the DRIVERS model as they are not present in it's utility modeling shown in equation (3.1).

3.5.2 Calculating Demand Indicators

We will address the task of adjusting the relative weights of the components in equation (3.1)—namely FC, OC, and CI. This adjustment will be based on empirical evidence, specifically from the estimation results of the discrete choice experiment, which will provide foundational values for their respective weighting coefficients (μ^{FC}, μ^{OC}, and μ^{CI}).

Given the nature of the Logit model, where coefficients for each attribute do not directly reflect their relative importance, we usually employ metrics like elasticities or willingness to pay. However, in this scenario, we had multiple distinct monetary attributes, making the willingness-to-pay metric less applicable. Instead, we computed each monetary attribute's average elasticity (refer to Tables 3.3 and 3.4),

Figure 3.3: Mixed Logit model estimates used in the original study

	MXL Model (Small Sample)		MXL Model (Medium Sample)	
	Coefficient (T.rat)	Coeff. Std. (T.rat)	Coefficient (T.rat)	Coeff. Std. (T.rat)
. Attributes				
. ASC Electric	-0.226242	3.584724***	-1.126147**	-3.813379***
	(-0.36997)	(7.59768)	(-2.3556)	(-8.6324)
. ASC Hybrid	0.423217*	-3.163132***	-0.792059***	-3.094026***
	(1.62575)	(-13.84433)	(-3.5699)	(-12.1071)
. Purchase Price	-3.3579e-04***	-2.7068e-04	-2.8998e-04***	-1.9414e-04***
	(-13.50292)	(-7.07566)	(-13.2423)	(-11.4597)
. Fuel Cost	-0.002160***	0.002453***	-0.002431***	0.001847***
	(-6.62057)	(5.51622)	(-11.3478)	(8.1590)
. Maintenance Cost	-0.003157***	-0.003450***	-0.002882***	0.004197***
	(-5.60274)	(-3.24903)	(-7.2205)	(10.4066)
. Vehicle Range (ln)	1.451906***	1.510565***	2.022135***	3.098812***
	(3.56066)	(4.21927)	(4.2900)	(6.3351)
. Environmental Label	0.195786***	-0.562470***	0.291206***	0.329417***
	(3.12799)	(-2.94077)	(5.3593)	(3.0566)
. Recharging Infrastructure :				
. (RI_1) *1/5 Stations*	-1.220412***	1.767976***	-1.812170***	-1.582598**
	(-3.20339)	(4.47323)	(-4.7721)	(-2.0305)
. (RI_2) *50% 1/5 Stations*	-0.758856**	-0.847976	-0.889568***	-0.327087
50% 3/5 Stations	(-2.40786)	(-1.35032)	(-2.6190)	(-0.5638)
. (RI_3) *50% 1/5 Stations*	-1.055063***	-0.686936	-1.509114***	0.699295**
50% 5/5 Stations	(-3.44753)	(-0.51467)	(-4.9924)	(2.1704)
. (RI_4) *3/5 Stations*	-0.013544	0.324817	-0.633828**	1.218201***
	(-0.06409)	(0.93958)	(-2.4647)	(3.0400)
. (RI_5) *50% 3/5 Stations*	0.123727	0.214686	-0.422133*	0.743168
50% 5/5 Stations	(0.55844)	(0.48014)	(-1.8669)	(1.4124)
N (ind.)	512		510	
N (obs.)	4096		4080	
Adjusted R2	0.3861		0.3692	
Log Likelihood	-2738.448		-2803.327	
AIC	5524.9		5654.65	
BIC	5676.52		5806.19	

ASC: Alternative Specific Constant. **** indicates significance at 1%, ** at 5% and * at 10%.*

Table 3.1: Small Vehicle Choice Experiment Conditional Logit Model Results

Parameter	Estimate
ASC Electric	0.109091
	(0.17840)
ASC Hybrid	0.025384
	(0.10584)
Purchase Price	-9.685e-05***
	(7.579e-06)
Fuel Cost	-7.4517e-04***
	(1.3182e-04)
Maintenance Cost	-0.001007***
	(2.1978e-04)
Vehicle Range	0.382135*
	(0.14993)
Recharging Infrastructure	-0.098143***
	(0.02591)
Infrastructure Risk	-0.16570
	(0.16314)
Infrastructure * Risk	0.019159
	(0.05760)
Environmental Label	0.039636
	(0.02411)
Individuals	512
Modelled Outcomes	4096
Log-Likelihood	-4188.987
Rho-square	0.0691
Adjusted Rho-square	0.0669
AIC	8397.97
BIC	8461.15

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors are in parenthesis.

which indicates how much the utility changes with a small change in the attribute. In order to calculate the elasticities we used the arc elasticity method (Allen, 1934), considered to be the most precise method (Litman, 2017), which is in a logarithmic form. Arc elasticities are commonly used in transportation research in order to analyse changes in demand to fare prices (Pratt and Evans IV (2004), Wardman (2022)). The arc price elasticity of demand (E_d) can be calculated using the following formula:

$$E_d = \frac{\log Q2 - \log Q1}{\log P2 - \log P1} \tag{3.19}$$

Table 3.2: Medium Vehicle Choice Experiment Conditional Logit Model Results

Parameter	Estimate
ASC Electric	-0.33216*
	(0.20037)
ASC Hybrid	-0.25634**
	(0.08712)
Purchase Price_price	-9.37E-05***
	(5.56E-06)
Fuel Cost	-7.90E-04***
	(8.27E-05)
Maintenance Cost	-9.30E-04***
	(1.59E-04)
Vehicle Range	0.52196**
	(0.19827)
Recharging Infrastructure	-0.12043***
	(0.02521)
Infrastructure Risk	-0.01224
	(0.14275)
Infrastructure * Risk	0.0105
	(0.05256)
Environmental Label	0.11091***
	(0.01928)
Individuals	510
Modelled outcomes	4080
Log-Likelihood	-4077.08
Rho-square	0.0904
Adjusted Rho-square	0.0882
AIC	8174.16
BIC	8237.3

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors are in parenthesis.

Table 3.3: Small Vehicle Elasticities

Description	Elasticity Value
Conventional Purchase Price Elasticity	-0.8277672
Conventional Fuel Price Elasticity	-0.3388311
Conventional Maintenance Price Elasticity	-0.1612831
Conventional Station Elasticity	-0.05236355
Electric Purchase Price Elasticity	-1.86622
Electric Fuel Price Elasticity	-0.1129192
Electric Maintenance Price Elasticity	-0.1157932
Electric Station Elasticity	-0.2214587
Hybrid Purchase Price Elasticity	-1.522831
Hybrid Fuel Price Elasticity	-0.2152817
Hybrid Maintenance Price Elasticity	-0.1605829
Hybrid Station Elasticity	-0.06446373
Averages	
Purchase Price	-1.405606067
Fuel Cost	-0.222344
Maintenance Cost	-0.1458864
Station Amount	-0.112761993

where:

- E_d is the price elasticity of demand,
- $Q1$ and $Q2$ are the initial and final quantities demanded,
- $P1$ and $P2$ are the initial and final prices.

In order to calculate the elasticities, we used the method for calculating elasticities for logit model derived from choice probabilities formulated by Ben-Akiva and Lerman (1985) and Abdelwahab (1998). Where a 1% uniform change in the list prices of all conventional cars was simulated. With these simulated values, the predicted market shares of all vehicle technologies were then recalculated. The log of changes in aggregate market shares were then divided by the log in price change in or to measure the market's response to a 1% price change for conventional cars, which represents the vehicle technology's own arc elasticities. This method was then replicated for each other technology used in the study among PHEV and BEV vehicles and each attribute of interest show in tables 3.3 and 3.4. Cross-price elasticities, which represent the change in vehicle demand to a change in the price another vehicle technology (OECD, 2021), were not calculated. This is due to the modelling framework of the DRIVERS model, which only requires own technology vehicle elasticities, across all technologies, as an input and then calculates through the Nested

Table 3.4: Medium Vehicle Elasticities

Description	Elasticity Value
Conventional Purchase Price Elasticity	-1.957956
Conventional Fuel Price Elasticity	-0.6768922
Conventional Maintenance Price Elasticity	-0.4219874
Conventional Station Elasticity	-0.0839922
Electric Purchase Price Elasticity	-1.902742
Electric Fuel Price Elasticity	-0.1637651
Electric Maintenance Price Elasticity	-0.1468306
Electric Station Elasticity	-0.1988217
Hybrid Purchase Price Elasticity	-1.498161
Hybrid Fuel Price Elasticity	-0.3716853
Hybrid Maintenance Price Elasticity	-0.2079361
Hybrid Station Elasticity	-0.06494434
Averages	
Purchase Price	-1.786286333
Fuel Cost	-0.4041142
Maintenance Cost	-0.258918033
Station Amount	-0.115919413

Logit model the relation between vehicle technologies. This is also the reason why we calculated the average of the three vehicle technologies's elasticities as the basis for further analysis.

The study by Fridstrøm and Østli (2021) derives direct and cross-demand market response functions for automobile powertrains and their energy carriers using a discrete choice model on new passenger car transactions in Norway from 2002 to 2016. They find that the own-price elasticity of gasoline-driven cars is estimated at -1.08, those of diesel-driven, battery electric, and plug-in hybrid electric cars at -0.99, -1.27, and -1.72, respectively, as of 2016 in Norway. While the cross-price elasticities of demand for gasoline cars with respect to the price of diesel cars, and vice versa, are estimated at 0.64 and 0.51. When comparing with our results in tables 3.3 and 3.4, we can see that the purchase price elasticity for conventional, which represents both diesel and gasoline vehicles, is lower at -0.82. While the demand for electric vehicles is more elastic, at -1.86 than the study by Fridstrøm and Østli (2021), and the demand for PHEV's is less elastic at -1.52 in our study. Given that our results come from a simple conditional logit model, which has a much lower model fit than a nested logit model, and that our results only vary by a few decimals, these results form a solid basis for the rest of our analysis.

3.5.3 Addition to the DRIVERS model

We saw in equation (3.1), that the DRIVER's utility modelling is comprised of two monetary elements, "Fuel Costs" and "Other Costs", a term reflecting the level of recharging infrastructure "Charging Infrastructure", each weighted through their respective coefficient $\mu_F C$, $\mu_O C$ and $\mu_C I$.

However we have previously seen that the model we wish to incorporate is comprised of three monetary elements and not two. We have seen in equation (3.5), that the original DRIVERS model, the element "Other Costs" encompassed ownership costs other than energy costs, notably vehicle maintenance, insurance and purchase costs. Given that our Discrete Choice Experiment model estimated all monetary costs individually, we removed costs associated to vehicle maintenance from the updated "Other Cost" element $\widehat{OC}$, and created a new "Maintenance Cost" component MC. Thus equation (3.5) becomes :

$$\widehat{OC}_{j,c,t} = \frac{\sum_{\tau=0}^{T} (Front_{j,c,t} + Loan_{j,c,t} + IC_{j,c,t} * CC_{j,c,t} * (1+a)^{-\tau})}{\sum_{\tau_r=0}^{\tau} (MA_{j,c,t}) * (1+a)^{-\tau}} \tag{3.20}$$

The newly expressed maintenance cost component is defined as following:

$$\widehat{MC}_{j,c,t} = \frac{\sum_{\tau=0}^{T} (MC_{j,c,t} * MA_{j,c,t} * (1+a)^{-\tau})}{\sum_{\tau_r=0}^{\tau} (MA_{j,c,t}) * (1+a)^{-\tau}} \tag{3.21}$$

Consequently, the updated DRIVERS model now includes "Fuel Costs," "Other Costs," "Maintenance Costs," and "Infrastructure Level", with their respective weighting coefficients μ_{FC}, $\mu_{\widehat{OC}}$, μ_{MC} and μ_{CI}. Thus equation (3.1) is updated as follows :

$$\begin{aligned} U_{j,c,t} = {} & \mu_{FC} \sum_{\tau=t}^{t+15} df(\tau - t) FC_{j,c,t,\tau} + \mu_{\widehat{OC}} \sum_{\tau=t}^{t+15} df(\tau - t) \widehat{OC}_{j,c,t,\tau} \\ & + \mu_{\widehat{MC}} \sum_{\tau=t}^{t+15} df(\tau - t) \widehat{MC}_{j,c,t,\tau} + \mu_{CI} \sum_{\tau=t}^{t+15} df(\tau - t)(2 - CI_{j,c,t,\tau}) \end{aligned} \tag{3.22}$$

3.5.4 Adapting Metrics for the Modelling Process

We previously updated the cost components inside of DRIVERS's utility function and calculated the elasticities from the behavioral study that show how the demand responds to vehicle characteristic changes. In the original DRIVERS, the way that the demand responds to changes in vehicle costs or characteristics is modelled through the utility weighting coefficients, μ^{FC}, μ^{OC} and μ^{CI} , seen in the original utility (equation 3.1), that when summed take the value -0.75. However originally these coefficients were not obtained through elasticites, but rather through calibration, in order for the DRIVERS model to fit with the historical data on vehicle sales and stocks. In order to not interfere with the calibration process, we need to cater the elasticity metrics to the calibrated values already present shown in equation (3.1). Where:

$$\mu^{FC} + \mu^{OC} + \mu^{CI} = -0.75 \tag{3.23}$$

We have seen in section 3.2, that the behavioural study used as the basis for the new insights in the model is seperated in two samples, small and medium, with different estimates (as seen in tables 3.1 and 3.2) and elasticities (as seen in tables 3.3 and 3.4). In order to reflect the differences in behaviour between users of vehicles of different sizes, we need to make the weighting coefficients depend on vehicle size. However the behavioral study grouped vehicle sizes medium and large into the same category, therefore we need the weighting coefficients for the medium and large sizes to have the same value in the revised DRIVERS model. We have also updated the utility modelling by adding a new cost element and an additional utility weighting coefficient that represent maintenance costs. Everything taken into consideration, we now need to respect the following conditions:

$$\begin{aligned} U_{j,c,t} = \mu^S_{FC} \sum_{\tau=t}^{t+15} df(\tau - t) FC_{j,c,t,\tau} + \mu^S_{\widehat{OC}} \sum_{\tau=t}^{t+15} df(\tau - t) \widehat{OC}_{j,c,t,\tau} \\ + \mu^S_{MC} \sum_{\tau=t}^{t+15} df(\tau - t) MC_{j,c,t,\tau} + \mu^S_{CI} \sum_{\tau=t}^{t+15} df(\tau - t)(2 - CI_{j,c,t,\tau}) \end{aligned} \tag{3.24}$$

Where:

$$\mu^S_{FC} + \mu^S_{OC} + \mu^S_{MC} + \mu^S_{CI} = -0.75 \tag{3.25}$$

And $S = \{\widehat{S}_S, \widehat{S}_{M/B}\}$

In order to maintain this calibration score, while using the insights of the elasticities from the different vehicle attributes, we decided to calculate elasticity ratios, in order to obtain the importance of each attribute relative to the purchase price attribute, which has in all cases the highest elasticity. The elasticity ratios relative to one another based from the Discrete Choice Experiment are displayed in table 3.5 and 3.6.

Table 3.5: Small Vehicle Elasticities Ratios

Attribute	Value
Conventional Fuel Cost/Purchase Price	41%
Conventional Maintenance Cost/Purchase Price	19%
Conventional Station Amount/Purchase Price	6%
Electric Fuel Cost/Purchase Price	6%
Electric Maintenance Cost/Purchase Price	6%
Electric Station Station Amount/Purchase Price	12%
Hybrid Fuel Cost/Purchase Price	14%
Hybrid Maintenance Cost/Purchase Price	11%
Hybrid Station Amount/Purchase Price	4%
Averages	
Fuel Cost/Purchase Price	16%
Maintenance Cost/Purchase Price	10%
Station Amount/Purchase Price	8%

Notes: All elasticities are divided by the Purchase Price elasticity for their respective vehicle technology. Average elasticities ratio are taken with equal weighting across the three available technologies.

We can see in tables 3.5 and 3.6 that the demand for vehicles is the most responsive to changes in immediate costs, especially for smaller vehicles. While the demand seems to be the least responsive to small changes in recharging infrastructure levels.

Table 3.6: Medium Vehicle Elasticities Ratios

Attribute	Value
Conventional Fuel Cost/Purchase Price	35%
Conventional Maintenance Cost/Purchase Price	22%
Conventional Station Amount/Purchase Price	4%
Electric Fuel Cost/Purchase Price	9%
Electric Maintenance Cost/Purchase Price	8%
Electric Station Amount/Purchase Price	10%
Hybrid Fuel Cost/Purchase Price	25%
Hybrid Maintenance Cost/Purchase Price	14%
Hybrid Station Amount/Purchase Price	4%
Averages	
Fuel Cost/Purchase Price	23%
Maintenance Cost/Purchase Price	14%
Station Amount/Purchase Price	6%

Notes: All elasticities are divided by the Purchase Price elasticity for their respective vehicle technology. Average elasticities ratio are taken with equal weighting across the three available technologies.

We now know what value each utility weighting coefficient should take relative to each other, and what their sum should amount to. This adjustment maintains the utility relative to the vehicle attributes' role in the calibration but alters its individual components. Since the utility weighting coefficients do not discriminate between vehicle technologies, we only used the ratios of the average elasticities. The values of the original utility weighting coefficients from equation (3.1) and their updated values that solve for the sum in equation (3.25) and the elasticities ratios for the small and medium/large vehicles are displayed in tables 3.7 and 3.8.

Table 3.7: Small Vehicle Utility Weighting Coefficients

Attribute	Original Value	New Value
μ^{OC}	-0.13	-0.56
μ^{FC}	-0.31	-0.09
μ^{CI}	-0.31	-0.045
μ^{MC}	–	-0.055
Sum	-0.75	-0.75

We have detailed how to adapt and include different metrics on how vehicle users respond to changes in vehicle characteristics from a behavioral study into the DRIVERS model, which relies on a Nested Logit model in order to make vehicle sales and stock predictions. Thus we applied the new values in table 3.7 for the small vehicle category and the new values in table 3.8 for the rest of the vehicle sizes

Table 3.8: Medium Vehicle Utility Weighting Coefficients

Attribute	Original Value	New Value
μ^{OC}	-0.13	-0.525
μ^{FC}	-0.31	-0.121
μ^{CI}	-0.31	-0,031
μ^{MC}	–	0.073
Sum	-0.75	-0.75

in order to obtain the predictions detailed in section 3.7.

3.6 Scenarios used in the DRIVERS model

In this section we will detail the different scenarios used in the DRIVERS model for a better comprehension of the following section presenting the model's results. In order to establish a long-term vision of the development of electric vehicles in France, several scenarios have been constructed. They describe the different situations that could occur in the country in the next two decades, and that will potentially play a role in the choice of buyers. This section describes the scenarios used to estimate the effect of public policies on the evolution of the market share of electrified vehicles and their consequences on polluting emissions from the transport sector. They are based on several academic sources, IFP Energies Nouvelles expert statements and consultants' reports.

3.6.1 Types of scenarios

Five contextual or public policy scenarios were chosen: the first five, called contextual scenarios, "act" on the supply side and the last three, called public policy scenarios, on the demand side.

Contextual scenarios

This section details the nature of the contextual scenarios used in the model. They represent three key parameters that influence a new vehicle buyer's choice, independent of public policy choices. Figure 3.4 summarizes the characteristics of the five main contextual scenarios used. We will now detail the three contextual parameters in the next subsectionsz.

Figure 3.4: Set of contextual scenarios

Scenario n°	Fast awareness & Charging infrastructure	Hign energy prices	Quick efficiency progress for ICEs
A	○		
B	○		○
C	○	○	
D	○	○	○
E			

Recharging Infrastructure

Even if the number of charging stations is not the only criterion that determines the buyer's choice in favor of an electric vehicle, it is clear that this aspect plays an important role. Most of the charging stations in France are so-called "slow" domestic charging stations, installed in private homes. This is sufficient for everyday use of an electric vehicle: it is recharged every evening and ready to be used the next day. But to achieve a significant increase in EV sales, a relatively dense network of public charging stations is needed throughout the country. This would extend the scope of EV use even further. Along with the Netherlands, France is one of the European countries with the largest number of charging stations (see Figure 3.5). In France, there were approximately 30,000 public charging stations as of July 1, 2020.

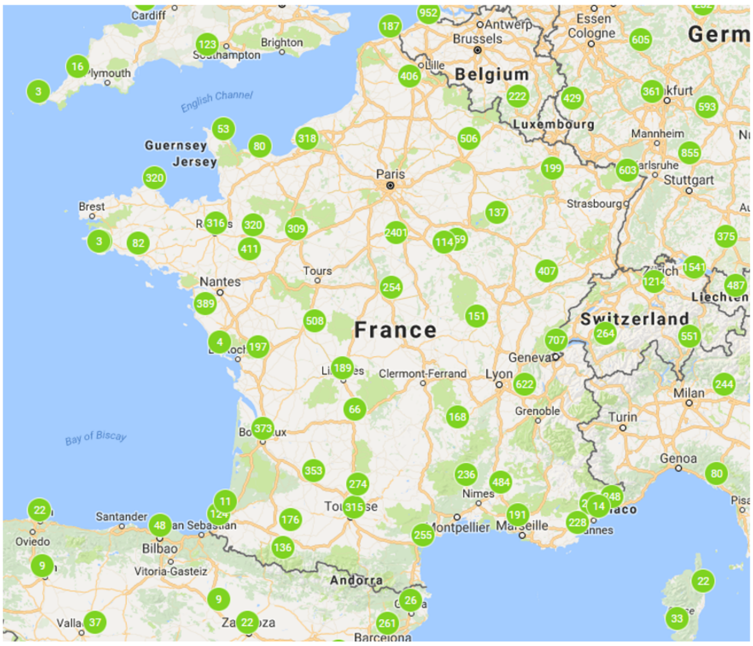


Figure 3.5: France recharging infrastructure map

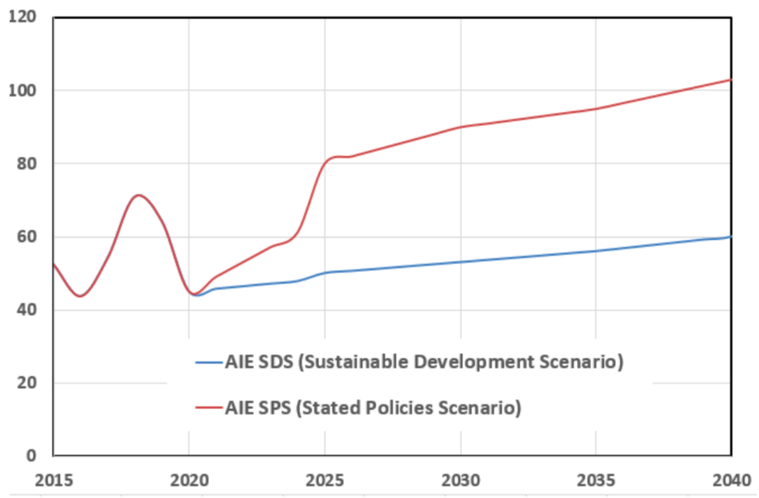
Two strongly contrasting scenarios are considered here. In the favorable scenario, it is assumed that 100% of service stations will be equipped with fast charging by

2050. In the less favorable scenario, only 25% of service stations will be equipped with fast charging by 2050.

Energy Prices

It is important to integrate two scenarios of oil price evolution between now and 2050. This has a direct impact on the price of fossil fuels at the pump, and therefore on the calculation of the TCO which is used as a basis for the model to define the choices made by economic actors in their purchasing decisions. More globally, the increase in energy prices can also lead to an overall decrease in the demand for mobility through a price effect but also through an income effect. To build the scenarios, the IEA projections (IEA, 2019) were used (see Figure 3.6). For each of these two scenarios, sustainable development and stated policies, the production cost of the different fuels (gasoline and diesel) is deduced.

Figure 3.6: Brent oil price [$/bbl] - Fuel price hypothesis - IEA(2019)

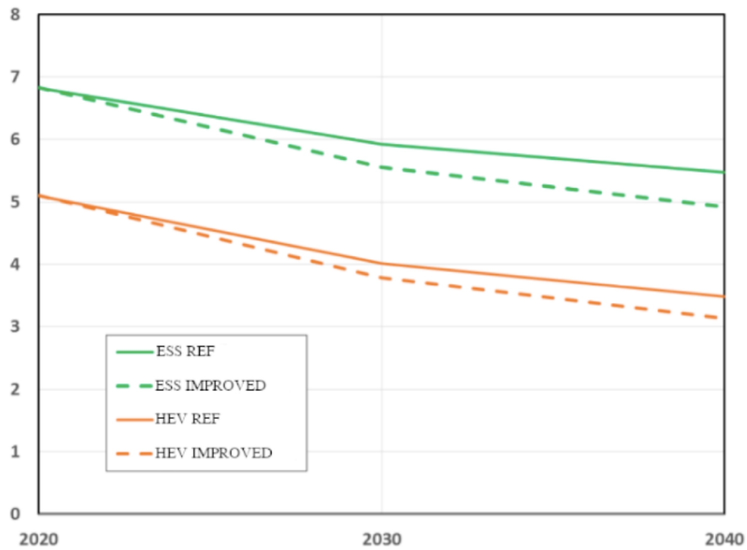


Technical advances in thermal engines

The basic assumption for technical progress in thermal engines is a relative improvement in efficiency (about 15% gain by 2050), and thus a gradual decrease in fuel consumption (gasoline, diesel or CNG) by 2050. This is the base scenario for most of the simulations in this study. However, another scenario has been constructed, which assumes increased progress of combustion engines by 2050 (about 27% gain by 2050), driven by the willingness of manufacturers and suppliers to give a second life to combustion vehicles.

Figure 3.7 shows an example of the consumption used for the two scenarios. In

Figure 3.7: Urban cycle fuel consumption hypothesis for mid-range thermal vehicles - Worldwide Harmonised Light Vehicle Test Procedure Consumption [l/100km]



the reference scenario (REF), technical progress allows for a reasonable and realistic reduction in the consumption of combustion engines. In the improved scenario (IMPROVED) we can see that the decrease is more pronounced.

3.6.2 Public Policy Scenarios

We now detail in the next subsections the three public policies, displayed in figure , involved in these scenarios.

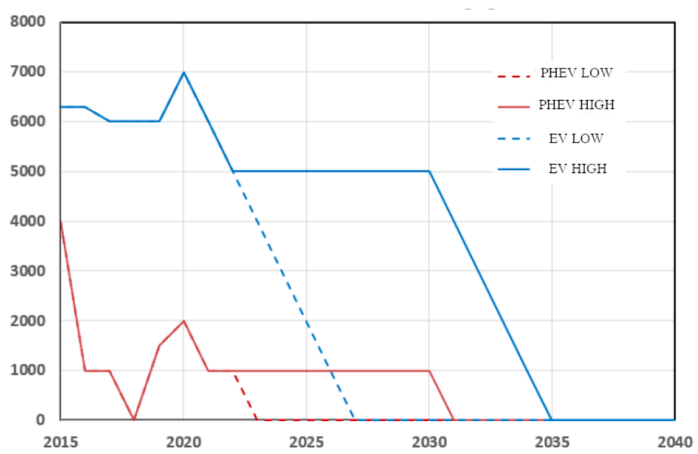
Figure 3.8: Set of public policy scenarios

Scenario n°	Subsidies for EVs	Tax on petroleum fuels	High carbon tax
1			
2			○
3		○	
4		○	○
5	○		
6	○		○
7	○	○	
8	○	○	○

Electric vehicle subsidies

Subsidies for electrified vehicles (BEV or PHEV) appeared in France in 2010. The maximum was reached in 2013 and then gradually decreased. Two scenarios, displayed in figure 3.9, have been retained in our analysis: - A low scenario where premiums for PHEVs are zero after 2023, and premiums for BEVs gradually disappear to reach 0 in 2027. - A high scenario where the purchase incentives are 1000€ for PHEVs until 2031 and 5000€ for BEVs until 2035. This scenario is deliberately ambitious.

Figure 3.9: Hypothesis for the amount of subsidies for BEVs and PHEV [€]



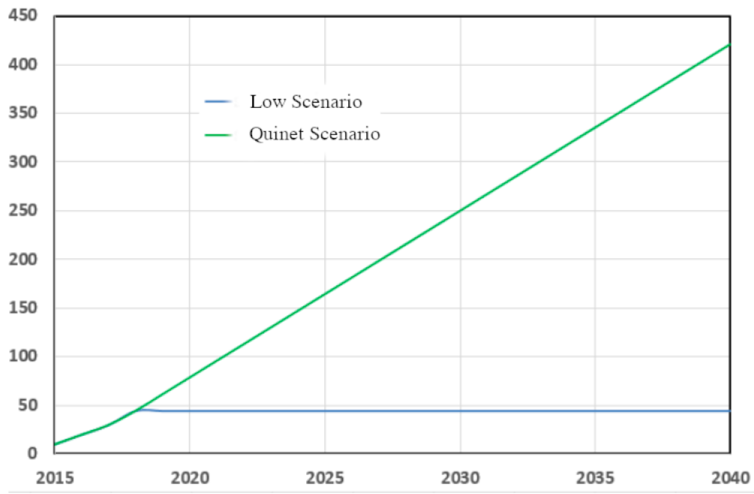
Carbon Tax

Regarding the evolution of the carbon tax, the two scenarios retained are the following: a low scenario with a freeze of the tax from 2018 at a value of 44.6€/t (0.10€/L), and a Quinet scenario based on a growth of the carbon tax up to 250€/t in 2030, according to the Quinet report's tutelary value for carbon (2019) (see figure 3.10).

Tax on petroleum products

In addition to the carbon tax which acts indirectly, it is possible to tax fossil fuels by directly increasing their price at the pump. Indeed, this price is broken down into the cost of the petroleum product, its transport and the distributor's margin, on the one hand, and government taxes on the other. In order to accelerate the transition to electrified transport, public policies could increase the value of these taxes. Figure 3.11 shows the selected scenarios for the amount of this tax for diesel

Figure 3.10: Assumptions for the value of the carbon tax up to 2050 [€/Tonne]



fuel by 2050. Now, if we look at the evolution of the pump price of gasoline and

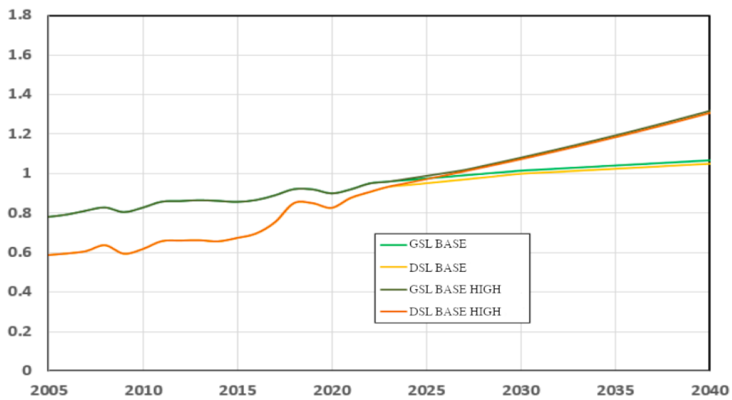


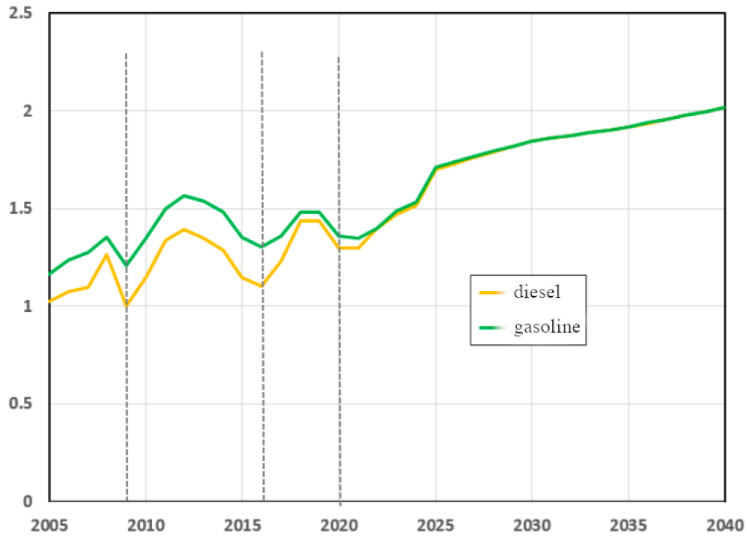
Figure 3.11: Assumptions on the evolution of taxes on diesel and gasoline up to 2050 [€/l]

diesel in the reference scenario, we can see that the national objective of convergence of the price of these two fuels in 2022 is well respected (Figure 3.12). With these assumptions, the price per liter reaches about 2€ in 2050.

Scenario Trees

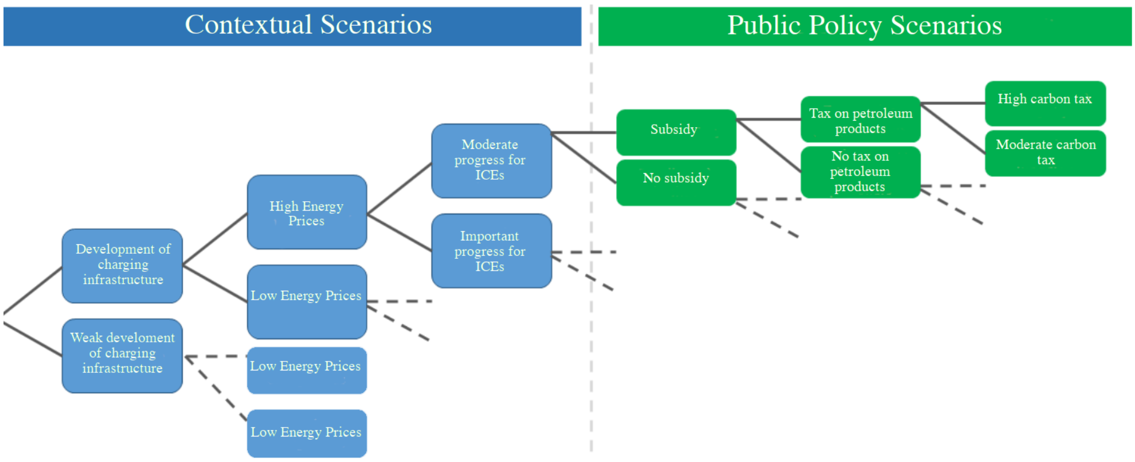
The contextual scenarios and the public policy scenarios have just been presented. They are used in the simulations to i) establish the main levers for the deployment of transport electrification in France by 2050 and ii) analyze the consequences in terms of reducing polluting emissions from this sector. The impact of public policies on these two criteria was evaluated on a set of 40 scenarios, with four of them being

Figure 3.12: Evolution of gasoline and diesel prices in the reference scenario in France by 2050 [€/l]



presented and compared in this chapter. These scenarios are built according to a tree logic where all the dimensions of each branch are crossed in order to evaluate the combined effects of these different policies, as illustrated in Figure 3.13.

Figure 3.13: Scenario Tree used for the analysis in the DRIVERS model



3.7 Results

This section analyses the projections made by DRIVERS for the scenarios described previously and compares the original and revised version of the model's results. The "upper branch" of the tree in figure 3.13 represents the scenario most favorable to electromobility: C8. The "lower branch" of the tree represents the scenario most unfavorable to electromobility: E1.

As we are unable to detail all the results of the forty scenarios considered here, we have chosen to illustrate the DRIVERS model's salient results by comparing contrasting scenarios for each model version. First, we compare the no-policy scenario, Business As Usual (BAU) E.1, with the scenario most favorable to the development of electric vehicles, C.8. Secondly, scenarios 1 and 8 of contextual scenario C are compared to assess the effectiveness of the various public policies envisaged in a context combining the elements most favorable to electromobility. Finally, we integrate an additional measures into scenario C.8.: the banning of combustion engine vehicles in 2035. In each case, we analyze separately the effect that these two versions of the DRIVERS model have on the predictions on the decarbonization of the road sector.

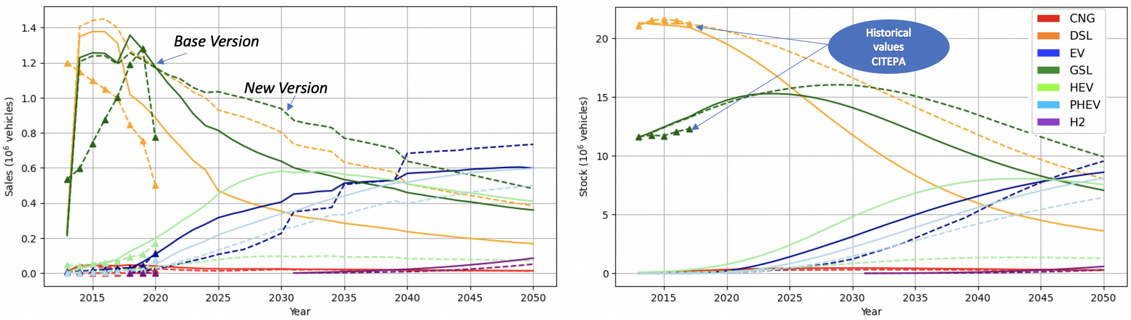
3.7.1 The E.1. scenario - business as usual

Analysis of Sales and Stocks

Figure 3.14 illustrates the evolution of technology-specific sales (left) and subsequent composition of the French fleet (right) under the E.1. scenario from 2013 to 2050. The E.1. scenario models the least favorable conditions for electric vehicles, absent of government intervention and favoring thermal vehicles. It predicts that by the year 2050, fast charging infrastructure will be available at merely 25% of all service stations, while the price of a fuel barrel is projected to reach $60. In the realm of Internal Combustion Engine (ICE) vehicles, fuel efficiency is expected to improve by 27%. Turning to public policies, it is anticipated that there will no longer be any subsidies offered for Electric Vehicles (EVs) or Plug-in Hybrid Electric Vehicles (PHEVs). Furthermore, the carbon tax is projected to increase to €50 per tonne, and the fuel tax will reach €1.05 per liter by the same year. The base version of the model (continuous lines) and the new version (dashed lines) are compared to show diverging trajectories.

Historical data (triangular series) from 2013 to 2020 is used to assess the calibration accuracy of the DRIVERS model. Each curve color denotes a unique technology type. Beginning in 2025, the new version projects over 200,000 more BEV sales than the base version, a gap that expands until 2027. It takes more than 15 years for the new version to achieve 600,000 sales/year compared to the base version (2050 versus 2045, respectively). Post-2030, BEV cost reductions occur incrementally due to technical advancements in battery technology and recycling, represented in sales as a 'staircase' pattern for both versions (Figure 3.14, left). This staircase shape is amplified in the new model, implying a heightened sensitivity to changes in vehicle purchase price.

Figure 3.14: Temporal evolution of sales and stocks by technology in E1 scenario for base (solid lines) and new (dotted lines) model versions.



Notes: The legend displayed applies for both figures. The vehicle technologies in their respective order described in the legend correspond to: compressed natural gas, diesel, electric, gasoline, hybrid electric, plug-in hybrid and hydrogen. Lines with triangle point-markers correspond to historical values for the respective technology. Due to missing data, historical values for some technologies are omitted.

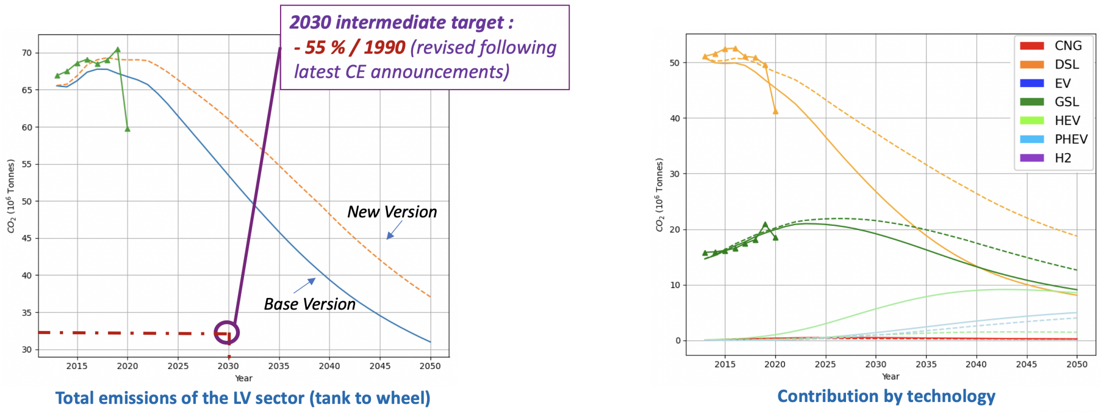
An examination of sales shows that for gasoline vehicles, the highest disparity is seen in 2025, with 500,000 sales for the base version and 900,000 sales for the new version, marking an 80% increase. The base model more closely matches historical data from the 2013-2020 period. For hybrid vehicles, the base version better approximates historical sales, with the maximum difference appearing in 2030, where 600,000 sales are forecasted for the base version compared to only 100,000 for the new version, resulting in a six-fold difference. Meanwhile, the difference in projected sales for plug-in hybrid vehicles peaks in 2050, with 450,000 sales for the new version and 600,000 sales for the base version, constituting a 33% increase. For electric vehicles, the base version aligns more accurately with historical sales. The maximum difference is in 2030, where 400,000 sales are projected for the base version and 200,000 for the new version, a two-fold difference. The staircase pattern in both versions, indicative of technological advancements affecting electric vehicle costs, is more pronounced in the new model.

Looking ahead to 2050, the base model predicts roughly 500,000 annual internal combustion engine (ICE) sales (gasoline and diesel), as compared to 1.4 million in the new model. In terms of the fleet, this equates to around 11 million ICEs in the base model and 18 million in the new model.

Energy Consumption and Environmental Impact Assessment

Figure 3.15 charts the temporal progression of CO2 emissions from the transport sector under scenario E.1., comparing outputs from both the base and the new model versions (left), and the corresponding contribution of each technology to these emissions (right). Even in the absence of deliberate public policy interventions (as depicted in scenario E.1.), CO2 emissions from private vehicles drop from 68 Mt to 40 Mt between 2020 and 2050 in the base model version. This decline of over 40% is attributed to the organic integration of low-carbon technologies into the fleet. However, the revised model, which includes alterations in utility parameters, provides a less optimistic forecast, predicting 47 Mt of CO2 emissions.

Figure 3.15: Temporal evolution of tank-to-wheel CO2 emissions from the fleet (left) and by technology (right) under the E1 scenario for the base (solid lines) and new (dotted lines) model versions.



Notes: The vehicle technologies in their respective order described in the legend correspond to: compressed natural gas, diesel, electric, gasoline, hybrid electric, plug-in hybrid and hydrogen. Lines with triangle point-markers correspond to historical values for the respective technology. Due to missing data, historical values for some technologies are omitted.

Reviewing the total emissions from the Light Vehicle (LV) sector (left graph), it is evident that until the onset of the COVID-19 pandemic in 2020, the new DRIVERS model version aligns more closely with historical data compared to the baseline. Over time, the discrepancy between the two model versions grows, culminating in 2050 with the new model predicting 15% higher global emissions than the base model – 32 Tonnes of CO2 for the base version versus 37 Tonnes for the new version, under the E1 scenario (a 'business as usual' assumption).

Observing technology-specific contributions (right graph), the primary difference between the global emissions projections of the two model versions appears to be due to projections for Diesel vehicle emissions. The base version anticipates that CO2 emissions from Diesel vehicles will be surpassed by those from Gasoline vehicles by 2035. However, the new DRIVERS model version never sees this crossover happen, and the reduction in emissions from Diesel vehicles is projected to be much more gradual. In 2050, Diesel vehicles' contribution to emissions is predicted to be 18 Tonnes in the new version and only 9 Tonnes in the base version, marking a 100% increase.

Gasoline vehicles' emissions contribution in 2050 is projected to be 12 Tonnes in the new version and 9 Tonnes in the base version, indicating a 33% increase. For hybrid vehicles, emissions contribution increases nine-fold, from 1 Tonne in the base version to 9 Tonnes in the new version. Lastly, for plug-in hybrid vehicles, emissions contribution is projected to rise by 25%, from 4 Tonnes in the base version to 5 Tonnes in the new version. In all instances, the largest disparities in emissions between the model versions occur in 2050.

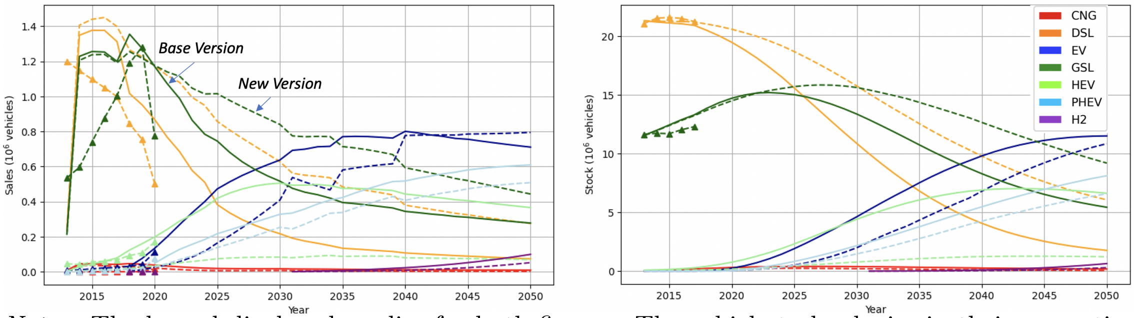
Despite a substantial reduction in CO2 emissions, carbon neutrality remains unattained by 2050. Thermal engines continue to contribute the bulk of CO2 emissions through to 2050 (Figure 3.15, right). The substantial decrease in their sales (Figure 3.14, left), while notable, has a delayed effect on the fleet composition and thus on CO2 emissions reduction. Most concerning is that none of these scenarios meet the European Commission's "Fit for 55" 2030 intermediary target, a prerequisite for achieving carbon neutrality by 2050 (Figure 3.15, left).

3.7.2 The C.8. scenario - electric favourable context and policies

Sales and Stocks

Figure 3.16 presents the progression of sales across different technologies (left), and the subsequent composition of the French fleet (right) from 2035 to 2050 under scenario C.8., both for the base version (continuous lines) and new version (dashed lines) of the model. Scenario C.8., with favorable conditions for electric vehicles such as government intervention through taxation of polluting vehicles, subsidies for cleaner ones, high fuel prices, investment into recharging infrastructure, and slow progress in thermal vehicle efficiency, is the most "electric vehicle friendly" scenario. It predicts that by the year 2050, fast charging infrastructure will be available at

Figure 3.16: temporal evolution of sales and stocks by technology of the C8 scenario for the base version (solid lines) and new version (dotted lines) of the model.



Notes: The legend displayed applies for both figures. The vehicle technologies in their respective order described in the legend correspond to: compressed natural gas, diesel, electric, gasoline, hybrid electric, plug-in hybrid and hydrogen. Lines with triangle point-markers correspond to historical values for the respective technology. Due to missing data, historical values for some technologies are omitted.

100% of all service stations, while the price of a fuel barrel is projected to reach \$100. In the realm of Internal Combustion Engine (ICE) vehicles, fuel efficiency is expected to only improve by 15%. Turning to public policies, it is anticipated that subsidies offered for Battery Electric Vehicles (BEVs) or Plug-in Hybrid Electric Vehicles (PHEVs) will start dropping off after 2030. Furthermore, the carbon tax is projected to increase to €425 per tonne, and the fuel tax will reach €1.3 per liter by 2050. The base version of the model (continuous lines) and the new version (dashed lines) are compared to show diverging trajectories.

Yet, even under the most electromobility-friendly scenario, C.8., in the absence of a ban, the base DRIVERS model still projects approximately 500,000 annual sales of internal combustion engines (gasoline and diesel) in 2050. The forecast from the new DRIVERS model version is even more conservative, with around 1 million annual sales of internal combustion engines in the same year.

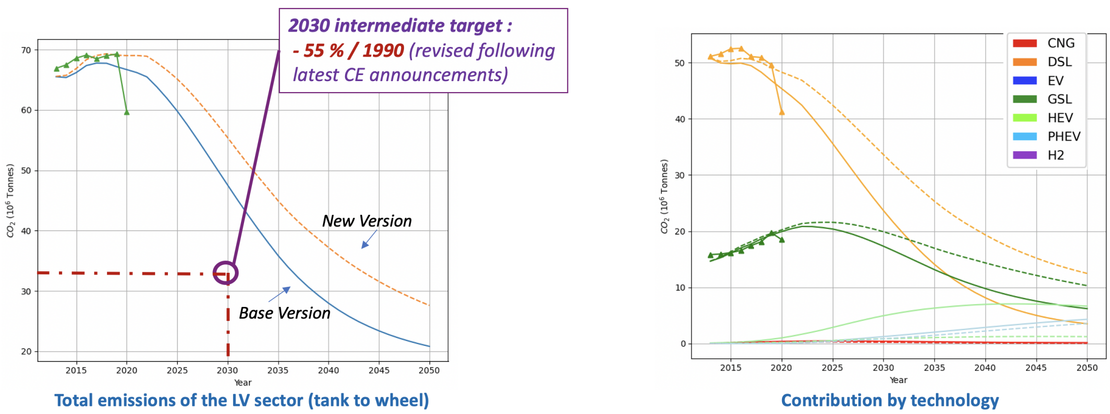
Turning to the entire fleet, for the base model, around 11 million thermal vehicles are anticipated to remain in 2050, compared to 22.5 million for the new model version.

The differences in electric vehicle sales between the base and new model are most pronounced in 2030, with 400,000 for the new version and 650,000 for the base version. This represents a 62% increase, which is more significant than in the E1 scenario. The influence of public policies and favorable conditions for clean technologies in scenario C.8., compared to scenario E.1., on electric vehicle sales in 2030, is more impactful for the new model, with a 95% increase for the new model and a 62% increase for the base model, despite the lower sales. There are slightly greater differences in gasoline vehicle sales between models in the C8 scenario (Figure 3.16, left) than in the E1 scenario (Figure 3.14, left). The maximum difference is in 2035, with 400,000 sales for the base model and 750,000 sales for the new version, which represents an 87% increase.

Energy Consumption and Environmental Analysis

Figure 3.17 depicts the temporal evolution of CO2 emissions from the transport sector under scenario C.8. for both the base and new model versions (left), and the contribution of each technology to these emissions (right). By 2050, under the electromobility-favorable scenario (C8), tailpipe CO2 emissions reduce by almost 60% compared with 2020 for the base model, and 45% for the new one. However, in this scenario, 28 million tonnes of CO2 are still emitted in 2050 for the base model, and 37 million tonnes for the new model due to the significant presence of combustion-powered vehicles in the fleet. By 2050, gasoline and diesel vehicles alone account for around 20 million tonnes of CO2 for the base model and 22 million tonnes for the new model, which is more than two-thirds of the sector's total emissions in both models.

Figure 3.17: temporal evolution of CO_2 emissions in tank to wheel of the fleet (left) and by technology (right) of the C8 scenario for the basic version (solid lines) and the new version (dotted lines) of the model.



Notes: The legend displayed applies for both figures. The vehicle technologies in their respective order described in the legend correspond to: compressed natural gas, diesel, electric, gasoline, hybrid electric, plug-in hybrid and hydrogen. Lines with triangle point-markers correspond to historical values for the respective technology. Due to missing data, historical values for some technologies are omitted.

When compared to the Business As Usual (E.1.) scenario, the implementation of voluntary public policy measures combined with a favorable context (scenario C.8.) reduces CO_2 emissions to 28 Mt in 2050 for the base model, representing almost 60% decrease compared to 2020 and an additional 30% reduction compared to the 2050 emissions of scenario E.1. For the new model version, public policy measures help reduce CO_2 emissions to 38 Mt in 2050, down from 68 Mt in 2020, marking a 44% decrease. A comparison of the emissions in 2050 between E.1. and C.8. for the new model reveals a 20% reduction. Not only does the new model version paint a less optimistic picture of CO_2 emission reduction, but it also suggests that public policies and favorable conditions are less effective at reducing emissions compared with the business as usual scenario.

This is evident in the contributions by technology, with a 50% reduction in emissions from diesel vehicles for both the new and base model between scenarios E.1. and C.8. in 2050. In the same period, the new model registers a 12% reduction in emissions from gasoline vehicles between scenarios, while the base model registers a 28% reduction. The base model shows a 10% reduction in emissions from hybrid vehicles between scenarios E.1. and C.8. in 2050, while the new model version records no reduction between scenarios.

3.7.3 Comparison of policies: focus on contextual scenario C.1.

Sales and Stocks

This section presents a comparative analysis of the results derived from Scenarios 1 and 8 under the Contextual Scenario C for both the new and base versions of the DRIVERS model. The intention is to gauge the effectiveness of different public policies within a context that incorporates the most favorable elements for electromobility (Contextual Scenario C, see Figure 3.4) for each model type. The evolution of sales and stocks for these two scenarios is explored first (Appendix Figure 3.13).

Figure 3.18 displays the evolution of sales for different technologies (left) and the resultant composition of the French fleet (right) from 2015 to 2050 under Scenario C.1. for both the base version (continuous lines) and new version (dashed lines) of the model. In this scenario, the economic context is favorable for BEV's but there will no longer be any subsidies offered for Battery Electric Vehicles (BEVs) or Plug-in Hybrid Electric Vehicles (PHEVs) in 2050. Furthermore, the carbon tax is projected to increase to €50 per tonne, and the fuel tax will reach €1.05 per liter by the same year.

In comparison with the C8 scenario, the cumulative effect of public policies targeted at shaping the demand for electric vehicles (Scenario C1) becomes apparent from 2025 onwards in the sales of these vehicles (Figure 3.18, left) for both versions of the model.

From 2025, the two scenarios diverge, with higher annual sales in the C8 scenario (Figure 3.16, left). This divergence results in a gap of around 100,000 electric vehicles sold in 2050 for both the base and new model (700,000 for the C1 scenario vs. 800,000 for the C8 scenario).

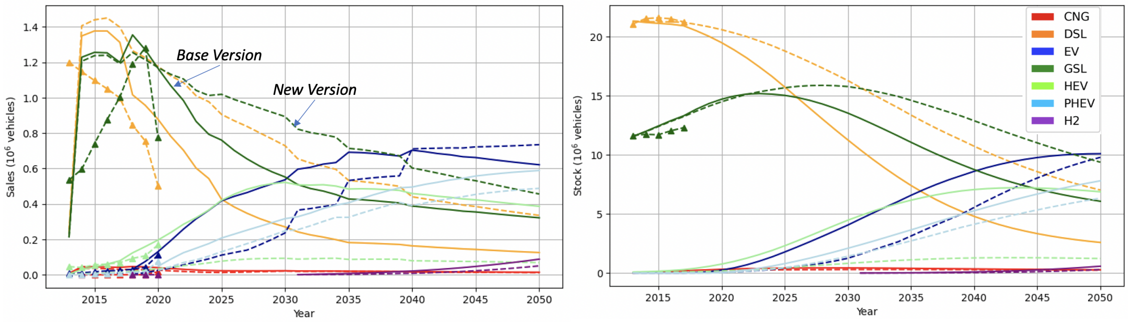
The tipping point between sales of thermal vehicles (diesel and gasoline) and electric vehicles is reached between 2030 and 2035 for the base DRIVERS model. However, for the new DRIVERS model version, this point is not achieved until 2045 and only under the C8 scenario (see Figure 3.16). Without the public policies distinguishing the C8 scenario from the C1 scenario, this tipping point isn't reached even in 2050 for the new model version.

In terms of vehicle stocks (Figure 3.18, right), the envisioned incentive policies permit the attainment of this tipping point between 2050 and 2045 for the base model, with approximately 10 million combustion vehicles and 10 million electric vehicles in the fleet. The remainder, between 13 and 14 million vehicles, are hybrids for the base DRIVERS model. Conversely, for the new version of the DRIVERS model, the tipping point between sales of thermal vehicles and electric vehicles is never reached in the C1 scenario. In 2050, the new model projects 10 million electric vehicles and 16 million combustion vehicles in the fleet, with the remainder (around 7 million) being hybrid vehicles for the new DRIVERS model.

Energy Consumption and Environmental Analysis

In 2050, under the electromobility favorable scenario but without public policy (C1), tailpipe CO2 emissions reduce by almost 56% compared with 2020 (Figure 3.19, left) for the base model, and 43% for the new one. These reductions, when compared with the previous scenario (C8), are slightly lower for the base model (a 4% difference in reduction) and minimal for the new model (a 1% difference in reduction). This indicates that, in the new model, emissions are less sensitive to public policies than in the base DRIVERS model.

Figure 3.18: temporal evolution of sales and stocks by technology of the C1 scenario for the base version (solid lines) and new version (dotted lines) of the model.



Notes: The legend displayed applies for both figures. The vehicle technologies in their respective order described in the legend correspond to: compressed natural gas, diesel, electric, gasoline, hybrid electric, plug-in hybrid and hydrogen. Lines with triangle point-markers correspond to historical values for the respective technology. Due to missing data, historical values for some technologies are omitted.

3.7.4 The ban on thermal vehicles in 2035: consequences for electromobility and decarbonization of the sector

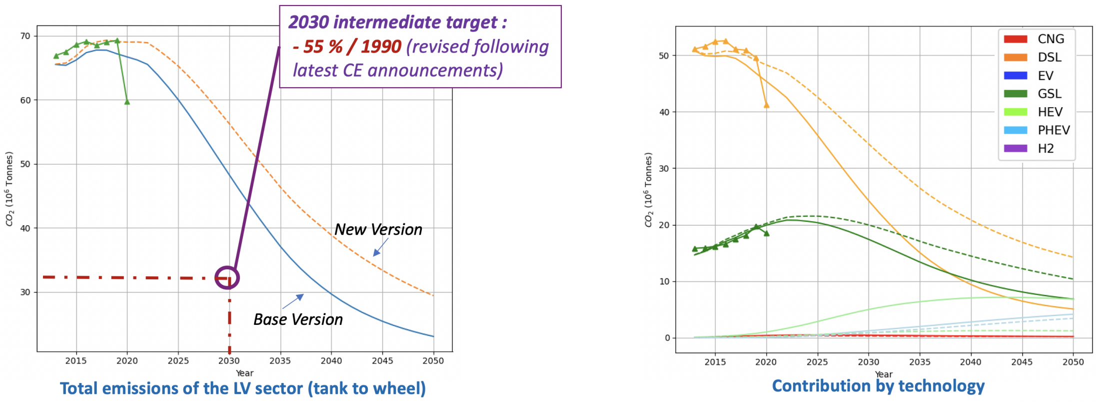
This section focuses on the potential consequences for the French fleet following the introduction of a ban on sales of thermal vehicles (gasoline and diesel) by 2035. This new scenario introduces a ban on ICE vehicles in addition to the favorable conditions and public policies introduce in scenario C.8. Our simulation results (Scenario C.8. with ban) are compared to the reference case, which corresponds to a favorable context for the emergence of electromobility (Scenario C.8. without ban) for the original model and it's revised version.

Sales and Stocks

Figure 3.20 (left) illustrates the evolution of sales for the base (solid line) and new (dotted lines) DRIVER model in France under Scenario C.8 after the introduction of the vehicle ban measure. Sales of gasoline and diesel vehicles cease in 2035, with a significant drop in 2025 (sales of these vehicles fall by 22% compared to the reference C8 scenario in figure 3.16) for the base model type. This drop is less dramatic (an 11% reduction compared to the reference scenario) for the new model type.

Sales of less polluting technologies increase proportionally between the two scenarios in 2025, with a 50% rise in sales of hybrid and plug-in hybrid vehicles for the base model, and a 20% increase for the new model. Meanwhile, a 20% increase in sales of electric vehicles is observed compared to the reference scenario for the base model, and a 40% increase for electric vehicle sales in the new model.

Figure 3.19: temporal evolution of CO_2 emissions in tank to wheel of the fleet (left) and by technology (right) of the C1 scenario for the basic version (solid lines) and the new version (dotted lines) of the model.



Notes: The legend displayed applies for both figures. The vehicle technologies in their respective order described in the legend correspond to: compressed natural gas, diesel, electric, gasoline, hybrid electric, plug-in hybrid and hydrogen. Lines with triangle point-markers correspond to historical values for the respective technology. Due to missing data, historical values for some technologies are omitted.

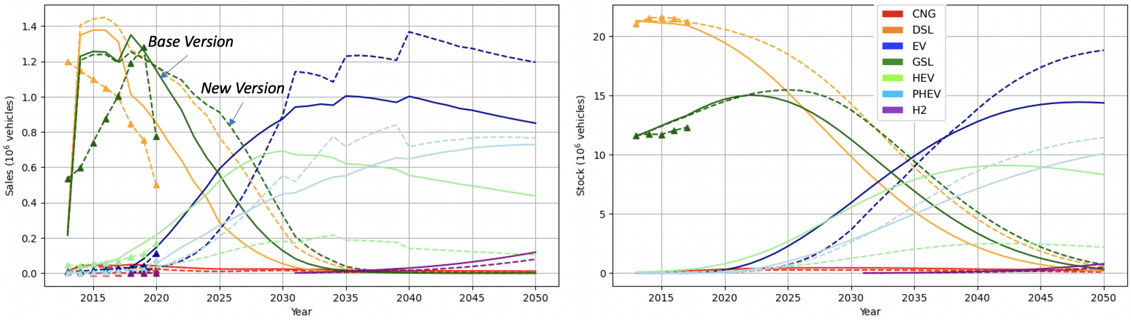
By 2050, battery electric vehicles (BEVs) reach one million sales per year for the base model, and almost 1.4 million for the new model. This policy, therefore, has a significant impact on sales. The composition of the fleet also shifts as a result of the ban, with the number of electric vehicles surpassing the number of diesel vehicles from 2033 onwards in Scenario C.8. with the ban (Figure 3.20, right) for the base model and 2035 onwards for the new model version. The ban also benefits hybrid and plug-in hybrid vehicles. However, gasoline and diesel vehicles don't entirely disappear from the fleet until 2050 (Figure 3.20, right) for both model versions, a delay of 15 years after the ban takes effect.

Energy Consumption and Environmental Analysis

Figure 3.21 presents the evolution of CO2 emissions from the French car fleet under the C.8. reference scenario following the introduction of the vehicle ban measure for both the base DRIVERS model (continuous lines) and new model (dashed lines). The influence of this policy on the decarbonization of the transport sector is pronounced, as it reduces CO2 emissions by 20% compared to the C.8. reference scenario in 2050 (Figure 3.21, left) for the base model and 34% for the new model version.

Moreover, this measure brings us closer to achieving carbon neutrality in the trans-

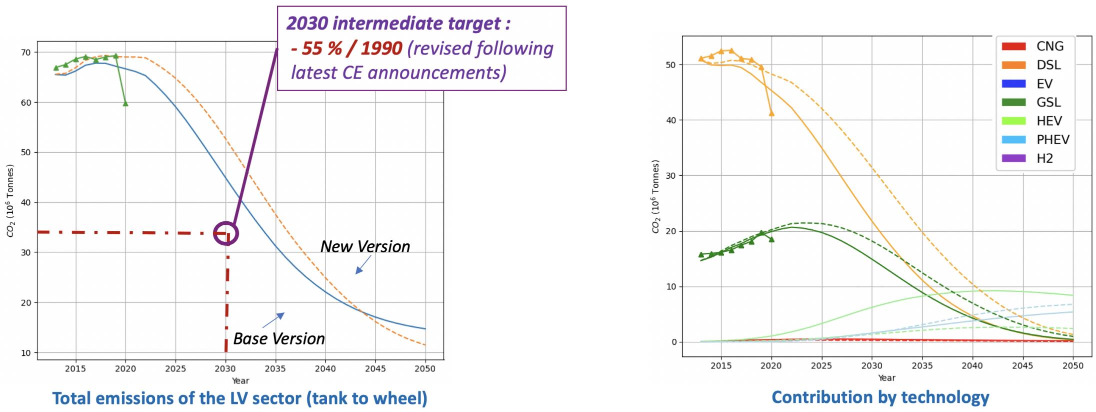
Figure 3.20: temporal evolution of sales and stocks by technology of the C8 scenario with thermal vehicle ban in 2035 for the base version (solid lines) and new version (dotted lines) of the model.



Notes: The legend displayed applies for both figures. The vehicle technologies in their respective order described in the legend correspond to: compressed natural gas, diesel, electric, gasoline, hybrid electric, plug-in hybrid and hydrogen. Lines with triangle point-markers correspond to historical values for the respective technology. Due to missing data, historical values for some technologies are omitted.

port sector by 2050, with CO2 emissions dropping below 15 million tons (Figure 3.21, left) for both model versions. The remaining emissions stem entirely from the hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEVs) that continue to comprise the fleet (Figure 3.21, right). These results underscore the effectiveness of public policies aimed at removing the most polluting vehicles from the fleet, although this measure alone is insufficient to meet the reduction target by 2030.

Figure 3.21: temporal evolution of CO_2 emissions in tank to wheel of the fleet (left) and by technology (right) of the C8 scenario with thermal vehicle ban in 2035 for the basic version (solid lines) and the new version (dotted lines) of the model.



Notes: The legend displayed applies for both figures. The vehicle technologies in their respective order described in the legend correspond to: compressed natural gas, diesel, electric, gasoline, hybrid electric, plug-in hybrid and hydrogen. Lines with triangle point-markers correspond to historical values for the respective technology. Due to missing data, historical values for some technologies are omitted.

3.8 Discussion

The prospective analysis of the French light vehicle fleet using both versions of the DRIVERS model allows us to draw several conclusions. Adding results from behavioral economics (Table 3.1 and 3.2) into how vehicle users respond to different ownership costs has an important effect on the model results for each scenario. Several new insights have been gained into the forecasted landscape of electromobility and the effects of public policies within. These insights consist in a higher importance given from the representative vehicle user to immediate costs (Table 3.7 and 3.8) compared to usage costs from fuel costs and maintenance costs or of inconveniences from the lack of infrastructure. The modified model, incorporating behavioral economics aspects, has refined our understanding of how the sales and composition of vehicle fleets may evolve, especially under different policy measures.

3.8.1 Model Comparaison

When comparing the outcomes of the new and old DRIVERS models, a few key differences emerge. The revised model, which considers behavioral factors, predicts fewer early sales of electric vehicles, and consequently, longer periods where thermal vehicles dominate both the market and the fleet. This results in a wider gap between the predicted vehicle emissions and the targets set by the French state, thereby underlining the increased need for more drastic public policies, such as vehicle bans. However, when compared to the base DRIVERS model, the new version seems less responsive to favorable conditions for electromobility in the absence of public policies. The base model forecasts a higher sales volume of electric vehicles and predicts the tipping point between electric and thermal vehicles to occur earlier, between 2030 and 2035.

To sum up, the revised DRIVERS model offers a more realistic view of the future of electromobility and the potential effects of public policies. It demonstrates the importance of considering behavioral factors when modeling complex systems, showing how individual preferences can drastically shape the market and environmental outcomes. Nevertheless, despite these improvements, both versions of the model highlight the crucial role of policy interventions through both regulations and price mechanisms in promoting sustainable transport and achieving climate goals.

3.8.2 Base Case

In the "Business as usual" (BAU) scenario, which does not include any policy interventions, the revised DRIVERS model predicts an increase in BEV sales, reaching 750,000 units annually by 2050. However, this scenario suggests that the vehicle fleet would predominantly be composed of ICE vehicles, accounting for around 60% of the total. The CO2 emissions from the transport sector would moderately decrease but would remain substantially above the targets set by the French government. In comparison, the original DRIVERS model anticipated a more rapid adoption of BEVs in the Base Case scenario, reflecting its more optimistic view on the natural transition towards electric vehicles.

3.8.3 EV Friendly Context

In the absence of targeted public policies but with BEV favorable conditions, the new model predicts substantial sales of electric vehicles, with a notable increase from 2025 onwards. However, despite this rise, combustion vehicle sales maintain a strong presence in the market. Even by 2050, the gap between electric and combustion vehicle sales is around 100,000 units, indicating a continued dominance of combustion vehicles. In terms of the overall vehicle fleet, by 2050, the new model projects a considerable difference between the numbers of combustion and electric vehicles under Scenario C1, forecasting 16 million combustion vehicles compared to 10 million electric vehicles.

3.8.4 Fuel Tax

The public policy scenario involves substantial hikes in fuel and carbon taxes as well as subsidies on BEV's. The new model results shows how the difference in purchasing price between the new technologies and conventional ones is seen as a major barrier to adoption and has long term effects on vehicle sales and fleet composition forecasts when compared with the base model. When specific public policies targeted at stimulating electric vehicle demand are introduced, a marked divergence in the sales of electric vehicles begins to appear from 2025 onwards. This divergence suggests that public policies play a key role in steering market trends towards a more sustainable transportation sector.

The revised model suggests that the implementation of such policies would result in a 15% decrease in ICE vehicles sales, a 20% increase in hybrid vehicles sales, and a 30% increase in BEV sales by 2025 compared to the BAU scenario. By 2050, annual

BEV sales reach about 1.2 million units. One of the major results from the new model is that policies that favor electric vehicles have a higher effect, as the difference in electric sales between the business as usual scenario and the public policy scenario that favors electric vehicles the most in 2030 is higher for the new model. In contrast, the original model projected a less pronounced shift in sales due to fuel tax increases, underestimating the elasticity of consumer response to changes in fuel costs. However, electric vehicles sales are lower in the new version of the DRIVERS model until they can guarantee that new technologies are as affordable as conventional ones, with electric sales being higher that diesel sales in the public policy scenario from 2024 onwards in the base and from 2034 onwards the new DRIVERS model. Notably, the new DRIVERS model does not predict a tipping point (a point where sales of electric vehicles surpass those of thermal vehicles) until 2045 under the public policy scenario. Even with EV favorable conditions, in the absence of these public policies, the new model does not anticipate this tipping point even by 2050. Even in the case of the most favorable scenario for the sale of electrified vehicles (scenario C.8), the objectives of the Green Deal (-90% of CO2 emissions from the fleet in 2050 compared to 1990) are not reached. In fact, CO2 emissions will be equal to 21 Mt in 2050 in the most optimistic model version and 28 Mt for the least optimistic one. As a reminder, they were 70 Mt in 1990.

3.8.5 Vehicle Ban

The policy of banning thermal vehicles by 2035 in addition to the public policies already in place yields a dramatic shift in vehicle sales. The revised model predicts a noticeable drop in sales of gasoline and diesel vehicles by 2025, followed by a complete halt in 2035. Concurrently, sales of hybrid, plug-in hybrid, and electric vehicles increase proportionally, reaching significant numbers by 2050. This indicates that policies limiting thermal vehicle mobility have a substantial impact on market trends, rapidly accelerating the transition away from fossil fuel vehicles. The revised model also shines a light on the environmental impact of these policies. The CO2 emissions reduction from the transport sector is significant, making it possible to approach carbon neutrality by 2050. Which is confirmed from the results of the new model that show a higher decrease in emissions (34% for the new and 20% for the base model), when compared to the same scenario without vehicle bans. This reaffirms the effectiveness of policies aimed at phasing out the most polluting vehicles, although falling short of the ambitious reduction target for 2030. These results suggest that even before trying to introduce low-carbon vehicles into the fleet, the most effective policies to decarbonize the road transport sector are first those that aim to remove the oldest, most polluting vehicles from the fleet. These policies would rapidly improve air quality, while effectively contributing to decarbonizing road transport.

3.9 Conclusion

This chapter has showcased the integration of behavioral economics insights into the DRIVERS model, a transition from traditional approach to a more nuanced depiction of vehicle purchase dynamics. We carefully adapted these behavioral results to align with the utility model of DRIVERS, and then further described the theory underpinning the sequential estimation of nested logit models that enabled us to integrate the insights from another model. Through a detailed methodology, we incorporated the findings from the behavioral study into the DRIVERS model, highlighting the limitations and necessary concessions in the process. The modified model was then compared with the original across four different scenarios, elaborating on the significant influence of behavioral insights on the model's outcomes.

The new DRIVERS model displayed a propensity for higher thermal vehicle sales across all scenarios, suggesting their enduring presence in the fleet. Consequently, total emissions from the French vehicle fleet, as projected by the new DRIVERS model, exceeded those predicted by the original version. Up until 2035, electric vehicle sales were seen to lag in the new model across all scenarios, but thereafter, they accelerated, surpassing the original model's predictions. Further examination of the revised model's responses revealed a heightened sensitivity to public policies, technological advancements, and economic conditions that affect the purchase price of vehicles. We noted the profound impact of banning thermal vehicle sales by 2035, which significantly boosted electric vehicle sales while simultaneously curtailing thermal vehicle demand. The integration of behavioral economics into the DRIVERS model serves as a stark reminder of the pivotal role affordability plays in catalyzing the transition towards greener vehicle technologies. The new, less optimistic predictions underscore the urgency to reduce the stock of polluting vehicles in the fleet. Accordingly, we recommend a strong emphasis on implementing bans on thermal vehicle sales, supplemented by price-targeting public policies.

Although the new DRIVERS model provides valuable forecasts, it requires calibration, particularly in its initial values where, for certain vehicles, its predictions align less with historical data than the original DRIVERS model. In this study, we opted for the simplest model from the behavioral study to align with DRIVERS's methodology. However, further consideration of representative individual heterogeneity could facilitate the integration of more complex models such as Mixed Logit models and Latent Class models. This could potentially enhance estimation accuracy or yield insights into public policies targeting specific population demographics.

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3.10 Appendix A: Vehicle Demand and Stock Projections

3.10.1 Projections of private vehicle demand

In this section we will look into how the projections on private vehicle demand up to 2050 are obtained through detailing the econometric models used for the simulation. Once the projections are detailed for each step of time we will explain how we derive the total level of vehicles sales per year.

Total Stock of Vehicles and Vehicle/Kilometers Travelled

Projections of transport demand are based on econometric models estimating and quantifying the influence of the major determinants of good transport demand on the total number of kilometers travelled and the total stock of vehicles, respectively. These models estimate from historical data the relationship between demand for transport at date t and a number of exogeneous variables including past demand for transport $(t-1, t-2)$. These variables are expressed in terms of growth rates to (i) facilitate interpretations by directly estimating elasticities (ii) and ensure that one is really working on stationary time series in the statistical sense of the term.

Equation (3.26) specifies the relationship between the total number of kilometers travelled in the country c at time t with its main determinants :

$$\begin{aligned} VKM_{c,t} = \theta_c VKM_{c,t-1} \left(\frac{VKM_{c,t-1}}{VKM_{c,t-2}}\right)^{\theta^{VKM}_{g(c)}} \left(\frac{PGAS_{c,t}}{PGAS_{c,t-1}}\right)^{\theta^{PGAS}_{g(c)}} \\ \left(\frac{GDPP_{c,t}}{GDPP_{c,t-1}}\right)^{\theta^{GDPP}_{g(c)}} \left(\frac{RI_{c,t}}{RI_{c,t-1}}\right)^{\theta^{RI}_{g(c)}} \end{aligned} \tag{3.26}$$

Where VKM, PGAS, GDPP and RI represent "vehicle kilometers", "petrol prices", "GDP per capita" and a "road infrastructure development index" respectively. While $\theta^{VKM}_{g(c)}$, $\theta^{PGAS}_{g(c)}$, $\theta^{GDPP}_{g(c)}$ and $\theta^{RI}_{g(c)}$ represents their respective elasticities.

Similarly, the equation linking the total stock of vehicles to its main determinants is specified as follows:

$$ST_{c,t} = \theta_c ST_{c,t-1} \left(\frac{ST_{c,t-1}}{ST_{c,t-2}}\right)^{\theta^{ST}_{g(c)}} \left(\frac{PGAS_{c,t}}{PGAS_{c,t-1}}\right)^{\theta^{PGAS}_{g(c)}} \left(\frac{GDPP_{c,t}}{GDPP_{c,t-1}}\right)^{\theta^{GDPP}_{g(c)}} \quad (3.27)$$

Where ST is "total vehicle stock" and it's corresponding elasticity $\theta^{ST}_{g(c)}$.

3.10.2 Vehicle Survival Law and the Estimation of New Sales

The total stock of vehicles is projected for each period $t = \{2015, ..., 2050\}$.

Once the total stock of vehicles is projected for each year until 2050, we must remove vehicles that are scrapped "naturally" (accidents, old cars,etc.). To do this, and as is typically done in the litterature, we apply a survival law to the total stock of vehicles. Thus for each technology, j in K and for each vintage v the "total remaining stock of vehicles" SU at date t is defined as follows :

$$SU_{j,c,v,t} = SA_{j,c,v} e^{-(\frac{\beta_{j,c}+(t-v)}{\theta_{j,c}})^{j,c}} (3.28)$$

This survival law chosen here corresponds to the Weibull function. Where SU is the number of vehicles scrapped by the survival law, SA is the annual sales of technology j, with v year of vintage, for country c, for year t. β and θ represent respectively the speed and the acceleration of the vehicle scrapping process according to the vehicle's year of vintage. These parameters are essential for the calibration of the model according to historical data.

Following this, we calculate the "total number of new sales required" in order to meet the projected demand. The calculation is shown in equation (3.29) :

$$TSA_{c,t} = ST_{c,t} - \sum_{j \epsilon K} \sum_{v=t-30}^{t} SU_{j,v,c,t} \quad (3.29)$$

Where TSA is the total number of new sales, ST is the country c's projected stock of technology j belonging to the set K, for year t. We assume here that vehicles over 30 years old are automatically scraped. Thus we subtract the remaining non "scrapped" vehicles from the projected demand to obtain the year's new vehicles sales in the country c at time t.

3.11 Appendix B: Adoption of New Technologies

3.11.1 The integration of a Diffusion-Adoption Model for new technologies

Now that the purchasing behavior for traditional vehicles - internal combustion vehicles - is fairly well taken into account. We now introduce into our model, a behavioral component to better take into account individuals' preferences for new technologies and thus to better explain the purchasing behavior for electric vehicles.

To this end, we implement in our model - following Struben J. (2008) or MacManus W. (2009) - a model for the diffusion and adoption of new technologies. The Bass model in its most basic form Bass F. (1969) enables us to consider the inclination of consumers to factor in new technologies when making purchasing decisions.

Specifically, the Bass model assumes that a population of buyers is divided into two distinct classes : *The adopters and the followers.* The former are technophile in their interest in (owning) new technologies and their attributes. This part of the population will buy the new technology anyway, price not being the determining factor in their decision. As this new technology is spread throughout the public through adopters, its exposure within society increases, prompting followers to buy it as well.
Either $w_j(t)$ consumer's propensity to consider j technology as a possible alternative at date t. Or the adoption rate a or the imitation rate b. These parameters are assumed to be exogenous to the model. Then, according to the Bass model, the evolution of $w_j(t)$ is defined by the following differential equation :

$$w'_j = (a + bw_j)(1 - w_j) \tag{3.30}$$

This leads to the following solution:

$$w_j(t) = \frac{1 - e^{-(a_j+b_j)t}}{1 + \frac{b_j}{a_j}e^{-(a_j+b_j)t}} \tag{3.31}$$

This dynamic of logistical adoption $(w_j(t)\epsilon[0.1]\forall j, t)$ is then incorporated into our discrete choice model. The probability of purchasing a technology j on the date t, originally in equation (3.9) becomes :

$$P_{S_K,j}(t) = \frac{w_j(t)e^{\sigma_K U_j}}{e^{IV_K}}, IV_K = ln \sum_{j \epsilon S_K} w_j(t)e^{\sigma_K U_j} \tag{3.32}$$

It is the different levels of adoption obtained for new technologies that make it possible to discriminate between "modern" cars (HEV Diesel, HEV gasoline, hybrid CNG, BEV, Hydrogen) and old ones (Diesel, gasoline, CNG). Thus for internal combustion vehicles, we impose $w_j(t) = 1 \forall t$.

Conclusion

Despite the growth in the electric vehicle market in Europe, the large-scale integration of Battery Electric Vehicles (BEV) and Plug-in Hybrid Electric Vehicles (PHEV) into the vehicle fleet remains a distant prospect. The low rate of fleet renewal raises complex questions about consumer purchasing behavior and the design of public policies to promote the diffusion of low-carbon passenger vehicles. Building medium to long-term scenarios, anticipating technological breakthroughs, or changes in public policy and user behavior is a challenging task. This thesis produces knowledge and models which, in turn, can be leveraged to reach policy objectives. A discrete choice experiment survey was conducted among French residents to understand their preferences for electric vehicles, innovatively introducing an element of risk associated with charging infrastructure availability to mirror real-world uncertainties. A laboratory experiment utilized a transport mode choice game to simulate the influence of pollution-reducing policies on urban access, examining group-induced negative externalities like air pollution, with tangible monetary consequences, providing nuanced insights into policy acceptability. Additionally, behavioral economics were incorporated into a predictive model for vehicle purchase dynamics in France and Europe up to 2040, involving a detailed examination of vehicle stocks, technology, and emissions, capturing the multifarious influences on the adoption of low-carbon vehicles. These diverse empirical analyses paint a robust picture of the intricate interplay between consumer preferences, policy acceptability, technological advancements, and market dynamics, contributing to the broader understanding of transitioning to alternative vehicle technologies and aiding efforts in combating climate change.

Chapter 1, using a discrete choice experiment, assesses consumer preferences between conventional and alternative vehicle technologies. It employs a detailed analysis of different vehicle characteristics and psychological profiles, revealing a strong influence of fixed costs, vehicle range, and environmental impact on consumers' vehicle choices. The adoption of electric vehicles (EVs) is significantly driven by three distinct groups: the 'tech-savvy,' who prioritize technological advances when purchasing a car; the 'risk takers,' who possess a high tolerance for risk; and the 'environmentally minded,' who actively demonstrate 'green-friendly' behavior. Policy strategies must target the reduction of the high purchase price of electric vehicles (EVs) and the expansion of electric charging infrastructure, especially in rural areas, to encourage the widespread adoption of EVs. Furthermore, firm commitments to the future development of charging infrastructure will minimize the risk associated with purchasing an EV, promoting adoption not only among early adopters but also within the broader population.

Chapter 2, using a laboratory experiment, explores the acceptability of different public policy instruments and the impact of cultural worldviews on their acceptability. The study underscores the usefulness of implementing policy trials for localized environmental measures, like the seven-month trial of congestion charges in Stockholm in 2006, which culminated in a referendum. Such trials foster understanding and acceptance of measures that frequently face substantial opposition, including taxes. Furthermore, the influence of cultural attributes on policy acceptability needs careful consideration, indicating that merely replicating policies in different local areas might not be an effective solution.

Chapter 3 integrates findings from a behavioral economics study into the DRIVE modeling framework, enhancing its ability to accurately predict dynamics in vehicle purchasing behavior. The revised model highlights the persistent demand for thermal vehicles, and thus the corresponding emissions are projected to exceed the original model's predictions. It assigns greater importance to the influence of public policies, technological advancements, and purchase price incentives, on the predicted sales of electric vehicles. It recommends an urgent call for policy actions like imposing bans on thermal vehicle sales and implementing price-targeting public policies to stimulate the adoption of greener vehicle technologies.

Each of these chapters provides a unique perspective on the challenges of transitioning to alternative vehicle technologies. The stated preference study suggests targeted policy measures for promoting EV adoption, while the lab experiment study provides critical insights into the process of policy implementation. The incorporation of behavioral economics insights into a predictive model adds depth and nuance to our understanding of vehicle purchase dynamics. In doing so, this thesis contributes to the ongoing discussion on effective strategies to accelerate the transition towards greener vehicle technologies.

Based on the research findings presented in this thesis, it is clear that successful policy implementation to facilitate the transition to greener vehicles will need to be multi-faceted and context-aware. Hence, we propose the following policy recommendations:

First and foremost, economic measures to incentivize the adoption of electric vehicles are crucial. The higher upfront costs of these vehicles remain an important barrier and is prioritized over all other factors for many consumers. Hence, policies that provide subsidies for the purchase of electric vehicles while taxing more polluting ones are paramount to the adoption of cleaner technologies. The price incentives for electric vehicles should remain in place at least until the cost difference between electric and conventional vehicles has been eliminated. Furthermore, considering the impact of vehicle operating costs on decision-making, subsidizing the initial purchase of EVs would be more effective than subsidizing ongoing electricity costs for EV owners, given the same total expenditure.

Our findings indicate that individuals with greater knowledge about EVs and those with strong environmental values are more likely to overlook the disadvantages of EVs compared to ICEs than the general population. This underscores the importance of public awareness and education in promoting the uptake of green vehicles. Public campaigns highlighting the environmental advantages, overall ownership costs, and functionality of electric vehicles can play a crucial role in encouraging wider adoption.

Investment in infrastructure is also critical for promoting the widespread adoption of electric vehicles. A robust charging infrastructure that ensures the availability and accessibility of charging stations can help mitigate concerns about vehicle range and charging times. This is important in order to be able to reach the part of population that is not prone to adopting new and risky technologies. This is particularly relevant in non-urban areas, where anxiety over vehicle range is more pronounced. The government can play a crucial role here, using public investment and public-private partnerships to expand this infrastructure.

Regulatory measures should not be overlooked. Our study, based on a sample from

France, suggests that such measures may be more favorably received by this population than congestion taxes. Implementing more stringent emissions standards, including limits on the average fleet CO2 emissions for car manufacturers, can drive the transition towards green vehicles. Furthermore, given the significant impact of thermal vehicle bans on reducing emissions, policies aimed at phasing out the sales of new internal combustion engine vehicles by a specific date are necessary.

The potential of policy trials also deserves exploration, especially for countries where taxation policies face opposition. By making the societal benefits of these policies visible to individuals, they can enhance public support for such initiatives. Pilot projects in specific cities or regions demonstrating the practical benefits of green vehicles and the policies that support them can go a long way towards garnering broader public acceptance. Another key aspect of policy development involves recognizing the influence of cultural factors. Policy acceptance and effectiveness can significantly vary based on cultural worldviews. Tailoring the communication and design of policies to respect and address these cultural differences can enhance their effectiveness and acceptance.

In conclusion, to achieve the emission reduction targets, a unified and collaborative effort is required among governments, vehicle manufacturers, and consumers. The policy recommendations proposed in this study, grounded in a comprehensive analysis of the vehicle market dynamics, aim to guide this collective effort towards a sustainable transportation future.

This thesis provides significant insights into the complex dynamics of vehicle purchasing behavior and the influence of public policies on shaping a more sustainable future. However, as with any complex system, there is always room for further exploration and improvement.

When looking at the technical areas of improvements. Firstly, the new DRIVE model would benefit from additional calibration, particularly in the initial values where, for certain vehicles, its predictions align less with historical data than the original DRIVE model. Continuous recalibration and validation with emerging data would enhance the model's predictive accuracy and reliability.

Future research might also consider incorporating more detailed demographic and geographic heterogeneity into the model. Currently, the DRIVE model is representative of the average French citizen, but we know that vehicle preferences and affordability concerns can vary significantly across different demographics and geographical locations. Detailed segmentation would provide nuanced insights into how policies could be tailored to effectively target different demographic or regional groups. A potential extension to this research could also involve an international comparative study. Understanding the differences and similarities in vehicle purchasing behavior and policy impacts across different countries could offer valuable lessons and inspire more effective policy designs.

Owing to the need to align with the specific modeling requirements of the DRIVE model, this thesis has primarily overlooked the topic of multi-modality in transportation. This refers to the potential for vehicle users to switch between various modes of transport, a trend exemplified by the growing shift towards public transports and bicycle use in some European cities. To address this complexity, future work could involve broadening the consumer preference study to encompass public transport options, refining the policy acceptability study with a more nuanced understanding of transportation issues. As the journey towards sustainable transportation continues to unfold, research initiatives like these will play a vital role in steering our progress and ensuring the success of our efforts.

Furthermore, while the thesis focuses primarily on the effects of public policy on vehicle purchase decisions, there may be other external factors at play that warrant further examination. For example, the effects of societal trends, such as urbanization, changes in work patterns, and the adoption of shared mobility solutions, could also significantly influence vehicle purchasing dynamics.

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Résumé

Cette thèse examine le comportement des utilisateurs de véhicules face aux technologies émergentes et propose des initiatives pour une mobilité durable en France. Elle utilise une expérience de choix discret pour comprendre les préférences en matière d'innovations automobiles et une expérience en laboratoire pour évaluer les réponses aux politiques de mobilité verte. Elle enrichit le modèle "DRIVERS" - développé par IFP Énergies nouvelles - avec de nouvelles données pour les prévisions futures, suggérant des investissements dans l'infrastructure de recharge, surtout en régions rurales, des subventions pour les véhicules verts, des campagnes éducatives ciblées, et des mesures incitatives contre l'usage des véhicules traditionnels. La mise en œuvre de ces stratégies, en tenant compte de l'acceptation culturelle et des phases d'essai potentielles pour des politiques telles que les taxes, vise à accélérer le passage à des véhicules à faibles émissions, à contribuer à la réalisation des objectifs de réduction et à faire progresser la mobilité durable en France.

Mots-clefs : Economie comportementale, méthodes de choix discret, économie expérimentale, expérience en laboratoire, économie du transport.

Abstract

This thesis examines vehicle user behavior concerning emerging technologies and suggests initiatives for sustainable mobility in France. It utilizes a discrete choice experiment to understand preferences for automotive innovations and a lab experiment to gauge responses to green mobility policies. It enhances the "DRIVERS" model - developed by IFP Énergies nouvelles with new data for future forecasting. Key recommendations include investing in recharging stations, subsidizing eco-friendly vehicles, and conducting awareness campaigns, with a focus on non-urban regions for EV adoption. To discourage traditional combustion vehicles, the study suggests area bans, special tolls, and financial incentives. Implementing these strategies, considering cultural acceptance and potential trial phases for policies like taxes, aims to hasten the shift to low-emission vehicles, helping meet reduction targets and advancing sustainable mobility in France.

Keywords : Behavioral economics, discrete choice methods, experimental economics, laboratory experiments, transport economics.

JEL Codes : C92, C83, D90, D11, D80, L62