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Delivering the Next Generation of Open Integrated Assessment Models for Net-zero, Sustainable Development

D4.6 – Behavioural aspects and preferences for climate action

WP4 – Integrate & Expand

Funded by
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29/06/2026

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EC Summary Requirements

1. Changes with respect to the DoA

No changes with respect to the work described in the DoA.

2. Dissemination and uptake

The contents of this deliverable have been or will be published in peer-reviewed academic journals and book chapters. In addition to the published paper on the predictors of clean technology adoption, we plan to publish two more papers on the psychological insights from our data collection and the resulting soft link with three IAMs (CLEWs-EU, GCAM Europe, and OMNIA). The data foundation underlying this soft link can be flexibly adapted to the needs of different IAMs, making it interoperable and relevant to other integrated assessment modelling teams, energy system modellers, and researchers within and beyond the DIAMOND project interested in incorporating behavioural data into their models.

3. Short summary of results (<250 words)

Integrated Assessment Models (IAMs) shape climate policymaking by quantifying scenarios and evaluating climate policy pathways; however, there have been vivid discussions on their limitations, including the lack of actor heterogeneity representation and rational behaviour assumptions. These limitations are especially important in assessing household technology adoption given its volatility to individual and contextual influences. In an extensive literature review, we show that adopting clean technologies such as electric vehicles (EVs) is influenced by factors encompassing information processing, personal motivations, social motivations, and broader contextual conditions on different levels. These influences lead to (i) people behaving differently depending, for example, on their income and non-financial motivations, and (ii) people behaving non-rationally and not necessarily in a cost-optimising way. The significant disconnect between IAM assumptions and real-world behaviour might bias model results and subsequent policy recommendations. Here, we take a first step towards accurately representing these behavioural characteristics by updating IAM assumptions on EV adoption. Based on the review and an established behavioural theory—the Campbell paradigm—we formulate a model that accounts for individual differences, contextual factors, and the effect of technology attributes, before translating it into an online survey experiment that we administered across 15 European countries and a total of N = 6,204 participants. Based on the data, we estimate EV adoption rates for each country given different car and context configurations. These rates also consider different people having different inclinations to adopt EVs as well as social dynamics, and they represent an EV version of the behavioural module. We then link the module version with IAMs by providing minimum and maximum EV adoption rates given car and context attributes. The soft link produces different outcomes from the baseline models indicating the importance of behavioural heterogeneity and non-rational decision-making.

4. Evidence of accomplishment

This report, as well as the journal papers and book chapters that are either in preparation (Engel et al., in prep), in proof as a chapter in the Energy Transitions Handbook led by Kim Wolske (Engel et al., in proof), or published (Günther et al., 2025).

Preface

DIAMOND will update, upgrade, and fully open six Integrated Assessment Models (IAMs) that are emblematic in scientific and policy processes, improving their sectoral and technological detail, spatiotemporal resolution, and geographic granularity. It will further enhance modelling capacity to assess the feasibility and desirability of Paris-compliant mitigation pathways, their interplay with adaptation, circular economy, and other SDGs, their distributional and equity effects, and their resilience to extremes, as well as robust risk management and investment strategies. This will be done via integration of tools and insights from psychology, finance research, behavioural and labour economics, operational research, and physical science. The project will develop a transdisciplinary scientific approach to legitimise the implementation process and co-create research questions that stretch the frontiers of climate science, as well as establish vibrant communities of practice to transparently open model enhancements and to develop capacities, thereby lowering the entrance barriers to the established IAM community.

ICCS	INSTITUTE OF COMMUNICATION AND COMPUTER SYSTEMS	EL
BC3	ASOCIACION BC3 BASQUE CENTRE FOR CLIMATE CHANGE - KLIMA ALDAKETA IKERGAI	ES
CESAR	KRATENA KURT	AT
CICERO	CICERO SENTER FOR KLIMAFORSKNING	NO
CYI	THE CYPRUS INSTITUTE	CY
E4SMA	ENERGY ENGINEERING ECONOMIC ENVIRONMENT SYSTEMS MODELING AND ANALYSIS SRL	IT
HOLISTIC	HOLISTIC IKE	EL
COMILLAS	UNIVERSIDAD PONTIFICIA COMILLAS	ES
ISINNOVA	ISTITUTO DI STUDI PER L'INTEGRAZIONE DEI SISTEMI (I.S.I.S) - SOCIETA'COOPERATIVA	IT
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Oxford	THE CHANCELLOR, MASTERS AND SCHOLARS OF THE UNIVERSITY OF OXFORD	UK
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Executive Summary

Integrated assessment models (IAMs) compute climate scenarios and evaluate mitigation pathways, and thereby shape climate policymaking at the global, supra-national, and national levels. At the same time, the modelling community has extensively discussed the limitations of IAMs. Two of these are central to this deliverable: the limited representation of actor heterogeneity, and the reliance on rational, cost-optimising representations of technology diffusion. These limitations are particularly consequential for modelling household technology adoption, which is strongly shaped by individual and contextual influences. As a result, the assumptions embedded in many IAMs diverge from empirically observed behaviour, potentially biasing modelling results and the policy-relevant insights drawn from them.

In this report we first perform extensive literature review (also published in a peer-reviewed article; Günther et al., 2025), showing that the adoption of clean technologies, such as electric vehicles (EVs), is driven by factors ranging from information processing, personal motivations, social motivations, to broader contextual conditions at several levels. Therefore, people behave heterogeneously—for example, depending on their age, loss aversion tendency, non-financial motivations, and their immediate environment—and/or do not necessarily decide in a purely rational, cost-optimising way. This deliverable then takes a first step towards representing these behavioural characteristics in IAMs by updating their assumptions about EV adoption.

Building on the literature review and an established behavioural theory—the Campbell paradigm (which states that behaviour is determined by a person's motivations and the costs attached to a behaviour)—we formulate a behavioural model that extends this theory with a cognitive, information-processing component (temporal discounting) and embeds it in a multi-level structure that captures personal motivation (environmental attitude), social motivation (descriptive and injunctive norms), and individual- and country-level context. We translate this model into a preregistered online discrete choice experiment (DCE) on passenger-car purchases, administered across 15 European countries to a total of N = 6,204 participants, and complemented by psychological scales measuring environmental attitude, social norms, and temporal discounting. When populated with empirical data, this model constitutes the behavioural module to be used for the soft link with IAMs. However, the model can be populated with any behavioural data that can jointly account for attributes of the behaviour or technology, individual differences, and contextual factors, forming the basis for different behavioural modules across a range of behaviours.

The empirical findings are largely consistent with the behavioural model. The influence of car attributes on choice is as expected, with higher purchase and operating costs reducing, and longer driving range increasing the likelihood of choosing a vehicle. At the individual level, a stronger environmental attitude and more favourable social norms increase the likelihood of choosing an EV, in line with the Campbell paradigm. Temporal discounting appears to be the main exception to our hypotheses, as stronger discounters weighted all monetary attributes more heavily rather than only the upfront price. Effects of country-level predictors, including current EV diffusion, supportive EV policy, and the energy mix, are mostly consistent with our hypotheses and with previous literature.

Based on these data, we estimate EV adoption rates for each EU-27 country as a function of car configuration and car adoption in the previous year (capturing context-dependent social norms). Constituting the EV version of the behavioural module, these estimates reflect that different people have different inclinations to adopt EVs, and they incorporate social dynamics through a descriptive-norm mechanism, in which increasing adoption reinforces further adoption through positive feedback. We then soft-link the behavioural module to three IAMs (CLEWs-EU, OMNIA, and GCAM Europe) by providing lower and upper bounds on EV adoption given the relevant car and context attributes.

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This soft link produces IAM outputs that differ systematically from the respective baseline models, reinforcing the relevance of behavioural heterogeneity and non-rational decision-making. Regarding CLEWs-EU and OMNIA, the behavioural module changes the timing of EV adoption and attenuates the unrealistically high (100%) EV diffusion by 2050 reached originally in the models. Because total emissions are constrained by decarbonisation targets, the main consequences appear in the transport sector (in the timing of EV uptake, in residual sectoral emissions that must be compensated elsewhere, and in an investment-driven increase in transport-sector costs) rather than in the total system. For GCAM-Europe, model runs based on the soft link demonstrate higher EV adoption rates across all countries compared to a "no climate targets or policies" scenario.

Overall, the deliverable demonstrates that behaviourally grounded soft-linking is possible and affects modelling outcomes: taking realistic assumptions about human behaviour seriously has a visible impact on EV adoption trajectories, sectoral emissions and costs, and to a smaller degree on system-wide emission pathways. The behavioural model is not specific to EVs. It can be readily transferred to other climate-relevant behaviours, such as sustainable food consumption, once suitable data are available or collected. Challenges of our approach include the need for costly data collection, for further out-of-sample evaluation of the soft-link, and for more accurate projection of behavioural estimates to future contexts. In the next steps, we plan to address some of these challenges and further demonstrate the relevance of the behavioural module by testing different policy scenarios with and without the soft link in Deliverable D5.5 (due in M47 – October 2026). Importantly, our approach enables the implementation of group-specific instruments such as income-dependent EV subsidies.

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1 Introduction

Integrated Assessment Models (IAMs) have been useful for assessing climate change pathways and designing policies to effectively mitigate carbon emissions (Keppo et al., 2021; Weyant, 2017). Various IAMs contribute to reports from supra-national institutions such as the IPCC, which shape national climate strategies and climate jurisdiction (IPCC, 2022). However, IAMs – although heterogeneous in their modelling assumptions and approaches (e.g., Partial Equilibrium vs. General Equilibrium; top-down vs. bottom-up) – have some limitations in common that might affect scenario development and evaluation. These limitations have been prominently discussed by the research field itself (Keppo et al., 2021; Wilson et al., 2021) and among others include:

- **Lack of representing heterogeneous actors**
- **Inaccurate modelling of technology diffusion and dynamics**
- Inadequate representation of capital markets and finance
- Unrealistic energy-economy feedbacks
- Implementation of unrealistic policy scenarios

It has been argued that these limitations can skew modelling results and the resulting policy recommendations, for example, by providing overly optimistic or pessimistic technology diffusion estimates (McCollum et al., 2017; Wilson et al., 2021). Mainly focusing on financial drivers of decision-making (e.g., investment costs, operating costs) risks assuming actors to be rational (even though perceptions of financial outcomes are also biased and prone to heuristic decision-making; Kahneman, 2003; Tversky & Kahneman, 1974) and ignoring additional important drivers, such as social motivations, other personal motivations, and emotions or affective states (e.g., irrational focus on electric vehicle (EV) range because of range anxiety; Pettifor et al., 2017; Rezvani et al., 2015). In addition, the lack of actor heterogeneity limits modelling capabilities in various ways. First, it is impossible for IAMs that do not represent actor heterogeneity to give information about which societal groups adopt certain behaviours, like adopting a clean technology (McCollum et al., 2017; Rai & Henry, 2016). Second, these IAMs cannot capture which societal groups are most positively or negatively affected by implemented policies, such as carbon prices or technology subsidies (Borenstein & Davis, 2025; Stechemesser et al., 2024). Third, they can, therefore, also not implement group-specific policies well (e.g., income-sensitive subsidies).

In this deliverable, we address two of these prominent limitations of IAMs – lack of heterogeneity and inaccurate technology diffusion modelling – by updating their behavioural assumptions based on methods, insights, and empirical data from various research fields. We propose a behavioural model, which includes various psychological, socio-demographic, and contextual factors, and apply it to EV diffusion. When populated with empirical data, this model constitutes the behavioural module. To identify these important drivers of behaviour (e.g., income) that also define actor groups (e.g., heterogeneity in technology adoption across income deciles), we conducted a literature review on which contextual, psychological, and socio-demographic factors drive technology adoption.

We chose EV adoption as the target behaviour because: i) it represents a technology whose diffusion is heterogeneous across individuals depending on their socio-economic status, psychological characteristics, and contextual embedding (Günther et al., 2025), and ii) the transport sector is highly relevant for climate change. The transport sector accounts for around 20% of global CO_2-equivalent emissions (CO_2eq-emissions; Morfeldt et al., 2021; Ritchie, 2020), with around 40% of transport emissions coming from passenger cars or vans (IEA, 2025; IPCC, 2023). While effective solutions include the reduction of individualised mobility patterns and the expansion of the public transport sector, not every individual will be able to refrain from individualised mobility (IPCC, 2023). To

decouple the private transport sector from CO_2eq-emissions, one solution lies in the replacement of conventional, fossil fuel-powered cars with EVs (IEA, 2024). Given the importance of EV uptake for system-level emission reduction, accurate modelling of diffusion is key to preventing unrealistic technology adoption pathways and biased policy recommendations (McCollum et al., 2017).

To increase IAM accuracy (see **Section 4.2** for how IAM assumptions of EV adoption were updated), our behavioural module of EV adoption is based on a psychological behaviour explanation model – the Campbell paradigm (Kaiser, 2021) – according to which behaviour is driven by a person's motivation (e.g., in the EV case, their commitment to the goal of protecting the environment) and the behavioural costs attached to a behaviour (e.g., here, the purchase price of an EV compared to other cars). We expanded this base model with social norms to reflect the social context in which adoption decisions are made (Pettifor et al., 2017) as well as temporal discounting as a cognitive mechanism that affects the evaluation of (monetary) consequences of the acquisition of different vehicles (Haq & Weiss, 2018). In addition, we identified various contextual factors that affect EV diffusion, such as charging infrastructure and temperature fluctuations (Günther et al., 2025). For the empirical foundation of the module, we created an online survey and experiment based on the psychological model, the identified contextual factors, and common car attributes. We administered this survey in 15 European countries (N ≈ 400 participants per country), which were selected based on a cluster analytical approach.

We ran multinomial (and logit) mixed effect models with the survey data to calculate the effects of car and context attributes (e.g., purchase price and charging infrastructure), individual-level predictors (i.e., psychological and socio-demographic variables), and country-level predictors (e.g., GDP, average temperature) on hypothetical car purchase decisions. In addition, we used these models to compute EV adoption rates for different contextual conditions (e.g., defined by technology costs and previous adoption rates) and/or different population groups (e.g., defined by income, age, or temporal discounting rate). The module offers the flexibility to choose which factors one includes (different sets of predictors can be added to the mixed effect models) and can be adapted to the specific needs and configuration of the collaborating IAMs. For example, when an IAM does not represent heterogeneity in actors (e.g., by dividing the population based on income deciles), the module can only take into account the contextual predictors. For an IAM that represents different age and income groups, the module could provide age- and income-group-specific adoption rates.

The purpose of this report is to describe the psychological foundation of the module (**Section 2 "Psychological Foundation"**), outline the underlying data collection and experiments (**Section 3 "Psychological Experiment"**), and give first insights into the structure of the module, the soft-links with three IAMs, and the consequences of the soft-link for modelling outcomes (**Section 4 "Behavioural Module and Soft-Link"**). Importantly, we contrast current modelling assumptions behind EV adoption with the updated assumptions based on our module. Finally, we discuss planned and potential next steps for the soft-linking approach within and beyond DIAMOND (**Section 5 "Conclusion and Future Research"**).

1.1 Research Questions

This report contributes to two sets of research questions regarding the psychological experiment and the behavioural module soft-link with IAMs. First, we investigate the key predictors of EV adoption at a level of detail (i.e., on different levels simultaneously in different countries) that has not been previously done. Our study design allows the simultaneous investigation of the effect of car attributes, individual-level predictors, and country-level factors. The research question of how all these predictors link to EV adoption was substantiated through formulating and preregistering (preregistration link: https://osf.io/r6jpk) hypotheses for each specific predictor. This research question is highly relevant for behavioural sciences dealing with technology adoption by giving comprehensive insights into one technology.

Second, this report touches upon the question of how a more accurate modelling of technology diffusion affects modelling outcomes. Given the novelty of our approach, we have neither formulated nor preregistered any hypotheses for this question and rather follow an exploratory approach. Soft-linking the EV version of the behavioural module with CLEWs-EU, GCAM Europe, and OMNIA allows us to investigate its effects on broader system-level outcomes like emissions, and also on transport sector-specific outcomes like EV adoption rates or investment costs. This research question directly addresses IAM limitations discussed by Keppo et al. (2021) and McCollum et al. (2017) and, therefore, significantly contributes to the field of system modelling.

Table 1.1 gives an overview of the two research questions and the methodological approaches to answer them.

Table 1.1 Research Questions

Research question	Methodology	Exploratory/ Confirmatory
Which factors (i.e., car attributes, individual-level predictors, country-level factors) drive EV adoption?	• Online survey and experiment; retrieving country-level data • Mixed effects regression models regressing EV adoption decisions on various predicting factors	**Confirmatory** with preregistration *https://osf.io/r6jpk*
What are the effects of soft-linking our behavioural module with IAMs at the system and transportation sector levels?	• Populating the behavioural module with the survey, experiment and country-level data • Integrating the behavioural module in three different IAMs • Comparing model outputs with and without soft-link	**Exploratory**

2 Psychological Foundation

We conducted a literature review to inform our data collection, together with a PhD candidate from our group at the University of Basel, which has already been published in Nature Reviews Clean Technology (Günther et al., 2025). This review synthesises empirical evidence for the effects of different psychological, socio-demographic, and contextual factors on the adoption of four different clean energy technologies, including EVs. In the following, we summarise our findings with a specific focus on EV adoption and highlight interactions between factors from different categories throughout (for an overview, see **Figure 2.1**). Finally, we derive our psychological model – the extended Campbell paradigm – from this synthesis.

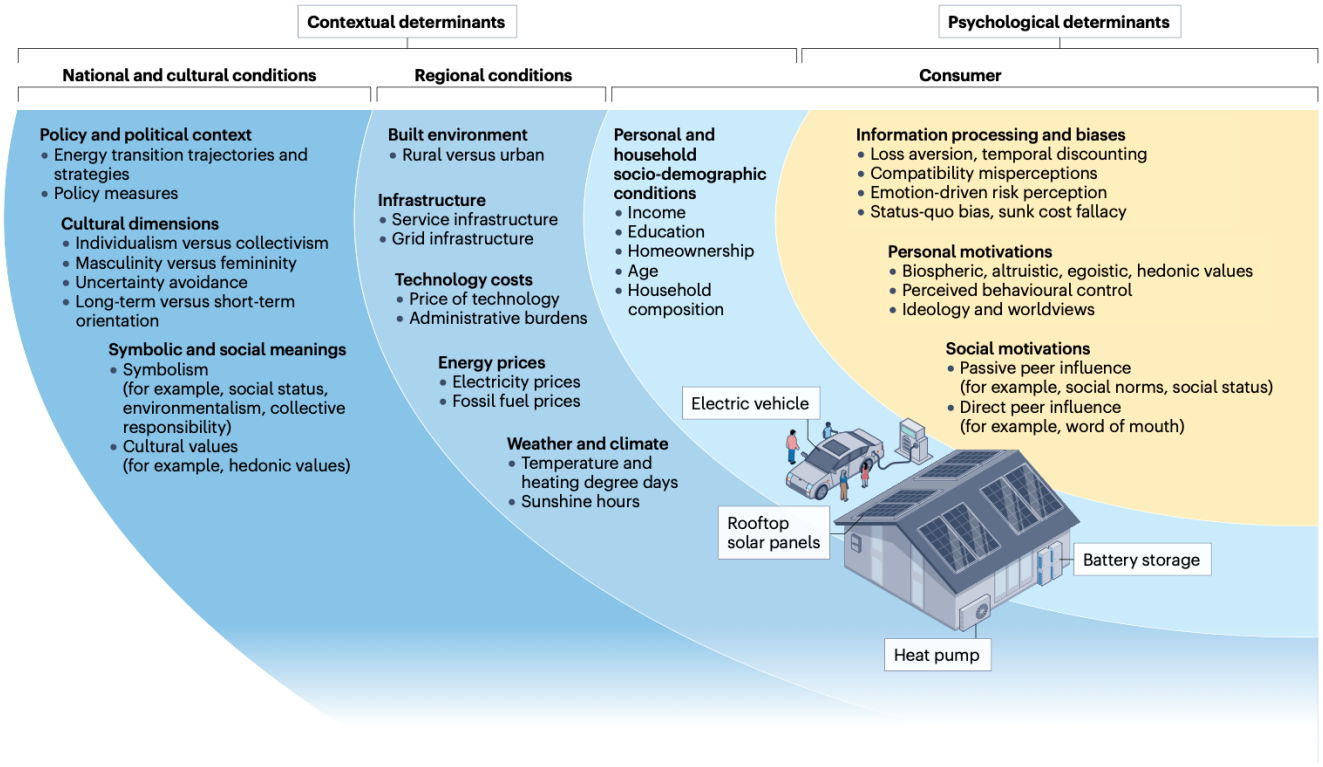

Figure 2.1 Key Psychological and Contextual Determinants of Clean Energy Technology Adoption. Interconnected psychological and contextual factors influence the adoption of clean energy technologies. Consumers are embedded within a multilevel context, including socio-demographic, regional, cultural and national dimensions, that influences psychological determinants and adoption behaviour directly. Reference: Günther et al., 2025, p. 549

2.1 Review of Psychological Drivers

Understanding the psychological determinants of EV adoption is essential for designing a behavioural module that reflects heterogeneous real-world decision processes. Although traditional modelling approaches rooted in economics assume rational, utility-maximising, and homogeneous consumers, an extensive body of empirical research shows that behaviour – including EV purchase decisions – is shaped by cognitive biases, personal motivations, emotions, and social context. This section synthesises evidence from psychology, behavioural economics, and environmental social science based on Günther et al. (2025). Our framework distinguishes between psychological determinants – including information-processing, personal motivations, and social motivations – and contextual determinants – including socio-demographic, regional, national as well as cultural factors – while emphasising that psychological and contextual drivers interact closely. The consideration of contextual factors on different levels (i.e., micro: socio-demographics, built environment; meso: neighbourhood, region; macro: country, culture) is in line with a multi-level perspective on behaviour (Hofmann, 2024).

2.1.1 Information Processing and Cognitive Biases

Consumers often rely on heuristics and simplified mental models when evaluating product choice alternatives, given the complexity of these decisions, limited cognitive capacity, and limited access to relevant information (referred to as bounded rationality; Gigerenzer & Gaissmaier, 2011; Kahneman, 2003). This extends to the adoption of EVs in light of the complexity of comparing and weighing purchase price, operating costs, range, charging infrastructure, and environmental impacts. Cognitive shortcuts and heuristics, although adaptive in some situations, can produce systematic biases that distort perceptions and choices (Gigerenzer & Gaissmaier, 2011; Tversky & Kahneman, 1974). At the same time, biases can also be rooted in underlying motivations and emotional reactions (Druckman & Bolsen, 2011; Finucane et al., 2000).

Loss aversion and reference dependence. One major psychological barrier is loss aversion – the tendency to weigh losses more heavily than equivalent gains (Kahneman & Tversky, 1979). Because EVs typically involve higher upfront purchase prices than conventional internal combustion engine vehicles (ICEVs), consumers often perceive the purchase price differential as a salient loss, while the financial benefits from lower operating costs are discounted or treated as uncertain future gains (Allcott & Wozny, 2014). This mechanism explains why consumers may reject EVs even when the lifetime costs of ownership are lower overall. Survey evidence indicates that loss aversion influences clean technology adoption, including EVs (Kim et al., 2020). Importantly, loss aversion can work in favour of adoption when non-adoption is framed as a missed financial or environmental opportunity, as demonstrated in field experiments on solar PV systems (Bär et al., 2023; Neumann et al., 2023).

Temporal discounting. Consumers also exhibit temporal discounting, placing disproportionate weight on immediate costs over delayed savings. This can lead to underestimating long-term fuel and maintenance savings from EVs (e.g., on average being willing to pay 0.5 € upfront for every 1 € of future gains from operating cost savings, which is well beyond realistic interest rates; for an example in the PV domain, see De Groote & Verboven, 2019). This bias is exacerbated by uncertainty about future electricity and petrol prices and the difficulty of evaluating lifetime cost trajectories. Empirical work suggests that temporal discounting affects EV purchase intentions (Wu et al., 2016) and contributes to the "energy paradox", whereby consumers underinvest in energy-efficient technologies (Allcott & Wozny, 2014).

Misperceptions and heuristics. EV adoption is strongly influenced by misperceptions about technology characteristics: range anxiety, rooted in an underestimation of the share of annual trips that can be completed on a single charge, is a dominant barrier. Consumers often judge battery ranges based on infrequent long-distance trips or on the range of petrol cars (i.e., availability heuristics and anchoring effect; e.g., Furnham & Boo, 2011; Sunstein, 2006), leading to unrealistic expectations for EV range. These misperceptions have been well documented in behavioural experiments (Herberz et al., 2022). In addition, consumers frequently misperceive long-term operating costs and environmental benefits associated with driving an EV (Bernardic et al., 2024). These misperceptions are also fuelled by misinformation – for example, including misinformation that EV batteries often catch fire – which simultaneously exaggerates perceived risks (Bretter et al., 2025). Addressing these misperceptions is crucial, with contextual factors being a potential lever to affect psychological processes: for instance, increasing charger availability reduces range anxiety, which in turn enhances adoption (Sierzchula et al., 2014; Wicki et al., 2022).

Affect and emotional responses. A growing body of research shows that emotional reactions play a decisive role in EV evaluation. Emotions influence both the depth of information processing and the direction of preferences: positive emotions, such as anticipatory pride, can increase perceived value of and willingness to adopt EVs as can negative emotions such as worry about climate impacts and guilt over fossil fuel use (He et al., 2023). Conversely, negative affect from unfamiliarity or perceived uncontrollability can inflate perceived risks independently of factual

information and, therefore, negatively affect EV adoption intentions (Loewenstein et al., 2001)

Status-quo bias and sunk-cost effects. Even when EVs are objectively advantageous, many consumers still prefer their current ICEVs. Status-quo bias, which refers to the tendency to maintain the current state over adopting an objectively better alternative, has been identified as a significant barrier to energy efficiency replacements (Blasch & Daminato, 2020). This status-quo bias can be further reinforced by sunk-cost considerations – emotional or financial attachment to existing vehicles because of the own prior investments in them – which deters switching (Blasch & Daminato, 2020; Kahneman et al., 1991). Experience reduces these barriers: test-drive trials have repeatedly shown that direct exposure to EVs increases acceptance (Jensen et al., 2013; Skippon et al., 2016).

2.1.2 Personal Motivations, Values, and Worldviews

Beyond cognitive biases, EV adoption is shaped by underlying motivational structures, including values, identity, and political ideology, and perceptions of behavioural feasibility.

Values. Values are general, cross-situational goals that serve as a guiding principle in one's life (Schwartz, 1992; Steg & de Groot, 2012) and are, therefore, conceptually close to what other researchers in environmental psychology refer to as attitudes (Kaiser, 2021), and economists as preferences (Falk et al., 2018). Values shape how people perceive the costs and benefits of EVs and directly affect EV adoption decisions. Four value types are particularly relevant (Schwartz, 1992): hedonic (valuing pleasure and comfort), egoistic (valuing status and money), altruistic (valuing the well-being of other people) and biospheric (valuing nature and the environment). Biospheric and altruistic values consistently predict higher EV adoption, as EVs are seen as environmentally beneficial. Egoistic and hedonic values tend to reduce adoption, especially in early markets where EVs may involve compromises in convenience or higher up-front costs (Higueras-Castillo et al., 2023). However, as EV technologies improve and become more cost-competitive, egoistic motivations increasingly support adoption (e.g., savings from low operating costs; Legault et al., 2024; Wolske et al., 2017).

Ideology, worldviews, and motivated reasoning. Ideological worldviews (e.g., one's political orientation) also shape EV-related beliefs and behaviour (e.g., Priessner et al., 2018). For example, people engage in motivated reasoning, selectively attending to information that aligns with their pre-existing beliefs or group identities (Druckman & Bolsen, 2011). Therefore, conservative individuals sceptical of climate policy may downplay EV benefits or be more receptive to misinformation (Herberz et al., 2022). Political identity can affect trust in EV technology and in institutions that promote it. These dynamics underline the need for targeted communication that resonates with different ideological groups.

Perceived behavioural control and self-efficacy. Perceived ease of adoption – including confidence in navigating subsidies, understanding charging procedures, or having access to installation services – shapes intentions (Ajzen, 1991; Günther et al., 2025). Simplified administrative processes and clear guidance can, therefore, influence psychological readiness to adopt clean technologies (e.g., solar PV, heat pumps) and are likely to matter for EVs as well (Pettifor et al., 2017).

2.1.3 Social Motivations and Social Influence

Human behaviour, including EV adoption, does not occur in isolation but is embedded in social networks, neighbourhoods, and cultural contexts (Cialdini et al., 1990; Tajfel & Turner, 2001). Social drivers include descriptive norms, injunctive norms, status considerations, and interpersonal communication.

Descriptive and injunctive social norms. Social norms exert strong influence on EV adoption: descriptive norms involve perceptions of how many others are adopting EVs. Higher local EV visibility (e.g., EVs in the neighbourhood) increases perceived normality and reduces uncertainty, thus promoting adoption (Heutel &

Muehlegger, 2015; Zhu & Liu, 2013). Injunctive norms involve perceived social approval or disapproval (i.e., do I think others evaluate EVs positively; Thøgersen, 2006). Empirically, EV uptake is associated with more EV positive injunctive norms (Barth et al., 2016).

Peer influence and word-of-mouth. Interpersonal communication – for example, conversations with EV owners or informal advice – is one of the strongest non-financial drivers of adoption: peer effects have been shown repeatedly in energy technologies such as solar PV, and emerging evidence suggests similar mechanisms for EVs. Ambassador programmes and peer-referral systems can effectively increase adoption (Günther et al., 2025).

Status, identity signalling, and symbolic meaning. EVs carry symbolic meanings related to modernity, environmentalism, technological leadership, or social status. These symbolic associations influence adoption choices: for some groups, EVs represent a desirable, future-oriented lifestyle, enhancing adoption. For others, symbolic associations may deter adoption if EVs are perceived as belonging to an "outgroup" (e.g., politically coded technologies or masculinity signalling). Identity-based processes, therefore, create heterogeneity in adoption likelihood and responsiveness to norms (Herziger & Sintov, 2023; Noppers et al., 2019).

2.2 Review of Contextual Drivers

While psychological factors shape how consumers perceive and evaluate EVs, contextual determinants define the structural conditions under which adoption occurs. Contextual factors include socio-demographic characteristics, economic conditions, infrastructure availability, cultural norms, political and regulatory environments, and more decision-proximal characteristics of the built environment. Importantly, as highlighted in Günther et al. (2025), contextual conditions not only exert direct effects on adoption but also influence psychological processes such as risk perception, perceived feasibility, and social norms. For the behavioural module, contextual determinants constitute key attributes in the discrete choice experiment (DCE) that interact with psychological variables to shape EV uptake.

2.2.1 Socio-Demographic and Household Characteristics

Socio-demographic conditions shape both the capacity and willingness of consumers to purchase EVs. Empirical studies show that income, education, homeownership, age, and household composition play major roles in shaping adoption patterns across clean energy technologies, including EVs.

Income. Income is one of the strongest predictors of EV adoption. Higher-income households have greater liquidity to deal with higher upfront purchase prices (Corradi et al., 2023). Income is further related to greater access to home charging (due to higher homeownership rates; Hajhashemi et al., 2024). In addition, empirical evidence suggests that many financial incentives disproportionately benefit high-income households. For example, in the US, the top income quintile received around 80% of EV tax credits from 2006 to 2021 (Borenstein & Davis, 2025).

Education and energy literacy. Higher education positively correlates with higher EV adoption, even when controlling for income (Westin et al., 2018). In addition, low levels of numeracy and energy literacy contribute to miscalculations of operating costs, which might have different effects on EV adoption depending on the direction of the miscalculation (Allcott, 2011).

Homeownership. Homeownership strongly predicts EV adoption because it enables home charging availability (Hajhashemi et al., 2024), which can reduce range anxiety and increase perceived convenience (Rezvani et al., 2015). Infrastructure constraints are far higher for renters, particularly in multi-family housing environments (Krishnamurthy & Kriström, 2015). Importantly, these effects remain when controlling for income.

Age and household composition. Age influences adoption indirectly via financial resources and risk attitudes. Younger consumers may be more open to innovative technologies but may lack financial means, while older consumers may have more resources but higher risk aversion (Spurlock et al., 2019). Household composition also matters: larger households or those with children may have more diverse mobility needs, with childless households being more likely to adopt EVs (Nayum et al., 2016).

2.2.2 Regional Conditions

Charging infrastructure. Public charging infrastructure remains one of the most critical contextual determinants of EV adoption by exerting direct and indirect effects: it not only enables flexible EV use (Wicki et al., 2022) but also reduces range anxiety, thereby shaping key psychological determinants of adoption (Rezvani et al., 2015). Several studies show that public chargers within a neighbourhood or region significantly increase EV uptake (White et al., 2022; Wicki et al., 2022). Home charging availability is one of the strongest facilitators of adoption. Access to workplace charging also encourages EV use by providing reliable daily charging opportunities. Both expand the perceived compatibility of EVs with everyday routines (Sierzchula et al., 2014; Wicki et al., 2022).

Urban and rural place of residency. Regional characteristics pertaining to the place of residency shape both mobility patterns and charging demands: urban areas typically provide better public charging coverage and shorter daily travel distances, favouring EV uptake. Rural areas often involve longer travel distances, less public infrastructure, and a higher need for large vehicles – all of which reduce the perceived suitability of EVs (Egnér & Trosvik, 2018). Studies consistently show higher likelihood for individual EV adoption in urban and suburban regions relative to rural contexts (Priessner et al., 2018).

Technology costs. High upfront EV purchase prices remain one of the strongest barriers to adoption and exert a direct effect (Singh et al., 2020). In addition, even when lifetime costs-of-ownership are favourable, upfront costs heavily influence consumer decisions due to temporal discounting and loss aversion (Allcott & Wozny, 2014; Wu et al., 2016).

Electricity and fuel prices. Energy prices influence adoption through changes in operating costs: lower electricity prices or higher petrol prices make EVs more financially attractive. Recent research shows that increases in gasoline prices positively correlate with EV sales (Bushnell et al., 2022). People living in regions with reliable, low-carbon electricity grids may perceive EVs as cleaner and more attractive. Conversely, in regions where electricity is fossil-intensive or expensive, EVs may not provide environmental or cost benefits (Holland et al., 2016).

2.2.3 National and Cultural Conditions

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Administrative and procedural burdens. Even where financial incentives exist, administrative burdens (e.g., complex application processes or unclear subsidy rules) can limit adoption. Simplified procedures and government-led facilitation have been shown to increase uptake of other technologies such as PV systems in Ireland and the U.S.

(Lades et al., 2021; Wolske et al., 2018). These insights translate directly to the EV context, particularly around home charger installation.

Policy and regulatory environment. Governments use various incentives to support EV adoption, including purchase subsidies, tax rebates or credits, low-interest loans, and reduced registration fees. Such measures can be highly effective but also increase inequalities unless targeted (Borenstein & Davis, 2025; Stechemesser et al., 2024). Furthermore, non-financial incentives (including access to bus lanes, free or discounted parking, zero-emission zones, and preferential license plate policies) have notable behavioural effects by reducing perceived inconvenience associated with EV ownership or directly affecting availability of EVs (Langbroek et al., 2016; Rietmann & Lieven, 2019; Zhang et al., 2018).

Climatic and weather conditions. Temperature and temperature variation shape EV performance perceptions and charging behaviour. For example, cold temperatures reduce battery range, increasing perceived and actual range risk (Jaguemont et al., 2016). Extreme temperatures may also affect EV adoption (Li et al., 2023).

Cultural differences. Adoption is embedded in broader societal structures. Cultural dimensions such as collectivism vs individualism, uncertainty avoidance, long-term orientation, and masculinity influence public attitudes toward emerging technologies (Khatua et al., 2023; Novotny et al., 2022; Tam & Milfont, 2020).

2.3 An Extended Campbell Paradigm

We chose the Campbell paradigm as our behaviour explanation model as it combines psychological and contextual factors, while at the same time offering the potential for extensions. The Campbell paradigm in its original form constitutes that the likelihood that person A shows behaviour B is a function of a characteristic of the person (i.e., their motivation) and a characteristic of the behaviour (i.e., its behavioural costs; Kaiser, 2021; Kaiser et al., 2021). Motivation – or attitude – reflects a person's commitment to specific goals. For example, how committed a person is to protect the environment (or to live a healthy life) is reflected in their environmental motivation or attitude (health motivation or attitude). The behavioural costs reflect the obstacles and required personal resources to show a behaviour (e.g., costs in terms of money, time, effort, or social sanctions). The Campbell paradigm assumes a compensatory relation between these two behavioural predictors: person A's motivation must offset the behavioural costs attached to behaviour B so that they are likely to show it (Kaiser, 2021; Kaiser et al., 2021). In the case of EV adoption, different motivations might play a role including environmental attitude (Qiu et al., 2025) and there are various costs associated with the adoption, such as purchase price, operating costs, potentially reduced flexibility due to longer charging times and shorter battery ranges, or social norms surrounding EV adoption. EV adoption becomes more likely when the motivational component is higher (i.e., a person with a stronger environmental attitude is more likely to adopt an EV than a person with weaker environmental attitude) or the behavioural costs are lower (e.g., when the purchase price of EVs decreases).

Based on the literature review, we extended this model with additional psychological factors and we embedded it in a multi-level perspective (see **Figure 2.2**, for an overview of the psychological model which represents the core of the behavioural module). Starting with the psychological factors, our goal was to represent the three different levels *Information Processing*, *Personal Motivations,* and *Social Motivations*. The original form of the Campbell paradigm already covers personal motivations through the environmental attitude component which is comparable to the concept of biospheric values described in **Section 2.1.2**. Due to the prevalence of temporal aspects involved in EV adoption decisions – for example, balancing immediate losses due to higher purchase prices compared to ICEVs and lower operating costs due to electricity being cheaper than fossil fuel – we chose temporal discounting as a cognitive, information-processing mechanism. In addition, the literature on the effects of temporal discounting on car purchase behaviour is scarce, which is a gap we wanted to address. Temporal

discounting refers to the preference for immediate gains over equivalent future gains, mostly related to monetary consequences. That is, if people have the choice between receiving 10€ now and receiving 10€ tomorrow, they tend to prefer the immediate payment. This tendency extends to situations in which future gains exceed immediate gains. For example, people still tend to prefer receiving 10€ now, when the other option is a payment of 12€ tomorrow (Ruggeri et al., 2022). In the case of car adoption decisions, we assume that people with a stronger tendency to prefer immediate gains take the purchase price to a larger extent into account in their decision-making and the operating costs to a lesser extent compared to people with weaker temporal discounting tendencies.

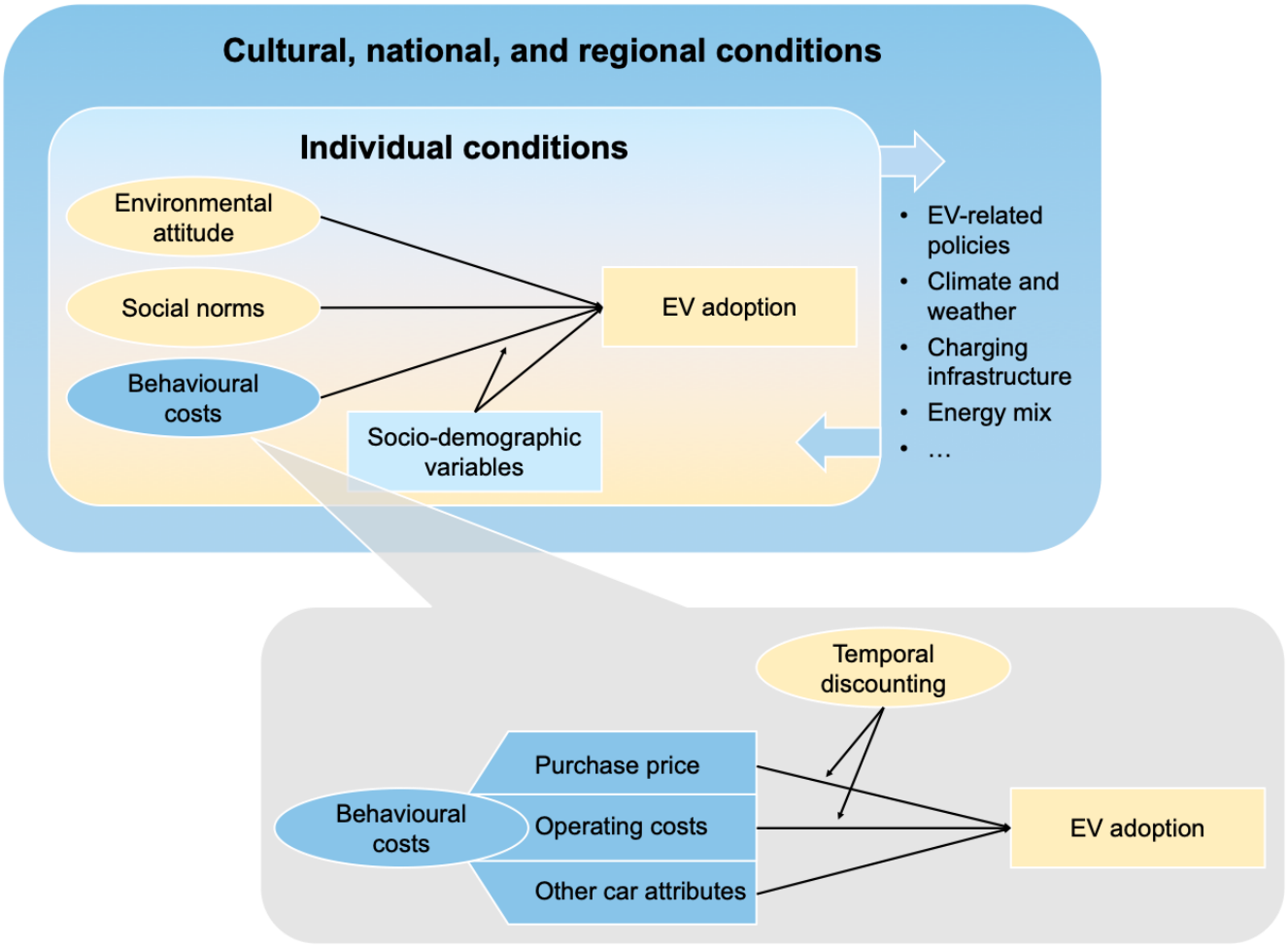

Figure 2.2 Schematic Visualisation of the Psychological Model Underlying the Behavioural Module. The colour-coding mirrors Figure 2.1. Socio-demographic variables affect EV adoption in two days: first, they have a direct effect on EV adoption. Second, they moderate the effect of behavioural costs on EV adoption (e.g., the high purchase price of EVs less strongly affects higher-income compared to lower-income buyers).

EV adoption is further affected by the social context, in which purchase decisions are being made (see **Section 2.1.3**). Even though this aspect is implicitly represented in the original Campbell paradigm – social norms can be interpreted as a behavioural cost component – we wanted to explicitly account for the social context. Therefore, we included social norms as an additional predictor of EV adoption in our extended model. We further distinguish social norms into descriptive and injunctive norms (Thøgersen, 2006). Descriptive norms refer to norms reflected in the behaviour of others (i.e., the norm is what most other people do). Here, we further differentiate between objective descriptive norms – the actual behaviour of others – and perceived descriptive norms – what people think others are doing, which can diverge. Descriptive norms in the domain of EV adoption represent the (perceived) current diffusion rate of EVs, so in most countries the descriptive norm would drive ICEV adoption.

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Injunctive norms refer to perceived opinions of others on which behaviour is appropriate (i.e., the norm is what I think others think is the right behaviour). Who "others" are can differ and depending on it the effect of the norm on behaviour changes (Thøgersen, 2006). In this study, we focus on the injunctive norms exerted on the level of one's peers (i.e., family and friends) as this is an important group.

Having covered all three psychological predictor clusters from **Section 2.1**, we turn to the contextual influences on behaviour. We take these contextual influences into account on different levels. Socio-demographic variables like age, gender, income, formal education, household size, and living in an urban or rural area are measured on the individual-level in the survey. Higher-level contextual factors are included in the DCE and as country-level predictors. Here, we investigate factors such as current and projected EV diffusion in the country (objective descriptive norm), e-mobility related policy landscape, charging infrastructure, energy mix and price, GDP, per-capita carbon emissions, air quality, weather, political landscape, and public infrastructure. Therefore, we cover a broad range of factors on different contextual levels that we hypothesise shape EV adoption decisions.

Importantly, this psychological framework and, therefore, the behavioural module can be easily applied to different climate-relevant behaviours allowing future soft-links with IAMs for various behaviours (when the corresponding data is collected or retrieved from other sources). Sustainable food consumption – in particular reducing the intake of meat and other animal-based products – is a prime candidate for such a transfer, as the food system accounts for roughly a quarter to a third of global greenhouse gas emissions and dietary change is among the most effective consumer-level levers for mitigation (Poore & Nemecek, 2018; Willett et al., 2019). The two core predictions of the Campbell paradigm can be directly applied to this domain. First, regarding the motivational component, the original Campbell paradigm has been successfully used to predict whether people follow a vegetarian diet (Kaiser et al., 2020; Kaiser & Byrka, 2015). The finding that environmental motivation is an important driver of food choice has also been shown in various other studies, with pro-environmental attitudes and environmental concern consistently predicting meat-reduction intentions and the adoption of plant-based diets (Hopwood et al., 2020; Milfont et al., 2021; Vainio et al., 2018). Second, behavioural costs can obstruct sustainable food choices when too high: higher (perceived) prices of plant-based products, limited convenience and availability, and taste expectations repeatedly emerge as barriers to sustainable diets (Graça et al., 2019; Rickerby & Green, 2024; Siegrist & Hartmann, 2019). In line with the compensatory logic of the paradigm, sustainable food choices, therefore, become more likely when environmental motivation is strong enough to offset these behavioural costs, or when the costs themselves are reduced. Findings from previous studies further provide evidence that the additional factors in our extended psychological framework – temporal discounting (Barlow et al., 2016; Willett et al., 2019), the social context (Çoker et al., 2022; Higgs, 2015; Robinson et al., 2014; Stea & Pickering, 2019), and broader contextual conditions (Clonan et al., 2016; De Gavelle et al., 2019; Kwasny et al., 2022; Reisch et al., 2021; Swinburn et al., 2019; see **Figure 2.2**) – also shape food-related behaviour, such that the model can be readily adjusted and applied to sustainable food consumption (see **Figure 2.3**).

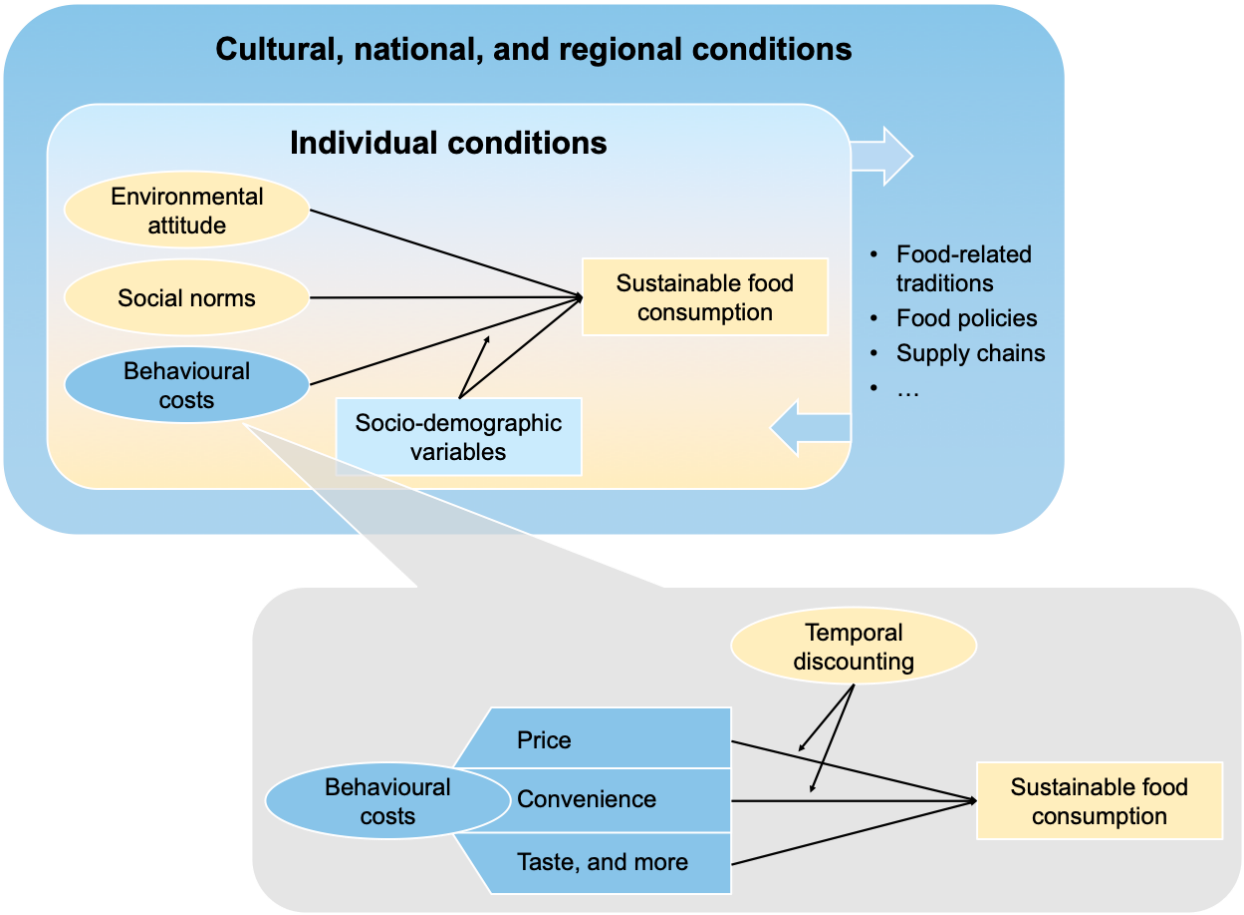

Figure 2.3 Adjustment of the Schematic Visualisation of the Psychological Model Underlying the Behavioural Module for Sustainable Food Consumption. The colour-coding mirrors **Figure 2.1**.

3 Psychological Experiment

Various methods to investigate EV adoption and its drivers exist. Approaches range from observations of behaviour in the real-world, field experiments, and DCEs, to one-shot intention measures and the analysis of past EV diffusion data (Liao et al., 2017). Each approach has its advantages and disadvantages regarding aspects like internal validity, external validity, control over conditions, representing counterfactual scenarios, and feasibility which we discuss below and summarise in **Table 3.1**.

A first, broad distinction can be drawn between revealed-preference approaches, which rely on observations of actual, consequential choices, and stated-preference approaches, which elicit preferences and choices under controlled, often hypothetical conditions (Ben-Akiva et al., 1994; Louviere et al., 2000). Observations of real-world behaviour and the analysis of past EV diffusion data are revealed-preference approaches: because they capture what people actually did, they offer high external validity and avoid the hypothetical bias that can affect self-reports (Brownstone et al., 2000; Hensher, 2010). However, they provide limited control over the decision context and suffer from confounding, since the attributes that drive choices (e.g., purchase price, range, charging availability) are correlated in the market and cannot be disentangled experimentally, which lowers their internal validity (Liao et al., 2017). They are also backwards-looking and, therefore, limited in extrapolating to technologies, attribute levels, or policy contexts that do not yet exist – a critical limitation when modelling future adoption pathways (Liao et al., 2017; Rotaris et al., 2021).

Field experiments are conceptually located between the two approaches. By randomly assigning participants to conditions in a real-world setting (e.g., offering test drives or varying incentives), they combine high external validity with randomisation, and they observe consequential behaviour rather than intentions (Harrison & List, 2004). For EVs, experimental exposure interventions such as test-drive trials have repeatedly been shown to increase acceptance (Skippon et al., 2016). Their disadvantages are practical and conceptual: they are too costly to run at scale, we can control only the manipulated factor while other attributes remain fixed at their current market levels, and – as with revealed-preference data – they cannot easily represent not-yet-existing attribute levels and policy scenarios (Harrison & List, 2004; Liao et al., 2017).

DCEs are a stated-preference method in which respondents repeatedly choose between hypothetical alternatives whose attributes are systematically varied according to an experimental design (Louviere et al., 2000). Their key strength is high internal validity and control: because attribute levels are assigned by design and orthogonal (or near-orthogonal), the independent effect of each attribute can be estimated cleanly, and attribute levels that do not yet exist on the market (e.g., future prices, ranges, or charging densities) can be presented, making the method suited to estimating future adoption rates (Hensher et al., 2015; Liao et al., 2017). DCEs are also a comparatively feasible research method: they can be administered to large, demographically representative online samples at relatively low cost. The principal disadvantage is lower external validity arising from the hypothetical nature of the task: stated choices need not coincide with real purchases, a discrepancy known as hypothetical bias (Fifer et al., 2014). Empirically, however, well-designed DCEs have been shown to predict real choices reasonably well, especially at the aggregate level (Brownstone et al., 2000; Quaife et al., 2018).

Finally, one-shot intention measures ask respondents directly about their willingness or intention to adopt an EV. They are the cheapest and easiest to implement, but they offer little control over the decision context, cannot isolate the effects of individual attributes, and constitute a distinct behaviour (i.e., stating an opinion or preference) from actual adoption with different cost structures (Fifer et al., 2014). They are, therefore, informative about general willingness to adopt, but too limited for this study's context.

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Table 3.1 Comparison of Methodological Approaches to Investigating EV Adoption. Plus and minus signs indicate the relative strength of each approach on a given criterion (-- low to ++ high; +/- is neither high nor low) and are intended as a qualitative summary based on the cited literature. The bold row highlights the approach chosen for the present study.

Approach	Internal validity	External validity	Control over attributes	Future / counter-factual scenarios	Feasibility / cost
Real-world observation / past diffusion data (revealed preference)	--	++	--	--	+ / -
Field experiment	+	+	+ / -	-	--
Discrete choice experiment (stated preference)	**++**	**+ / -**	**++**	**++**	**+**
One-shot intention measure	-	--	--	+	++

We chose DCEs because they allow us to experimentally vary different attributes (yielding higher internal validity than field experiments, though lower external validity) and, therefore, also to account for possible future contexts and not-yet-existing attribute levels (in contrast to observational data, field experiments, or one-shot intention measures), which is essential for informing forward-looking IAM scenarios.

3.1 Methodology

The study was quantitative with the assessment of multiple psychological scales and DCE trials to measure passenger car preferences. Simultaneously to getting the ethical approval for this study from the University of Basel, we preregistered the study design, hypotheses, and analyses. **Table 3.2** contains an overview of this study.

Table 3.2 Comprehensive Study Overview. *M* refers to mean.

Goals	Investigate passenger car purchase decisions (EVs and ICEVs), effects of car attributes, psychological, and country-level factors, and integrate survey data into IAMs to improve modelling assumptions.
Sample	Representative for respective country population in terms of age, gender, & NUTS-1 region (in countries with only one NUTS-1 region, NUTS-2); participants are at least 18 years old.
Sample size	Target: N = 6,000 ($N_{country}$ = 400) in 15 European countries Actual: N = 6,204 ($M(N_{country})$ = 414; 381 ≤ $N_{country}$ ≤ 506) in 15 European countries
Main variables	Hypothetical passenger car purchase decisions, environmental attitude, social norms (injunctive, descriptive), temporal discounting, country-level factors, & socio-demographic variables.

Data was collected in 15 European countries (see **Table 3.5**) via the panel provider Dynata (https://www.dynata.com) which necessitated providing the survey in multiple languages. We followed a three-step translation procedure following the machine translation with a post-editing approach (Zavala-Rojas et al., 2024): we first created the survey in English, then used Large Language Models (ChatGPT and Claude) to translate the English version into the respective language, and finally sent the translations to native speakers (either professional translators or experts in the study domain) to check and edit them.

3.1.1 Study Procedure

Participants completed the following procedure: they received an invitation email for the study by Dynata with a link that led to our online survey. After they had opened that link, we presented them with general information about the study and the data protection statement. Participants who gave their informed consent proceeded by answering socio-demographic questions based on which the quotas for age, gender, and region were evaluated. Participants who were part of a quota that had already been met were not forwarded to the remainder of the study but were redirected to a page explaining that they could not participate due to their demographic characteristics. The other participants received further socio-demographic and general car-related questions (e.g., preferred car size and condition). We assessed the following socio-demographic variables: citizenship, mother tongue, age, gender, monthly household income after taxes, formal education, place of residency (urban vs. rural), NUTS-1 and/or NUTS-3 region, driver's license, car ownership, preferred car size and condition, and household size. In this section, we also added a first attention check (i.e., "To show that you are carefully reading the instructions of this survey, please do not select any of the following options and click "Next" to continue the survey". Participants answering the attention check incorrectly saw an additional page with a warning urging them to read carefully).

Afterwards, participants received an explanation of the DCE for assessing car preferences (for electric, diesel, and gasoline cars), including a general explanation of greenhouse gas emissions and their relation to passenger cars. We then presented participants with 18 choice tasks varying the car attributes on 18 separate pages. We randomly assigned each participant to one of two groups that received different car configurations based on a D-efficient fractional factorial design (see **Section 3.1.2**). A D-efficient fractional factorial design chooses a subset of all attribute-level combinations to increase reliability of the estimated parameters, by choosing the most informative set of choice tasks for a given number of choice tasks.

In the following section, we assessed socio-psychological variables, including participants' environmental attitude, social norms regarding EV adoption, and political orientation (from 1 = left to 7 = right) as well as party affiliation (dependent on country). We measured participants' environmental attitude with the General Ecological Behaviour Scale (GEB; Kaiser & Wilson, 2004) which comprises self-reports for 50 environmentally relevant behaviours (e.g., taking short-distance flights, keeping the engine running at red lights, being vegetarian) from which we infer a person's motivation (Kaiser & Lange, 2021). We did not assess all of the 50 GEB items for each participant, but instead, implemented a planned missingness design with four overlapping item sets of 30 items that were randomly assigned to the participants. In addition, we measured social norms, differentiating between descriptive and injunctive norms, for which we applied different reference groups. Following Göckeritz et al. (2010) and Noppers et al. (2019), we assessed descriptive norms by asking participants to estimate the percentage of people in their country, as well as people in their country and income decile who drive an EV. This approach allows us to investigate potential ingroup biases (e.g., overestimating ingroup performance compared to the general population) and pluralistic ignorance (e.g., overestimating a minority behaviour). Injunctive norms were measured with three items adapted from Cherchi (2017) and Wang et al. (2016). Here, the reference group was close peers (i.e., friends and family) and item content was related to whether the participants think these peers believe that EV adoption is something positive.

We then assessed temporal discounting with an adaptive task, meaning that participants received different questions dependent on their previous answers. Participants answered between 10 and 13 items. This approach improves the measure's reliability and ability to differentiate between participants with a similar tendency to temporally discount and has already been applied in a study in 61 countries (Ruggeri et al., 2022). This section also included a second attention check ("Which of the two following options would you prefer?" *Receiving £290 right now, or Paying £290 in 12 months*.; the currency was country-adapted). Participants answering both attention

checks incorrectly were screened out and excluded from the analyses, while only answering this attention check incorrectly led to receiving the same warning described for the previous attention check.

In the final part of the survey, we assessed various variables related to the perception of climate change-related risks. This part is independent of the soft-links with the IAMs and pertains to a different research question. The participants were then debriefed and had the opportunity to make any final comments on the survey or their own answers before being redirected to the panel provider to ensure compensation. The survey took on average of around 19 minutes and 30 seconds. **Figure 3.1** gives an overview of the whole study procedure.

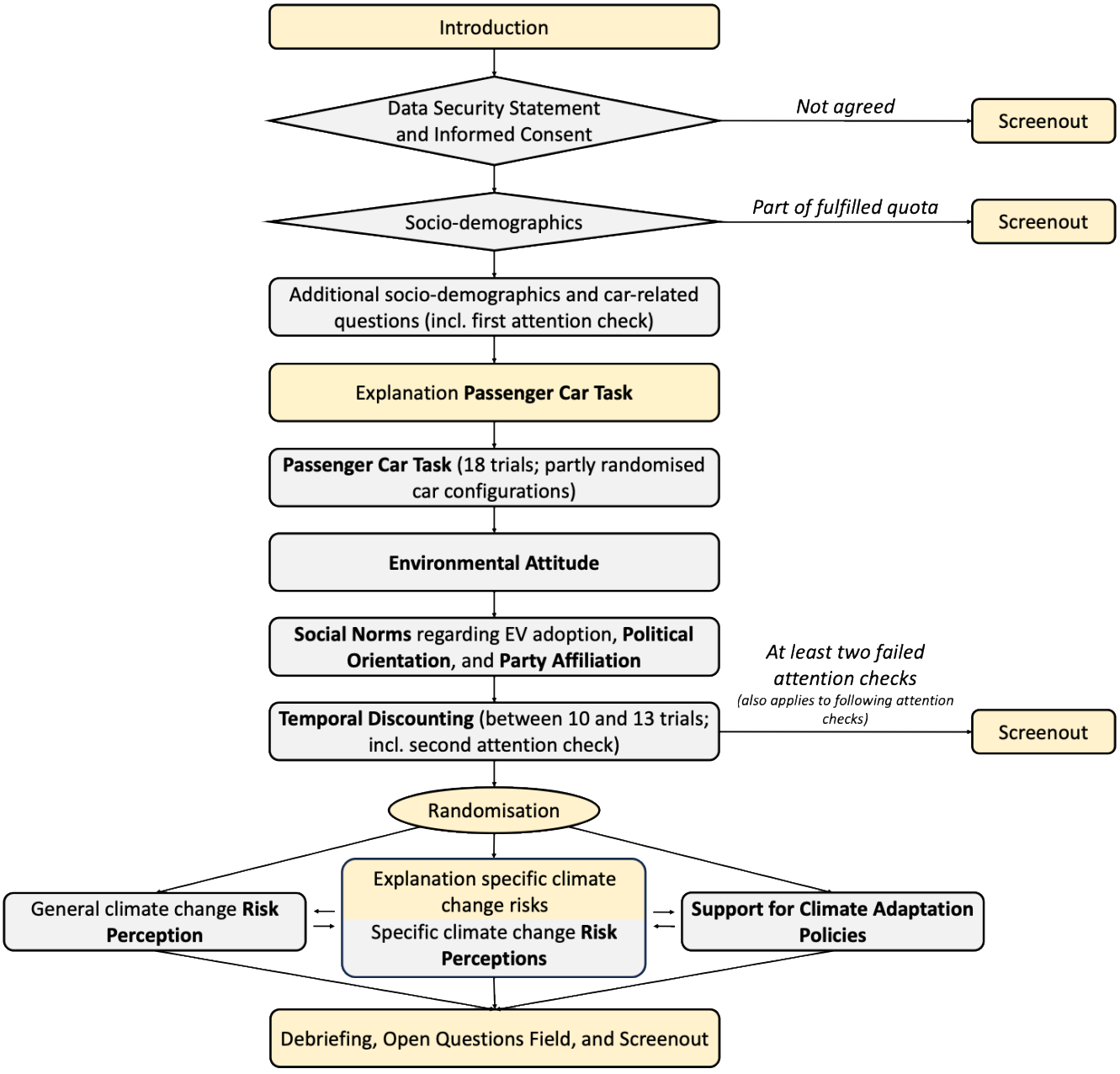

Figure 3.1 Overview of the Study Procedure

3.1.2 Discrete Choice Experiment for EV Adoption

We varied seven attributes in the DCE on car preferences. In each of the 18 trials per person, participants were presented with four different car options. The main outcome variable was passenger car choice. Participants also had the option of not choosing any of the four cars. The number of cars of a specific vehicle type (i.e., EVs, gasoline

and diesel) varied between one and two between tasks. The seven attributes can be classified into car attributes and contextual attributes, and are presented in **Table 3.3**. Contextual attributes were held constant within trials, meaning that per trial, we presented participants with one charging infrastructure configuration, one environmental impact of EVs, and one EV diffusion estimate.

Table 3.3 Car and Context Attributes and Attribute Levels for the Discrete Choice Experiment on EV Adoption. Attribute levels and units were adjusted to each country context (e.g., miles in UK and km in all other countries).

Car attributes	Context attributes
Vehicle type (*gasoline, diesel, electric*)	Charging infrastructure (*50% of available fuel pumps, 75% of available fuel pumps, same amount as available fuel pumps*)
Purchase price (*50%, 75%, 100%, 125%, 150% of average price in country for car size*)	Environmental impact (*30% reduction, 50% reduction, 70% reduction of carbon emissions when using electric vs. gasoline*)
Operating costs (*low, medium, high*)	Electric vehicle diffusion in country (*10%, 35%, 60%*)
Range (gasoline/diesel: *400km, 500km, 600km, 700km, 1000km;* electric: *200km, 300km, 400km, 500km, 700km*)	

The monetary attribute levels of purchase price and operating costs depended on the country and the vehicle size that the participant preferred and were defined to cover the range of technological assumptions represented in the IAMs (e.g., increasing fuel efficiency of gasoline and diesel vehicles over time). For vehicle size, participants were able to indicate whether they prefer to buy small, medium or large cars. Due to the high number of possible car profiles (i.e., attribute combinations), a random generation of profiles would significantly decrease the efficiency of the experimental design. Hence, we computed a d-efficient fractional factorial design with two blocks of 18 sets of four unique passenger cars for each of the three car sizes with the R-package idefix (Traets et al., 2020). Each passenger car comprised all car attributes and the scenario attributes when applicable. The charging infrastructure attribute was only presented in the column of the EVs, environmental impact was presented for all car types (with the gasoline vehicles being the baseline and diesel vehicles having a fixed emission reduction depending on vehicle size), and vehicle diffusion was also shown for all car types (with diffusion for gasoline and diesel vehicles being the complement of the EV diffusion; i.e., 90%, 65%, 40%). Each participant was randomly allocated to one of the two fractional factorial task blocks for their preferred vehicle size and none of the participants saw the same car profile twice. In **Figure 3.2**, we provide an exemplary trial from the DCE as it was presented to the participants.

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Passenger Car Choice Task 1 of 18

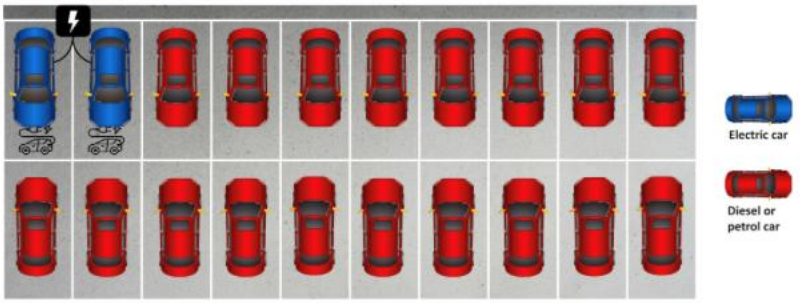
	Car 1	Car 2	Car 3	Car 4	
Car type	Petrol vehicle	Diesel vehicle	Electric vehicle	Electric vehicle	
Purchase price	£20,400	£40,800	£13,600	£34,000	
Fuel costs per 62 miles (100km)	£12.74 per 62 miles	£6.75 per 62 miles	£4.85 per 62 miles	£3.14 per 62 miles	
Range	620 miles	370 miles	185 miles	125 miles	
Number of available electric vehicle charging points			75% of available fuel pumps	75% of available fuel pumps	
Greenhouse gas emissions per 62 miles (100km) (compared to petrol car)	14.4kg	11.6kg (19% less than petrol car)	↘ 4.3kg (70% less than petrol car)	↘ 4.3kg (70% less than petrol car)	
Share of drivers in the UK owning this car type (petrol and diesel are considered as one group here)	90%	90%	10%	10%	
Visual representation: Share of drivers in the UK owning this car type					
	Which of the four cars would you prefer to buy? If you would refrain from owning a car, when these were the only available options, please choose **none**. ○ Car 1 ○ Car 2 ○ Car 3 ○ Car 4 ○ None				

Figure 3.2 Exemplary Trial from the Discrete Choice Experiment on EV Adoption

3.1.3 Hypotheses and Analyses

Our hypotheses, the analyses used to test them, and the analyses underlying the behavioural module were preregistered prior to data collection (https://osf.io/r6jpk). The hypotheses follow directly from the extended Campbell paradigm and its multi-level embedding (**Figure 2.2**): each predictor (cluster) in the framework – car attributes, environmental attitude, temporal discounting, social norms, socio-demographic variables, and country-level contextual factors – maps onto one or more hypotheses. Below, we first summarise the hypotheses (**Table 3.4**), then describe the inferential analyses used to test them and, in more detail, the prediction analyses that constitute the EV version of the behavioural module.

Hypotheses. We preregistered three sets of hypotheses, corresponding to the three predictor levels of the framework: car and context attributes varied in the DCE (H.CA), individual differences (H.ID), and country-level factors (H.CF). Regarding the car and context attributes that constitute the behavioural costs and benefits of

adoption, we hypothesised that the likelihood of choosing a vehicle increases as its purchase price (H.CA 1) and its operating costs (H.CA 2) decrease, and increases with a longer range (H.CA 3). For the context attributes, we expected the likelihood of choosing an EV to increase with greater charging-infrastructure availability (H.CA 4), with a larger emission-mitigation potential of EVs (H.CA 5), and with a higher EV diffusion in the country (H.CA 6).

At the individual-difference level, we hypothesised that a stronger environmental attitude raises the likelihood of choosing an EV (H.ID 1), that a more strongly perceived social norm to purchase EVs – both descriptive and injunctive – raises that likelihood (H.ID 2), and that stronger temporal discounting strengthens the effect of the purchase-price attribute and weakens the effect of the operating-cost attribute on choice (H.ID 3).

At the country level, we hypothesised that the likelihood of choosing an EV is higher with higher current EV diffusion as an indicator of the actual descriptive norm (H.CF 1), a more favourable policy landscape as an indicator of an injunctive norm (Rinscheid et al., 2021; H.CF 2), more installed EV chargers (H.CF 3), a higher share of renewables in the electricity mix (H.CF 4), a lower electricity price (H.CF 5), and a higher GDP (H.CF 6). We further assumed higher per-capita carbon emission level (H.CF 7) and worse air quality (H.CF 8) to be associated with a higher likelihood of choosing an EV (given a higher need in these contexts), more extreme average temperatures (higher temperature variance) with a lower likelihood (H.CF 9), stronger populist tendencies with a lower likelihood (H.CF 10), a higher Green-Party vote share with a higher likelihood (H.CF 11), and worse public-transport infrastructure with a higher likelihood of choosing an EV (H.CF 12). Socio-demographic variables served as control variables across the relevant models. The full set of preregistered hypotheses is summarised in **Table 3.4**, organised by the components of **Figure 2.2**.

Table 3.4 Preregistered Hypotheses Organised by the Components of the Extended Campbell Paradigm. + indicates an assumed positive effect, – an assumed negative effect, and * hypotheses that apply to all car types.

Level	ID	Predictor	Hypothesised effect on the likelihood of choosing the (electric) vehicle
Car & context attributes	H.CA 1	Purchase price	– *
	H.CA 2	Operating costs (fuel/electricity)	– *
	H.CA 3	Range	+ *
	H.CA 4	Charging infrastructure	+
	H.CA 5	Emission-mitigation potential	+
	H.CA 6	EV diffusion in country	+
Individual differences	H.ID 1	Environmental attitude	+
	H.ID 2	Social norms (descriptive & injunctive)	+
	H.ID 3	Temporal discounting	Stronger discounting strengthens the purchase-price effect and weakens the operating-cost effect (moderation).

Level	ID	Predictor	Hypothesised effect on the likelihood of choosing the (electric) vehicle
Country-level factors	H.CF 1	EV diffusion (objective descriptive norm)	+
	H.CF 2	Policy landscape (injunctive norm)	+
	H.CF 3	Installed EV chargers	+
	H.CF 4	Share of renewables in electricity mix	+
	H.CF 5	Electricity price	–
	H.CF 6	GDP	+
	H.CF 7	Per-capita carbon emissions	+
	H.CF 8	(Deaths associated with bad) Air quality	+
	H.CF 9	Temperature extremity (variance)	–
	H.CF 10	Populist tendency	–
	H.CF 11	Green-Party vote share	+
	H.CF 12	Public-transport infrastructure	–

Psychological predictor scores. Before testing the hypotheses, we computed the scores for our psychological variables as preregistered. In line with the Campbell paradigm, environmental attitude was estimated with a dichotomous Rasch model fitted to the GEB items, and each respondent's environmental-attitude score was the person parameter estimated from the calibrated model using a Maximum Likelihood algorithm (Kaiser & Lange, 2021; Kaiser & Wilson, 2004). The score ranged from -4.18 to 4.92 across all countries and showed sufficient reliability in most countries ($.56 \leq r_{WLE} \leq .73$). The temporal discounting score was computed as the number of times a respondent preferred the immediate gain or the delayed loss across tasks, yielding a discounting score from 0 (always preferring delayed gains/earlier losses) to 19 (always preferring immediate gains/delayed losses). Items not presented because of test adaptivity were imputed under the assumption of transitivity of temporal preferences (i.e., someone who prefers receiving 100€ now over 120€ in a year should also prefer 110€ now over 120€ in a year; Ruggeri et al., 2022). The injunctive norm score was computed based on the mean of the three corresponding items. For the descriptive norms, we used two scores by simply taking the responses to the two respective items.

Analyses for hypotheses. The outcome variable is DCE car choice, a categorical variable with five options (the four cars and the no-choice/opt-out option), and the data are nested (choices within participants within countries). As preregistered, we adopt two different modelling approaches because no single readily available R-package combines multinomial regression models with random effects at several levels efficiently. To estimate the effects of the car and context attributes (their main effects and the interactions between context attributes and vehicle type; H.CA 1-6), we used a multinomial mixed-effects model (mlogit Croissant, 2020), which was also used to estimate the adoption rate boundaries for the soft-link with the IAMs. To estimate the effects of the individual-

and country-level predictors (H.ID 1–3, H.CF 1–12), we used logit mixed-effects models that include the DCE attributes as well as our hypothesised factors as predictors and random intercepts for participant and country (in lme4; Bates et al., 2015). As they treat each car option in the DCE as reflecting one trial (i.e., car option 1 chosen/not chosen, car option 2 chosen/not chosen, etc.), logit mixed-effect models cannot accurately account for the dependence between options in the same choice set, which biases the estimation of the DCE attributes. We accept this shortcoming as the focus is on individual- and country-level predictors in these models.

For the multinomial mixed-effects models, we tested a single configuration including all DCE attributes and the interaction of the contextual attributes – charging infrastructure, emission savings from EV, and EV diffusion in the country – with car type. In addition, we accounted for the opt-out option by including alternative-specific constants (ASCs) for the three car types, representing the average preference for the car types over the opt-out option. We also included a random intercept for participant and country and ran the model separately for each country to account for between-country differences in predictor effects.

Before computing the logit mixed-effect models for individual- and country-level predictors, all numerical variables were z-standardised[1]. For individual-level predictors, we tested a single model including all predictors at the same time as well as the DCE attributes. For country-level predictors, we also included the DCE attributes and first added each predictor independently (Model 1), then jointly with socio-demographic variables (Model 2), and finally jointly with socio-demographic variables and other country-level predictors (Model 3). We checked multicollinearity at every step as some of the country-level predictors were strongly correlated. This led to different Model 3 configurations depending on the predictor.

Psychological hypotheses were tested as interactions: environmental attitude and social norms were interacted with vehicle type (H.ID 1 and 2) and temporal discounting with the monetary attributes (H.ID 3). The country-level hypotheses (H.CF 1–12) were tested as interactions between the country-level predictor and vehicle-type.

Analyses for the behavioural module. The behavioural module is built on the multinomial regression model used for the attribute hypotheses, by using the converged regression model to estimate adoption rates. In this model the utility of each alternative is a function of the car and context attributes, with the opt-out alternative serving as the reference (utility fixed to zero). The model further includes interactions of price and range with car type to account for differences in their effect between EV and ICEVs. For any combination of DCE attribute values (a "scenario context"), the model returns the choice probability for each vehicle type. This probability is the predicted EV adoption rate for that scenario, and we computed 95% confidence intervals to provide EV adoption rate boundaries for the soft-link process (see **Section 4.3** for more details). Which attributes are represented in the prediction table for the IAM depends on the configuration of each IAM

Crucially, although the predicted adoption rates that are handed to the IAMs are expressed as a function of car and context attributes, the predictions implicitly carry the full set of predictors postulated in **Figure 2.2**. This works through three mechanisms. First, regarding the social context, descriptive norms are represented explicitly and dynamically with each alternative's utility depending on the current EV diffusion (for the adoption rate estimation, we used each country's 2024 EV registration share as the starting value for descriptive norms, and then used the adoption rate estimated in the respective previous year for all other years; see **Section 4** for more details). Second, regarding the personal-motivation and information-processing components (environmental attitude and

[1] For models estimating country-level predictor effects, we additionally centered individual-level predictors within each country to attenuate multicollinearity between predictors on the two levels (e.g., household income tends to be higher in countries with higher GDP).

temporal discounting) and the individual-level contextual factors (socio-demographics), estimated adoption rates represent an average of the behaviour of the people who actually made choices in our experiment. As this behaviour was driven by all these factors, the estimates implicitly account for them. Where an IAM does represent population heterogeneity (e.g., income deciles or age groups), the same model can also produce subgroup-specific adoption rates by evaluating the relevant person characteristics, so the heterogeneity postulated in **Figure 2.2** can be made explicit on demand. Third, regarding the higher-level contextual factors, the country-specific coefficients absorb macro-level conditions (e.g., charging infrastructure, policy, electricity price, energy mix, climate, and cultural dimensions), so that the same DCE attributes yield different adoption rates in different national contexts. Taken together, the prediction step, therefore, does not discard the psychological and contextual structure of the framework: the car and context attributes are the visible inputs, but the motivational, cognitive, and contextual influences of **Figure 2.2** are retained.

3.2 Sample

Participants were recruited via the panel provider Dynata and were sampled based on representative quotas on age, gender, and region (NUTS-1 or NUTS-2). Participants were contacted via email that contained a link to our online survey, and participants who completed the survey were compensated by the panel provider. The compensation level was determined by the panel provider in line with standard survey compensation. **Table 3.5** gives an overview of the 15 countries in which we collected data. The oversampling in Czechia, Greece, and the UK is the consequence of an inadequate sampling strategy by the panel provider (i.e., simultaneously inviting many new participants, so that quota checks are not effective).

Table 3.5 Country Selection for Sampling Process

Country	*N*	Cluster	Other countries from cluster
Austria	392	Cluster 1	Estonia, Malta
Bulgaria	409	Cluster 3	Croatia, Cyprus, Latvia, Romania
Czechia	439	Cluster 4	Hungary, Slovakia, Slovenia
Denmark	392	Cluster 5	Finland, Sweden
France	395	Cluster 6	-
Germany	397	Cluster 6	-
Greece	458	Cluster 3	Croatia, Cyprus, Latvia, Romania
Italy	434	Cluster 7	Spain
Lithuania	401	Cluster 3	Croatia, Cyprus, Latvia, Romania
Netherlands	381	Cluster 2	Belgium, Ireland, Luxembourg
Norway	401	Cluster 5	Finland, Sweden
Poland	399	Cluster 4	Hungary, Slovakia, Slovenia
Portugal	407	Cluster 3	Croatia, Cyprus, Latvia, Romania

Country	*N*	Cluster	Other countries from cluster
Switzerland	393	Cluster 2	Belgium, Ireland, Luxembourg
UK	506	Cluster 7	Spain

We decided to collect data in only 15 of the 30 potential countries (EU27 + CH, NO, UK) to balance representativeness and tractability of results. Country selection was based on a cluster analysis including variables like GDP, climate change vulnerability, income inequality, and classifications from previous EV-related studies (e.g., Aral & López-Sintas, 2023; Engwerth et al., 2025; Möring-Martínez et al., 2024). In the final country selection, we have at least one country representative for each of the seven clusters, so we are able to reasonably extrapolate (by assuming the same behavioural effects of relevant predictors in matching countries) from these representative countries to other cluster members. We also ensured broad geographical coverage in our country sample. The visualisation of the cluster analysis results can be found in **Figure 3.3**.

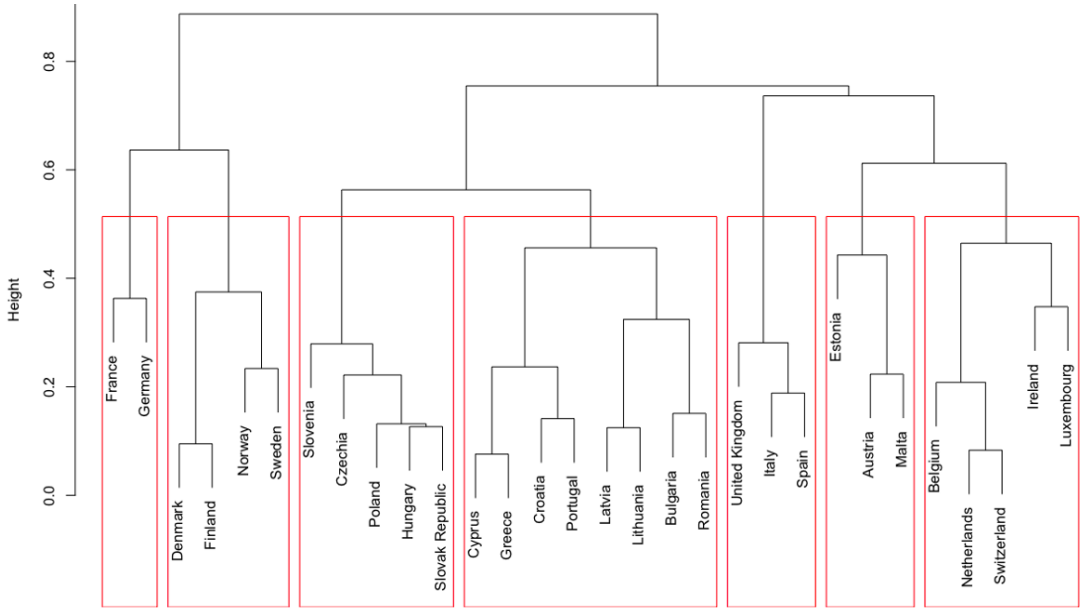


Figure 3.3 Dendrogram Country Cluster Analysis. Countries were clustered using agglomerative hierarchical clustering with complete linkage, based on Gower distances computed across 13 country-level indicators (e.g., GDP, climate change vulnerability, income inequality) to accommodate the mix of continuous and categorical variables. The red boxes mark the seven-cluster solution obtained by cutting the dendrogram at $k = 7$, which was supported by a silhouette analysis yielding a mostly positive silhouette profile and an average silhouette width of 0.35 (compared to 0.33 for six clusters). While this average is rather low (Kaufman & Rousseeuw, 2009), we do not claim that we can accurately cluster all European countries into seven groups, but we needed an indication of which countries might be similar. By assessing multiple countries in larger clusters, we further increase the representativeness of sampled countries for unsampled countries, although low overall similarity within clusters should be viewed as a limitation.

The final sample comprised $N = 6{,}204$ participants, with all participants holding a driver's licence, an eligibility criterion for the study. In line with the sampling targets, the sample was broadly representative of the national populations in terms of age and gender. Participants ranged from 18 to 86 years of age ($M = 46.7$, $SD = 15.2$), with very similar age distributions across countries (country means ranging from about 45 to 48 years). Gender was almost evenly split (50.5% women, 49.4% men, with 4 participants reporting another category or no answer), and this balance varied between countries based on the actual population distribution (from 48.6% women in the UK to 52.4% women in Switzerland).

Beyond quota variables, household income was assessed on a 10-point scale (country-specific income brackets based on income deciles described in DIAMOND deliverable D4.3). Our sample is skewed towards higher income groups (see **Figure 3.4**), most strongly in lower-income countries (i.e., Bulgaria, Czechia, Greece, and Poland), but also in some higher-income countries (i.e., Denmark, Germany, Switzerland, and the UK). Whether this actually reflects such extreme income skewness is questionable, as we only received average income per income decile from CESAR and not the decile boundaries. We assume that our boundary-generating process increased the size of the higher-income deciles (by including larger income ranges there), which could partly explain the extreme skewness in **Figure 3.4**. Roughly half of participants lived in urban areas (47%), with the remainder in suburban (26%) and rural (27%) areas. Self-reported political orientation (1 = left to 7 = right) averaged near the scale midpoint (M = 4.27, SD = 1.85; available for 4,995 participants). The large majority of participants had access to a car (94%), and most expressed a preference for medium-sized vehicles (58% vs. 24% small and 19% large).



Figure 3.4 Income Deciles by Country. For country-specific sample sizes, see **Table 3.5**.

3.3 Results

In the following subsections, we will briefly present the findings for the preregistered hypotheses that also underly the behavioural module, including descriptive findings, validity checks of the DCE outcomes, and results from mixed-effect models

3.3.1 Descriptive Results

Before the DCE, we assessed the general opinion our participants have about EVs (*To what extent do you consider buying an electric vehicle in the upcoming 10 years?* 1 = *Under no circumstances*, 7 = *Absolutely yes*, 8 = *I already own an electric vehicle*). Only 221 participants (3.6% of the sample) indicated already owning an EV, while the majority of participants answered with one of the lowest three categories (n = 3,128; 50.4%), indicating a general hesitancy towards EV adoption. This finding is corroborated when descriptively investigating our participants' behaviour in the DCE. Out of the 18 total choices, participants on average chose an EV option in 28.6% of the trials, an ICEV in 39.3% of the trials (gasoline: 21.6%; diesel: 17.7%), and the opt-out in 32.1% of the trials.

Turning to the psychological predictors, environmental attitude and temporal discounting approximate normal distributions in the full sample. For temporal discounting, the full range of the measure is covered, indicating that some people never preferred delayed gains, while others always preferred them. Our social norm measures provide two interesting descriptive insights: pro-EV injunctive norms seem to be stronger in countries that currently have higher EV adoption rates (e.g., Denmark, Norway, and the UK), while the actual EV share itself is overestimated in all countries (representing descriptive social norms; see **Figure 3.5**).

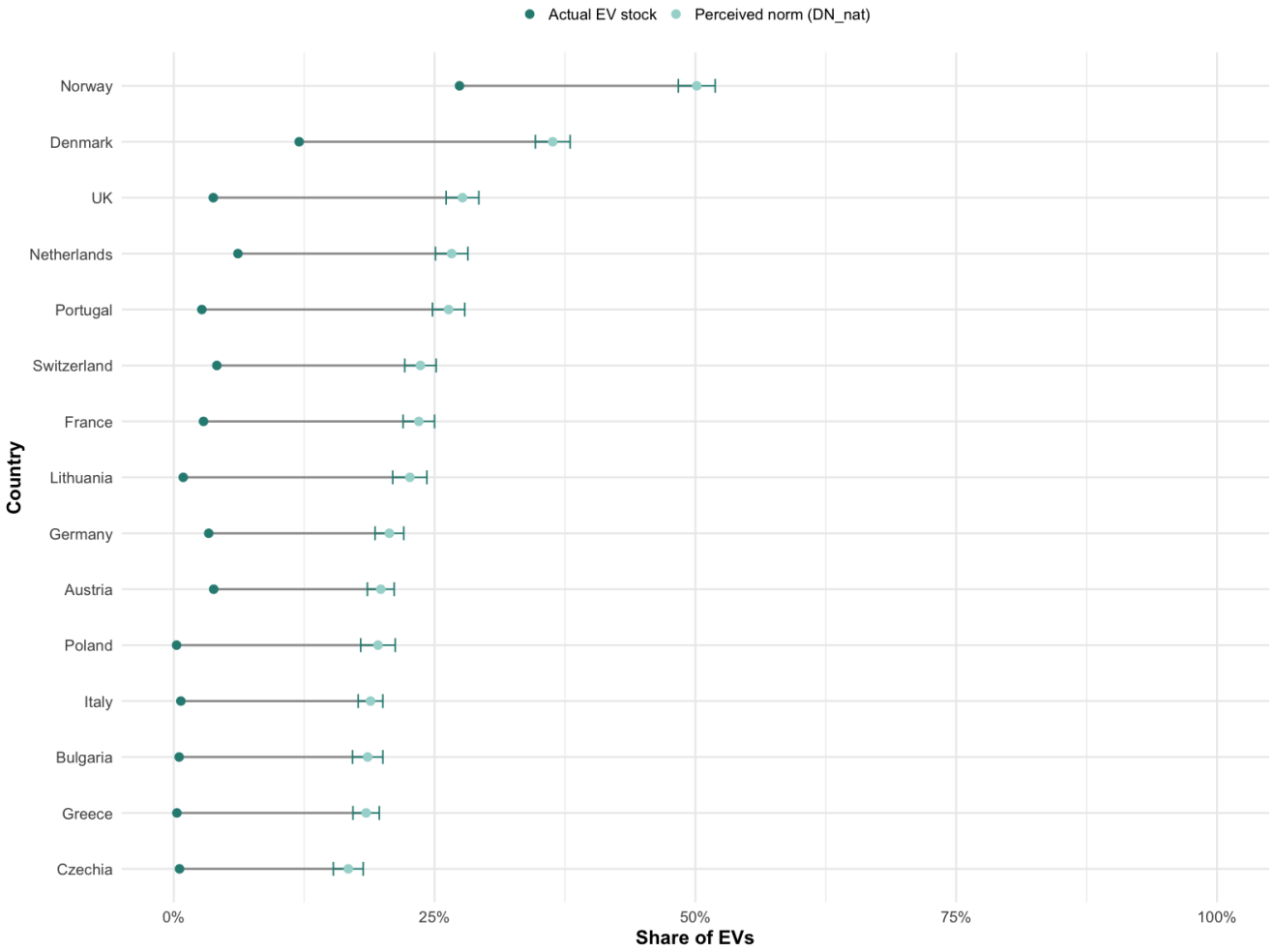


Figure 3.5 Nation-Specific Descriptive Norms. The actual EV stock refers to the current EV share in all registered passenger vehicles. Perceived norm (DN_nat) represents the average answer participants provided when asked to estimate the EV share in their country. The bars represent 95% confidence intervals. For country-specific sample sizes, see **Table 3.5**.

3.3.2 Validity Checks

To assess whether the survey responses are reasonable and match actual behaviour, we applied some validity

checks. The DCE choices are not directly comparable with current national EV shares, as the DCE attributes also reflect future contexts which are more favourable for EV adoption than the current context in most countries. We, therefore, computed the correlation between the share of EV choices in the DCE and the share of EVs for newly registered passenger cars on the country level. The moderate-to-strong correlation (r = .57, p = .03) suggests a substantial link between actual behaviour in the countries we investigated and behaviour in our experiment (see also **Figure 3.6**). The red line in the figure shows where the dots should have been located if the relation was perfect. The line further demonstrates in which countries EV adoption rates are underestimated based on the DCE (dots to the right of the red line) and in which countries they are overestimated (dots to the left of the red line). Here, we find a clear pattern that in countries that already have favourable conditions for EV adoption (Norway, Denmark, Netherlands), EV adoption is underestimated, while it is overestimated in currently less favourable contexts like Czechia or Portugal.

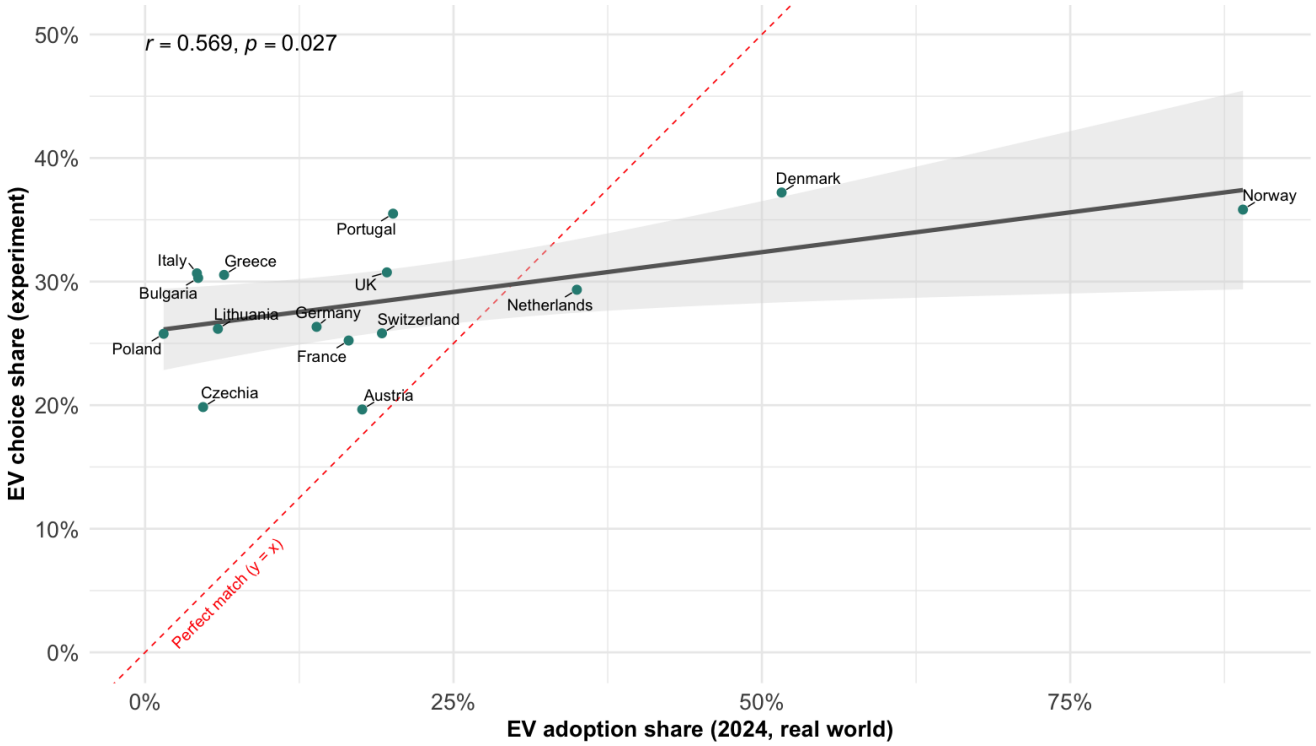


Figure 3.6 Relation Between EV Choice Share in Experiment and Real-World EV Adoption Share. The actual EV adoption share refers to the current EV share of all newly registered passenger vehicles. The grey area around the regression line represents the 95% confidence interval for the relation, and the dotted red line represents the line if both variables were perfectly correlated. For country-specific sample sizes, see **Table 3.5**.

We similarly investigated the validity of our temporal discounting measure by relating it to a common correlate on the country level, GDP. Previous studies have repeatedly shown a negative relation between GDP (and individual income) and country-averaged temporal discounting. Explanations range from cognitive resource scarcity (people with less income have different things to worry about and can spend less cognitive resources on accurately evaluating financial outcomes), to adaptive behaviour (people with less income need to take care of immediate financial costs necessary for survival and cannot wait for future gains), and bidirectionality (people are wealthier because they engage in less temporal discounting). Our findings align well with previous literature given the moderate-to-strong correlation between GDP and temporal discounting (r = -.56, p = .03; see also **Figure 3.7**).

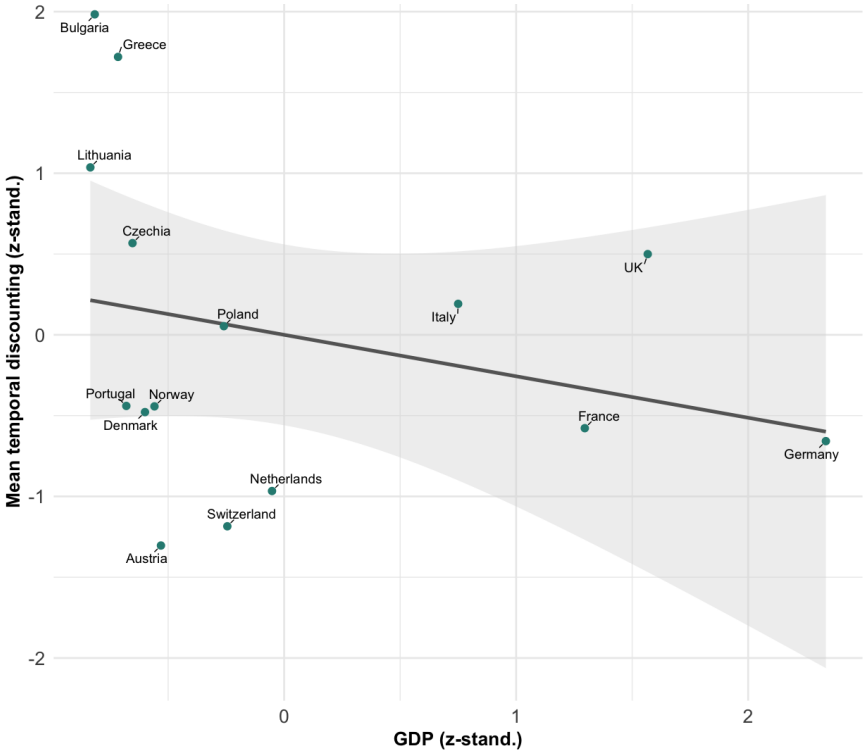


Figure 3.7 Relation Between Temporal Discounting and GDP. The grey area around the regression line represents the 95% confidence interval for the relation. For country-specific sample sizes, see **Table 3.5**.

3.3.3 DCE Attributes as EV Adoption Drivers

The car and context attributes in the DCE constitute the most important aspect of this study as their effects are the empirical foundation of the EV version of the behavioural module. **Figure 3.8** gives an overview of the corresponding regression model. When controlling for all the other attributes, EVs are generally preferred over the opt-out option and diesel vehicles as indicated by the ASCs, while there is no significant difference in the effect of gasoline vehicles compared to EVs. The other car attributes have the hypothesised effects on the likelihood of choosing a car. Independent of the car type, higher car prices and operating costs make it less likely that an option is chosen, while higher vehicle ranges increase the likelihood.

The effects of the contextual attributes – EV emission savings, EV charging infrastructure, and country-level EV diffusion – are less clear. Emissions worked in the opposite direction that we expected: the more emissions one saves by driving an EV compared to a gasoline vehicle, the less likely it is to choose an EV and a diesel vehicle over a gasoline vehicle, while there is no effect on choosing a gasoline vehicle over no vehicle. Taken together, higher EV emission savings increase the relative share of gasoline vehicles and opt-out decisions. For charging infrastructure, we find that more EV chargers increase the preference for EVs over opting out, but the same applies to gasoline over opt-out choices (and to a much smaller degree also to diesel vehicles). So, better EV charging infrastructure does not necessarily lead to an increased EV share as gasoline vehicle choices are also positively affected by it in our sample. Finally, EV (as well as gasoline and diesel) adoption in our experiment was not related to the diffusion attribute of the DCE (10%, 35%, 60% EV share in country).

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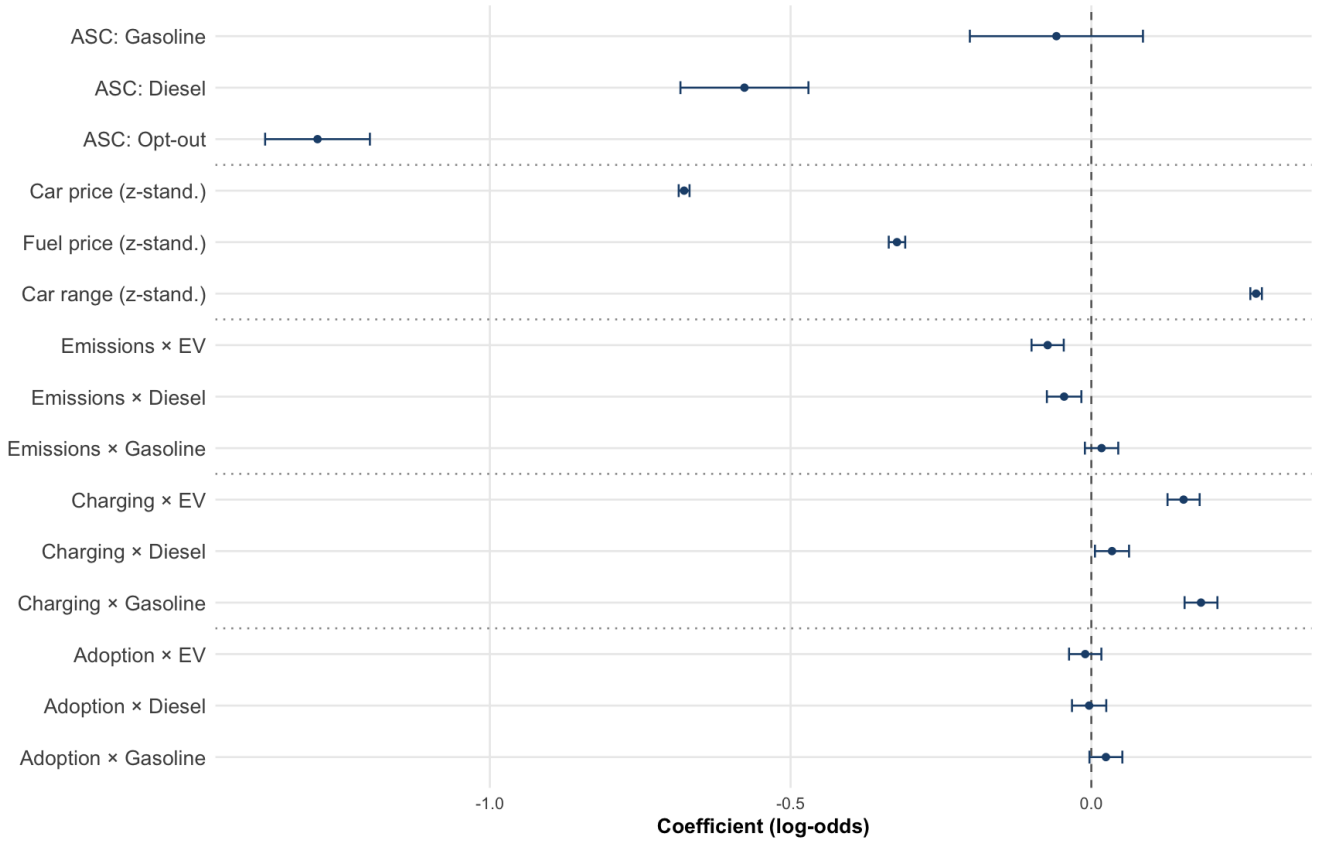

Figure 3.8 Effect of DCE Attributes on Choice. *N* = 6,204. The bars represent the 95% confidence interval for the effect. ASCs refer to alternative specific constants which represent the average preference of gasoline, diesel, and opt-out options over EVs. The effects were estimated in a multinomial mixed effect model including random effects of the ASCs on the individual and country level which correspond to random intercepts in logit or linear mixed effect models. McFadden's pseudo-R^2 = .32, relative to an ASC-only null model (without random effects).

The random ASCs estimated in the mixed-effect model provide additional insights into how the countries differ in adoption decisions. **Figure 3.9** displays them, computed as the pooled fixed-effect ASC (red dotted line) plus each country's random deviation, with the dashed line at zero marking indifference relative to EVs. Countries vary more in their gasoline ($SD_{random_gasoline}$ = 0.25) and diesel (SD_{random_diesel} = 0.16) constants than in their average opt-out preferences over EVs ($SD_{random_opt\text{-}out}$ = 0.11). In the opt-out panel the points cluster tightly around the pooled value, indicating low country-level variation in the general tendency to choose an EV over no car. For the gasoline and diesel contrasts, the country ordering is broadly consistent across the two panels: countries such as Portugal, Denmark, and Norway show the most EV-favourable constants (furthest left, i.e. the weakest relative preference for ICEVs over EVs), whereas Czechia, Lithuania, and Austria show the least EV-favourable constants. The Netherlands stands out by preferring gasoline vehicles over EVs while they on average are much more likely to choose an EV over a diesel vehicle compared to the whole sample.

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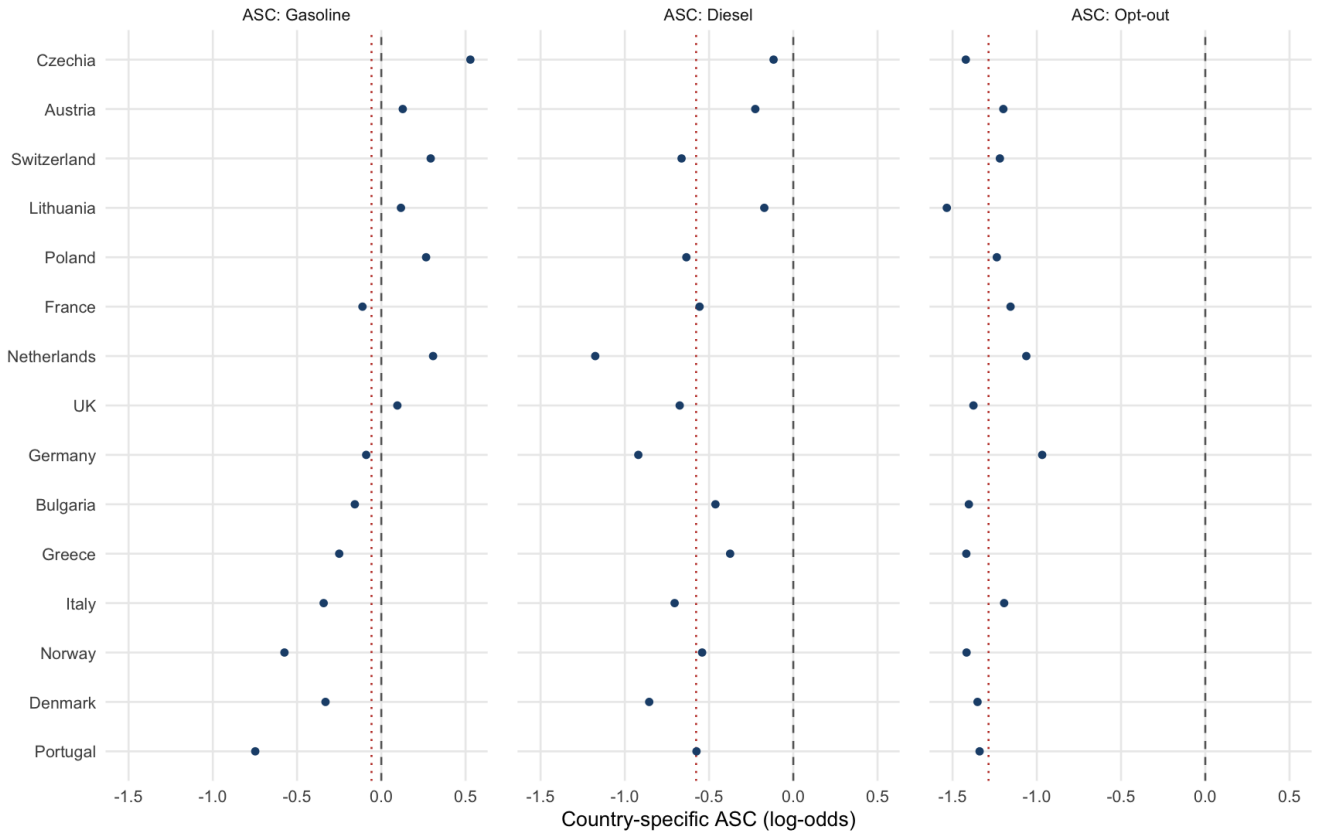

Figure 3.9 Country-Specific Effects of Car Type in DCE. *N* = 6,204. ASCs refer to alternative specific constants which represent the average preference of gasoline, diesel, and opt-out options over EVs. The effects were estimated in a multinomial mixed effect model including random effects of the ASCs on the individual and country level, which correspond to random intercepts in logit or linear mixed effect models. The model also included all other DCE attributes and is the same model that is presented in **Figure 3.8**. McFadden's pseudo-R^2 = .32, relative to an ASC-only null model (without random effects).

3.3.4 Individual Predictors as EV Adoption Drivers

Next, we tested how individual-level predictors – psychological (environmental attitude, social norms, and temporal discounting) and socio-demographic variables – relate to car choice. These effects were estimated in a logit mixed-effects model that included all individual-level predictors simultaneously, together with the DCE attributes, with each predictor interacted with vehicle type so that its effect on choosing an EV, diesel, or the opt-out option (each relative to the gasoline vehicle) can be extracted. **Figure 3.10** displays the resulting coefficients. Overall, the individual-level predictors behaved largely as hypothesised and explained a substantial amount of variance in car choice (McFadden's pseudo-R^2 = .46).

Two psychological predictors showed the expected pattern (supporting H.ID 1 and H.ID 2). A stronger environmental attitude increased the likelihood of choosing an EV or the opt-out option over a gasoline vehicle, consistent with the motivational component of the Campbell paradigm. Both norm types were positively associated with EV choice: the injunctive norm showed the strongest individual-level effect in the model, and descriptive norms (referenced to the country and to the respondent's income group) were also positively related to choosing an EV. We did not include the three social norm variables at the same time, but computed three different models. The coefficients of the other individual-level predictors were not affected by which social norm variable was included, so we present only the coefficients from the model including injunctive social norms for them.

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Temporal discounting was the one exception to our predictions (H.ID 3). We had expected that stronger temporal discounters would weight the immediate purchase price more heavily and the temporally distant operating costs less heavily; instead, respondents with higher temporal discounting reacted more strongly to both monetary attributes, that is, they took operating costs more rather than less strongly into account in their car choices. The hypothesised asymmetry between immediate and delayed monetary consequences, therefore, did not emerge.

Among the socio-demographic predictors, higher income was associated with a higher likelihood of choosing an EV, and older respondents were more likely to opt out of choosing any car. A more right-leaning political orientation was associated with a lower likelihood of choosing an EV and a generally larger preference of gasoline vehicles. Effects of gender and place of residency (suburban or rural vs. urban) were small. Taken together, the individual-level results reinforce the core Campbell-paradigm predictions – environmental motivation and social norms drive EV choice – while temporal discounting seems to make people generally more sensitive to monetary signals.

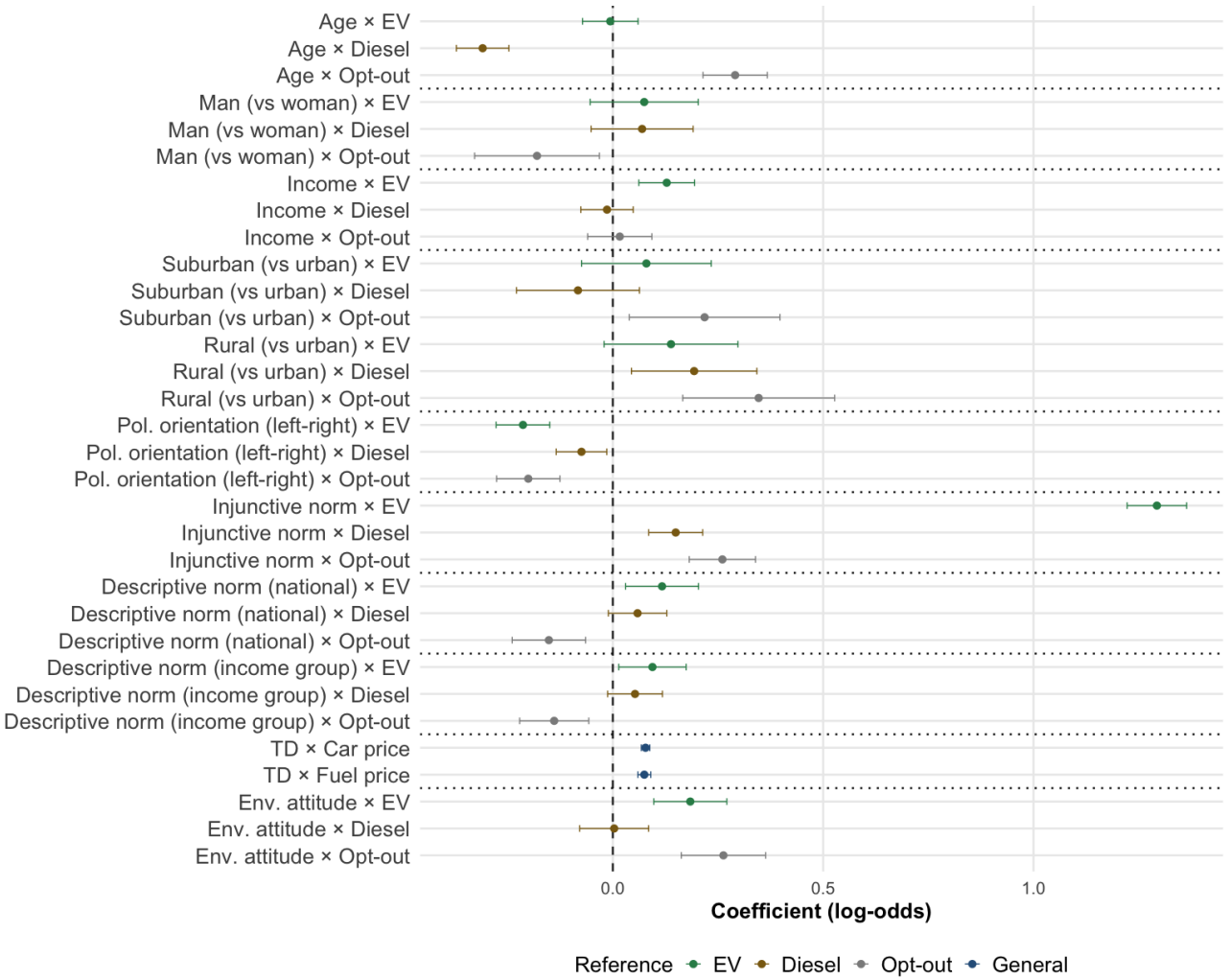

Figure 3.10 Individual-Level Predictors of Car Choice. *N* = 6,204. Points are coefficients (log-odds) and bars the 95% confidence intervals from a logit mixed-effects model that included all individual-level predictors and the DCE attributes simultaneously. Each predictor was interacted with vehicle type, so coefficients represent the effect on choosing an EV (green), diesel (brown), or opt-out (grey) vehicle relative to a gasoline vehicle. The interactions of temporal discounting with car and fuel price are not car type specific. Continuous predictors were z-standardised. TD = temporal discounting; Env. attitude = environmental attitude. The model included random alternative-specific constants at the individual level. McFadden's pseudo-R^2 = .46, relative to an ASC-only null model (without random effects).

3.3.5 Contextual Predictors as EV Adoption Drivers

At the highest contextual level, we tested how 19 country-level factors relate to EV choice (H.CF 1 to 12; for some hypotheses, we have more than one indicator, and for other country-level predictors, we did not have hypotheses). Each predictor was entered as its interaction with vehicle type in a logit mixed-effects model and tested in a stepwise fashion: first jointly with the DCE attributes (Model 1), then additionally with individual-level socio-demographic variables (Model 2), and finally together with the remaining country-level predictors that survived the multicollinearity checks (Model 3). **Figure 3.11** shows the estimated effect on EV choice for each predictor under these specifications. Because only 15 countries provide variation at this level and several macro-indicators are strongly correlated, the country-level estimates are less precise and more sensitive to model specification than the individual-level effects, and should be read as indicative rather than definitive.

The predictors most central to our hypotheses pointed in the expected direction. A higher current EV diffusion in the country (the objective descriptive norm; H.CF 1), a more supportive EV-related policy landscape (H.CF 2), and a higher share of renewables in the electricity mix (H.CF 4) were each associated with a higher likelihood of choosing an EV. The political-context predictors partly matched expectations: a higher populist vote share and a populist party in government (when included as the only country-level predictor) were associated with a lower likelihood of choosing an EV (H.CF 10), while green-party vote share was not robustly related to more EV adoption. Predictors capturing public-transport quality – the share of passenger trips covered by public transport and railway density – were negatively associated with EV choice, consistent with the idea that weaker public-transport alternatives raise private-vehicle (including EV) uptake (H.CF 12). The coefficients associated with mean annual temperature and variability in annual temperatures showed the expected directions in line with previous literature (H.CF 9): higher average temperature was associated with higher likelihood to choose an EV, while more temperature variability was associated with less EV choices.

Some predictors were sensitive to the model specification. Most strikingly, installed charging infrastructure (H.CF 3) showed essentially no association with EV choice once the DCE attributes and socio-demographics were accounted for, but turned strongly negative in the fully adjusted model with the other correlated country-level predictors – a pattern that most likely reflects collinearity with EV diffusion and policy. Similarly, the effect of per-capita carbon emissions (H.CF 7) turned from negative in the first two model configurations to positive when including the country-level baseline predictor set – the hypothesised direction. Electricity price was negatively related to EV choice (H.CF 5), as hypothesised. GDP (H.CF 6) showed only a small, specification-dependent association. Overall, and in line with previous literature, the country-level results were largely consistent with our hypotheses, with the strongest and most robust effects observed for EV diffusion, policy landscape, energy mix, political context, public-transport provision, and temperature indicators. Exceptions include air quality (H.CF 8; non-significant), GDP, per-capita carbon emissions, and green-party vote share. Interestingly, charging infrastructure was either not significantly or negatively associated with EV choice. This is opposite to what we hypothesized, but partly in line with the findings for the DCE charging infrastructure attribute (better charging infrastructure also increasing ICEV adoption).

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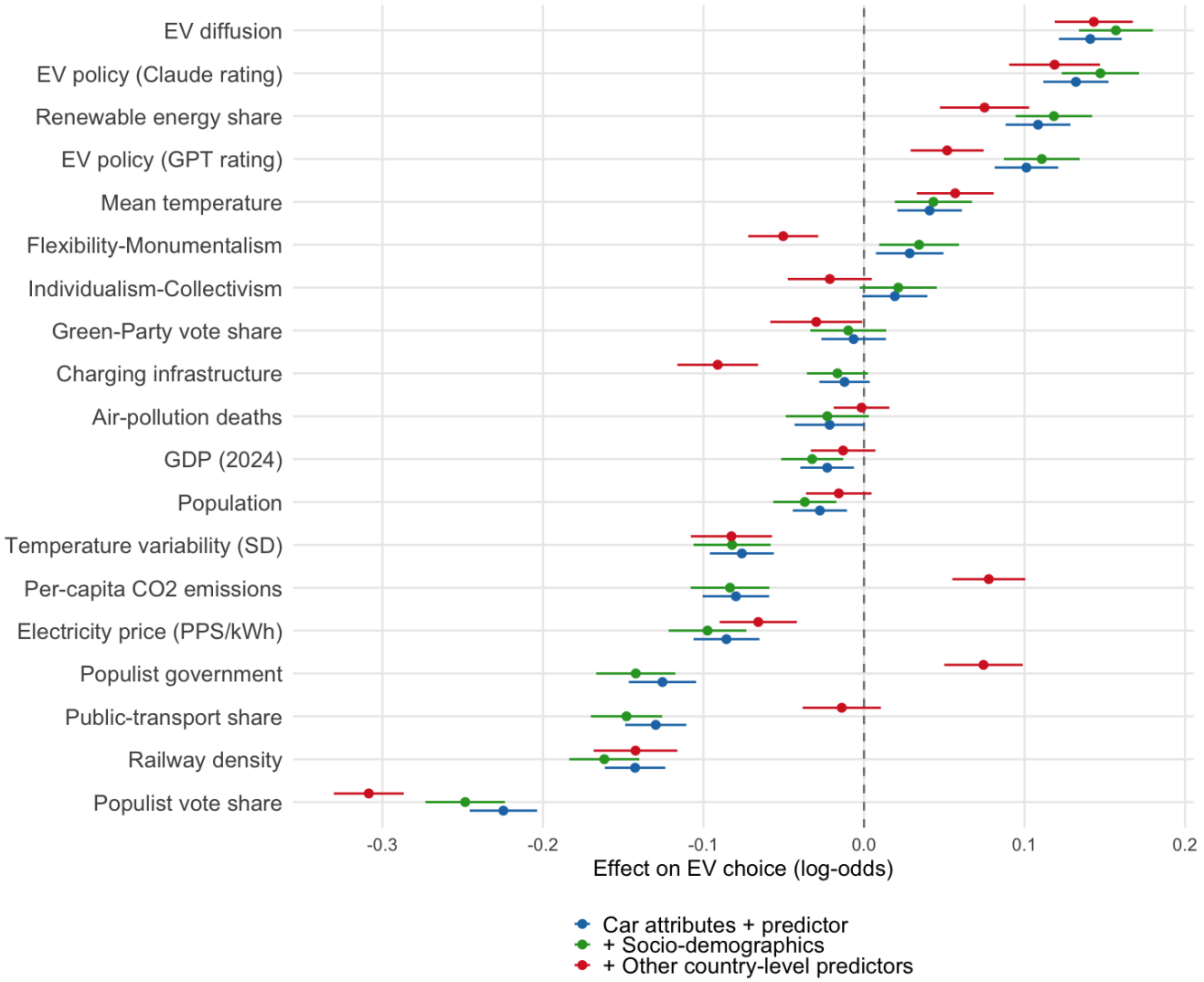

Figure 3.11 Country-Level Predictors of EV Choice. *N* = 6,204 respondents in 15 countries. Points are coefficients (log-odds) and bars the 95% confidence intervals for the effect of each country-level predictor on EV choice (predictor × vehicle type), estimated in logit mixed-effects models. Colours denote the model specification: the predictor jointly with the DCE attributes (Model 1), additionally with socio-demographic variables (Model 2), and together with the remaining (collinearity-screened) country-level predictors (Model 3). All predictors were z-standardised. Because only 15 countries provide variation at this level and several indicators are highly correlated, estimates are less precise and more specification-dependent than the individual-level effects. We also do not present an R^2-estimate here, as each model has its own value. We used EV policy evaluations from Claude and ChatGPT to get a measure that is comparable across countries. The evaluation was prompted to be based on https://alternative-fuels-observatory.ec.europa.eu/transport-mode/road and the LLMs were prompted to rate each country on a numerical index between 0 and 10 as well as provide extensive justification.

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4 Behavioural Module and Soft-Link

4.1 General Description of the Behavioural Module

The general idea of the behavioural module is to provide realistic boundaries for behavioural adoption based on psychological data that is linked to behavioural characteristics (e.g., costs) represented in IAMs. The multi-level structure of the psychological model underlying the module (see **Figure 2.2**) provides information on which factors drive climate-relevant behaviours, and can be used to provide different explicit behavioural modules depending on the target behaviour and corresponding IAM structure. When data is available for each factor in the same sample, we are able to create a behavioural module version that provides behavioural adoption boundaries for different population groups (defined by their psychological and socio-demographic characteristics as well as country or region of residency) at different points in time, given different contextual conditions (including technology characteristics, and country-level factors like temperature and infrastructure). In the reported study, we focused on one climate-relevant behaviour – EV adoption – and use the corresponding data to create IAM-specific behavioural module versions with different resolutions regarding geography and technology characteristics.

In our underlying DCE (see **Section 3.1.2**), the outcome variable "car choice" is a multinomial variable with five response options (Cars 1-4 and none of the cars). Hence, we used multinomial mixed-effect models to estimate the adoption rate boundaries necessary for establishing soft-links with the IAMs. A converged multinomial mixed effect model allows the estimation of adoption rates for every possible DCE attributes combination (and also for every possible population group defined by psychological and socio-demographic variables, as well as changing country characteristics) based on the regression coefficients. Given the lack of representing actor heterogeneity within IAMs themselves and in the pursuit of keeping a first version of the behavioural module simple, we focused solely on the DCE attributes as well as EV diffusion on the country-level as EV adoption predictors. These estimates with corresponding confidence intervals as well as the conditions that produced them (i.e., the car and context attributes) can be compiled in a table (see **Figure 4.1** for an example). Importantly, when an IAM does not include a specific car or context attribute (e.g., battery range or charging infrastructure), the estimates can be averaged across this attribute, leading to larger confidence intervals for a specific car-context combination.

Year	Country	Purchase price EV	Purchase price ICEV (petrol)	Purchase price ICEV (diesel)	Electricity costs (/100km)	Petrol costs (/100km)	Diesel costs (/100km)	Diffusion in country (at t-1)	EV range	Carbon reduction potential (EV)	Charging infrastructure	EV Adoption Rate	
												Lower Bound	Upper Bound
2025	Austria	40'800 €	13'600 €	13'600 €	3,80€	5,80€	4,00€	10%	200km	30%	low	0%	1%
2025	Austria	40'800 €	13'600 €	13'600 €	3,80€	5,80€	4,00€	10%	200km	30%	medium	1%	3%
2025	Austria	40'800 €	13'600 €	13'600 €	3,80€	5,80€	4,00€	10%	200km	30%	high	2%	3%
2025	Austria	40'800 €	13'600 €	13'600 €	3,80€	5,80€	4,00€	10%	300km	30%	low	1%	2%
2025	Austria	40'800 €	13'600 €	13'600 €	3,80€	5,80€	4,00€	10%	300km	30%	medium	2%	4%
...	...	...	...	...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2100	UK	£16400	£49300	£49300	£3,10	£12,70	£10,90	60%	500km	70%	medium	75%	80%
2100	UK	£16400	£49300	£49300	£3,10	£12,70	£10,90	60%	500km	70%	high	76%	82%
2100	UK	£16400	£49300	£49300	£3,10	£12,70	£10,90	60%	700km	70%	low	80%	86%
2100	UK	£16400	£49300	£49300	£3,10	£12,70	£10,90	60%	700km	70%	medium	82%	88%
2100	UK	£16400	£49300	£49300	£3,10	£12,70	£10,90	60%	700km	70%	high	84%	88%

- Based on multilevel regression models
- Adjustable to specific IAM (i.e., regarding represented variables and temporal resolution)

Constraint on minimum and maximum EV adoption rate (based on context and experiment)

Figure 4.1 Exemplary Output Table based on Behavioural Module

4.2 Updating IAM Assumptions of EV Adoption

The core idea of the behavioural module lies in updating the assumptions of IAMs associated with EV adoption. As postulated in **Section 1** and **2**, EV adoption decisions are complex, multi-faceted processes that are shaped both by the context in which they occur and by the psychological characteristics of the person that makes the decision (Günther et al., 2025). This complex interplay of various factors leads to heterogeneous adoption rates in different sub-populations and even further contextual predictors like technology costs can affect adoption decisions differently in different sub-populations. For example, low-income individuals tend to have higher levels of temporal discounting compared to individuals with higher incomes (Green et al., 1996; Ludwig et al., 2019). In addition, we saw that people that have a stronger tendency to discount future financial consequences rely more strongly on the upfront and operating costs in car purchase decisions (i.e., the purchase price). Combining both tendencies, we would assume that 1) individuals with low incomes have generally lower adoption rates due to limited financial capacity and 2) the financial attributes have a stronger effect on purchase decisions for low-income people compared to people with higher incomes. Such heterogeneous adoption patterns can be represented in our behavioural module as we assess the corresponding person characteristics. But even when we do not disentangle EV adoption rates by different sub-populations for the link with the IAMs that do not represent different groups, the heterogeneity is still implicitly reflected in the projected adoption rate as we collected data from these groups.

Table 4.1 gives an overview of the assumptions underlying the behavioural module as well as the conflicting and converging assumptions of the three IAMs CLEWs-EU, GCAM Europe, and OMNIA. The assumptions of our behavioural module can be clustered into two groups: assumptions related to the underlying psychological model and assumptions related to the DCE. The specific values for the monetary attributes in the DCE were adjusted to the country and the preferred car size of the participants. For the purchase price, we weighed the country-independent technology costs (representing country-independent purchase prices) from the EU Reference Scenario 2020 (European Commission, 2021) by the relative price level of passenger cars (Statista, 2021) in each country ($\frac{M(price\ in\ country)}{M(price\ in\ all\ countries)} \times technology\ costs$). For fuel or electricity costs, we computed three different levels for each country and car size (based on European Commission, 2021 and the Weekly Oil Bulletin from the European Commission, 2024). The three levels represent a minimum value ($lowest\ costs \times highest\ efficiency$), a medium value ($M(costs) \times M(efficiency)$), and a maximum value ($highest\ costs \times lowest\ efficiency$). An overview of the specific values for the monetary attributes can be found in **Tables 6.1** and **6.2**. For a more in-depth explanation of the assumptions from our psychological model, please refer to **Section 2.3**. Following the psychological literature, we assume that humans are boundedly rational and, therefore, rely on heuristics, which can lead to biased perceptions and decision-making. This is reflected in the temporal discounting construct in our module. Furthermore, behaviour is not solely driven by economic considerations, but various motives affect technology adoption decisions which is represented by including environmental attitudes as an important motivational driver of EV adoption. Lastly, behaviour is embedded in a larger context which goes beyond technology costs. Context includes social norms (e.g., current EV diffusion in country or prevalent opinions about EVs), regional factors like charging infrastructure, and national factors like policy and political landscape. We account for all these levels by incorporating a multi-level perspective in the behavioural module. These three core assumptions lead to heterogeneous adoption rates in different population groups and also allow for heterogeneous underlying decision-making processes.

In contrast to our behavioural module and its assumptions rooted in psychological theory and related empirical research, the assumptions of the IAMs are in line with techno-economic research assuming rational cost considerations and homogeneous preferences (Keppo et al., 2021; McCollum et al., 2017; Peng et al., 2021). Again, there are two types of assumptions: which factors determine EV adoption and how do these (technology-related)

determinants change over time. Assumptions on the technological parameters are straightforward, model-specific, and are displayed in **Table 4.1**. Regarding the mechanistic assumptions underlying EV adoption, the three IAMs follow similar approaches. Vehicle adoption is generally driven by demand for mobility (i.e., person or vehicle kilometres) and technology costs. Vehicles are adopted to satisfy mobility demand, and which vehicle types are adopted in what quantity depends on technology costs. Importantly, the models also include emission goals (maximum system-level emissions at specific time steps) that need to be met in the DIAMOND baseline scenario (based on which the soft-link with the behavioural module is evaluated). Taking this into account, EV adoption in the IAMs also depends on how many emissions are still available in the model at a specific time point. For example, CLEWs-EU takes this into account by estimating how expensive mitigation through EV adoption is compared to mitigation through other means in other sectors. If carbon mitigation is cheapest through EV adoption, EV adoption will be increased beyond the diffusion that would occur when only considering technology costs and transportation demands. Unrealistically high EV uptake arises when the transport sector is a cheap source of decarbonisation relative to other sectors under the system-wide carbon constraint. GCAM Europe implements a slightly different approach. The model adds an endogenously derived carbon price to all carbon emitted which in turn affects the fuel and electricity costs. GCAM Europe has another unique assumption, as it assumes an exogenously defined "preference parameter" for the different technologies, which typically is assumed to increase over time for technologies that are still rapidly developing, such as EVs in our case. Even though this parameter could be interpreted as changing behavioural preferences (but also as technological improvements beyond costs), the overall approach in the three IAMs is in contrast to the bounded rationality, heterogeneous preferences assumptions of our behavioural module.

Table 4.1 Overview of Assumptions in the Behavioural Module and Three IAMs

	Assumptions
Behavioural Module	*Psychological assumptions:* - Bounded rationality - Diverse motives for EV adoption (not purely economic) - Embedding of behaviour in diverse contexts (multi-level perspective) - Heterogeneous preferences and decision-making processes *Discrete choice experiment assumptions:* - Purchase price: EU Reference Scenario 2020 assumptions weighed by relative country differences in price - Fuel/electricity costs: EU Reference Scenario 2020 assumptions multiplied by country-specific fuel/electricity cost projections - Range: cover the currently available battery and tank ranges (EV Database, 2025) - Environmental impact: gasoline (August, 2020); diesel (Dornoff & Rodríguez, 2019)
CLEWs-EU	*Economic assumptions:* - Technology adoption driven by a. Demand for vehicle kilometres (JRC-IDEES-2021) b. Technology costs c. Emissions in the system *Data assumptions:* - Purchase price: EU reference scenario assumptions - Fuel/electricity costs: Weekly Oil Bulletin from the European Commission

	Assumptions
GCAM Europe	*Economic assumptions:* - Technology adoption driven by a. Demand for person kilometres b. Technology costs c. Emissions in the system through endogenously derived carbon price d. Exogenous "preference parameter" *Data assumptions:* - Purchase price: will be based on the updated model version - Fuel/electricity costs: will be based on the updated model version
OMNIA	*Economic assumptions:* - Technology adoption driven by a. Demand for person kilometres b. Technology costs c. Emissions in the system *Data assumptions:* - Costs depend on the time period (EU reference scenario assumptions)

4.3 General Soft-Linking Approach

We follow a two-step soft-linking procedure to increase the realism of how EV adoption is modelled in IAMs (for an overview, see **Figure 4.2**). The first step – a prerequisite step that enables the soft-link – is making sure that the DCE and the IAMs have shared technical assumptions. For example, purchase prices included in the DCE should cover the range of technology costs in the IAMs. Prior to designing the experiment, we approached the modelling teams and asked which EV attributes and what levels of these attributes are represented in the IAMs in order to adjust the attribute levels of our experiment accordingly. The idea was not to perfectly mirror each level, but to cover the whole range accounted for in the IAMs (e.g., minimum and maximum purchase price of EVs) as we can extrapolate adoption rates for values in between. We needed to make some additional adjustments and add attributes that are currently not represented in all IAMs (e.g., range of EVs and ICEVs) to increase the external validity of our experiment. Consumers take various attributes of a product into account in their decision-making and if these attributes were not included in the DCE, it could have yielded skewed adoption rate estimates. Of course, we are not able to include every attribute that may play a role in the decision-making, but we focused on the most relevant characteristics without being too simplistic. For example, even though some IAMs only include monetary drivers, excluding battery range in the choice experiment would neglect a large body of research demonstrating the importance of this attribute for the purchase decision (Wicki et al., 2023). In addition, participants received different attribute levels in the DCE depending on the car size (small, medium, large) that they usually prefer. Both the purchase price and the operating costs increased with increased car size.

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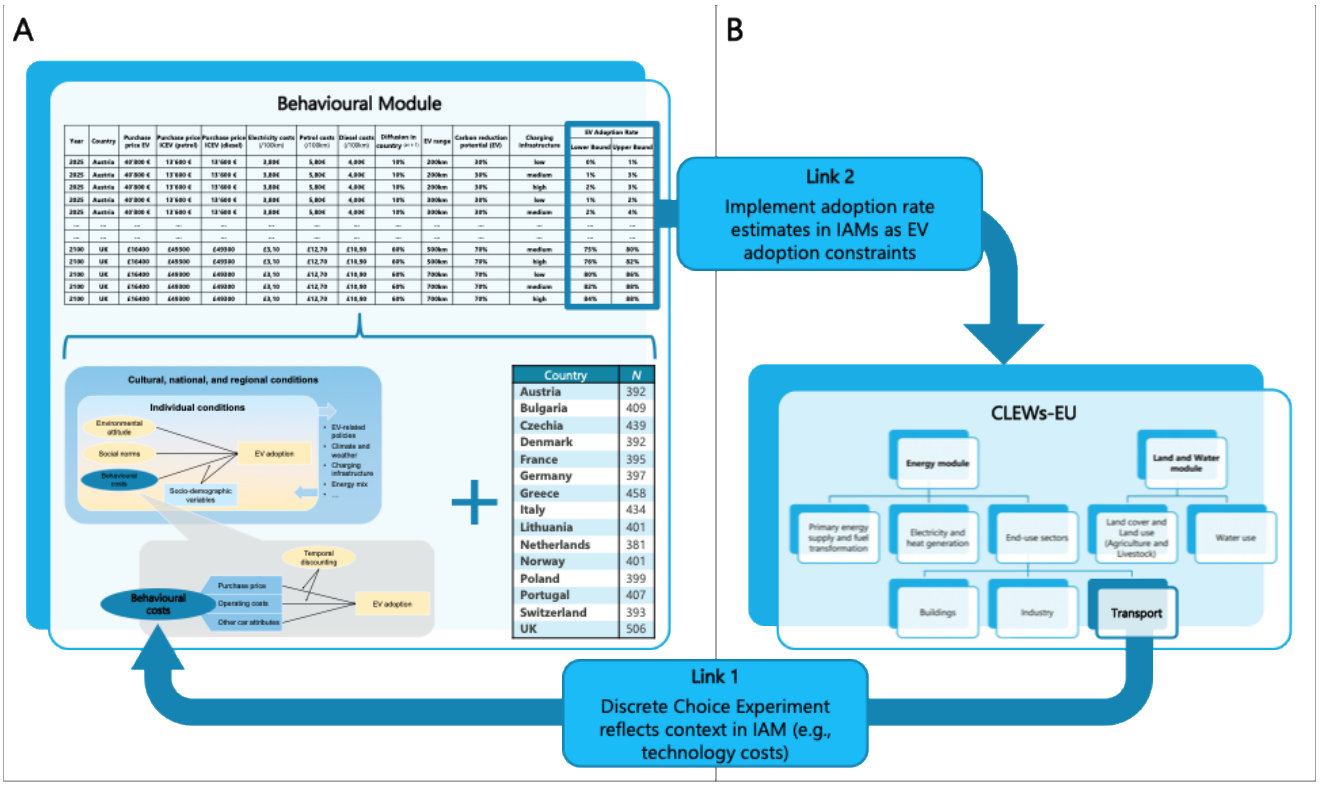

Figure 4.2 Schematic Visualisation of Soft-Linking Procedure with CLEWs-EU

After making sure that the attribute levels align with IAM assumptions, we ran the experiment and assessed the various adoption drivers on different levels in 15 European countries (see **Figure 4.2A**). Based on the resulting data, we calculated EV adoption rate estimates for all possible car-context combinations. We can even go beyond the levels assessed in the experiment by treating the attributes as numeric variables (and not ordered categorical variables) in the underlying mixed effect models. The resulting IAM-specific input-output tables (input being the car and context attributes and output being the potential range of EV adoption rates given these attributes) will serve as the second part of the soft-link with the IAMs. The output part of the table will inform a novel parameter in the IAM, namely a constraint parameter on the EV adoption that depends on the specific contextual characteristics in the IAM at a specific time step (e.g., purchase price of EVs in 2050). This constraint parameter will limit EV adoption at that time step to a rate within the lower and upper bounds. The link requires that the row in the behavioural module input-output table is chosen that resembles the context of the IAM at this time step.

Our behavioural module also includes a dynamic aspect by accounting for the effect of social norms. This makes the linking more difficult as our operationalisation of social norms constitutes a descriptive social norm (current EV diffusion in a country), which is time sensitive and usually refers to the diffusion at the time of purchase. At the same time, we want to estimate this diffusion based on the context, including the descriptive norms. There are two solutions, both with limitations, to this dilemma (for a visualisation of the dilemma, see **Figure 4.3**): either 1) we first estimate a biased EV diffusion based on our experiment excluding social norms and then use this diffusion rate as the social norm at this time step and recalculate the adoption rate given this context or 2) we calculate the adoption rate at any given time t based on the adoption rate from the previous time step (i.e., t-1) as the social norm.

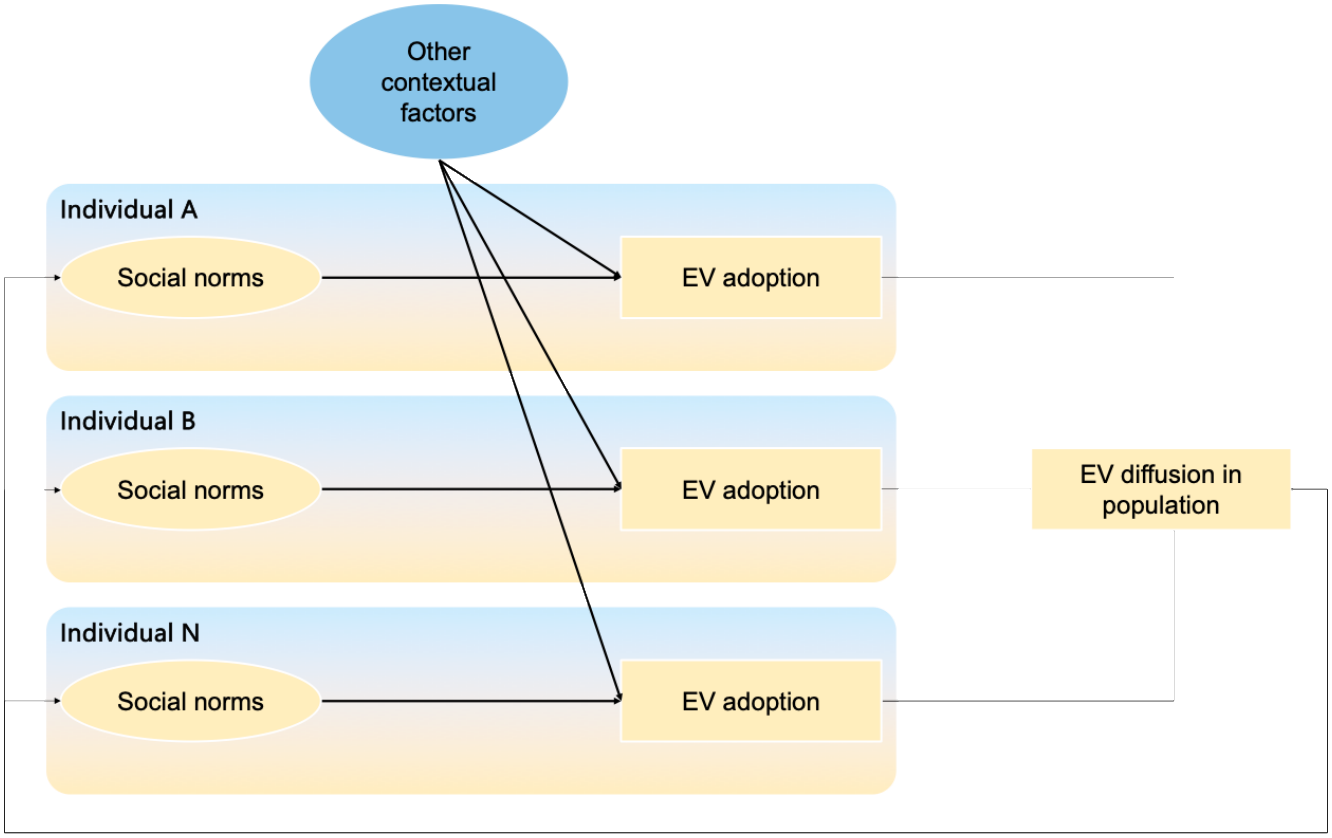

Figure 4.3 Visualisation of the Social Norm Dilemma. In an ideal world the social norm at a specific timepoint would be equal to the EV diffusion in the population at that same timepoint, but we need one of them to calculate the other.

To refrain from having to estimate adoption rates twice, and in light of the prolonged decision phase in car purchases (Klöckner, 2014), we chose the second approach. The obvious caveat with this approach arises when the temporal resolution of an IAM is rather low (e.g., 5 years), as the adoption rate at t-1 is outdated and not behaviourally relevant in this scenario. We suggest the following solution: assuming linear changes in contextual conditions (i.e., technology costs, fuel costs, electricity costs) between t-1 and t, we will estimate the adoption rates in the intermediate years based on the contextual conditions as well as the descriptive norm in the previous year. Therefore, we take into account the dynamism of the social context (and allowing for non-linear adoption trends due to this dynamism), while allowing for larger time steps. It is important to note that we did not use the effect of the descriptive norm DCE attribute to predict EV adoption rates (because the results were not in line with previous literature; Günther et al., 2025), but rather the effect of country-level EV diffusion (the effect does not vary across countries), as it was in line with our hypotheses.

An additional challenge lies in the geographical distribution of our sample, which only includes 15 European countries due to budgetary constraints. The cluster analysis at the beginning ensured that we included at least one representative country per cluster. We, therefore, extrapolated our findings to the countries that were not included in the data collection from the country that is representative for the respective cluster. When multiple countries from one cluster are included in the sample, we chose the one that is nearest to the excluded country in the multivariate space underlying the cluster analysis (i.e., closest regarding GDP, climate change vulnerability, income inequality, and previous country classifications).

Finally, the behavioural module-based input-output table is customised for each IAM depending on which car and context attributes they represent. The specific links and their effect on modelling outcomes will be described in more detail in the following subsections. Here, we want to highlight again that the behavioural module version presented here has the potential to deliver adoption rate estimates for specific population groups not only based

on socio-demographic but also psychological characteristics. The potential of this flexibility can only be explored when IAMs themselves represent heterogeneity in the actors.

4.4 Soft-Link with CLEWs-EU

4.4.1 Description

Table 4.2 gives an overview of the CLEWs-EU-specific version of the behavioural module which includes investment costs for each technology, operating costs, EV range, and the descriptive norm (i.e., EV adoption rate in the previous year). There is no explicit column for year as the technology assumptions in CLEWs-EU are computed endogenously making it impossible to link specific technology characteristics with a year a priori.

Table 4.2 Part of the Input-Output Table for CLEWs-EU. Price columns refer to purchase price and are presented as relative to the average passenger car purchase price within the country. Adoption at t-1 refers to the adoption rate in the year prior to the modelled year. In this part of the table adoption at t-1 increases by row which increases the estimated EV share. *SE* refers to the standard error.

Country	Range EV (in km)	Price EV	Fuel cost EV	Price diesel vehicle	Fuel cost diesel vehicle	Price gasoline vehicle	Fuel cost gasoline vehicle	Adoption at t-1 (in %)	Car type	Estimated share (in %)	*SE*	Lower bound (in %)	Upper bound (in %)
Austria	400	0.84	6.59	0.94	8	0.84	8	1	EV	17.44	0.84	15.80	19.08
Austria	400	0.84	6.59	0.94	8	0.84	8	3	EV	17.67	0.84	16.02	19.33
Austria	400	0.84	6.59	0.94	8	0.84	8	5	EV	17.91	0.85	16.24	19.58
Austria	400	0.84	6.59	0.94	8	0.84	8	7	EV	18.15	0.86	16.46	19.84
Austria	400	0.84	6.59	0.94	8	0.84	8	9	EV	18.39	0.87	16.68	20.09
Austria	400	0.84	6.59	0.94	8	0.84	8	11	EV	18.63	0.88	16.91	20.35
Austria	400	0.84	6.59	0.94	8	0.84	8	13	EV	18.88	0.89	17.14	20.62
Austria	400	0.84	6.59	0.94	8	0.84	8	15	EV	19.12	0.90	17.37	20.88
Austria	400	0.84	6.59	0.94	8	0.84	8	17	EV	19.37	0.91	17.60	21.15
Austria	400	0.84	6.59	0.94	8	0.84	8	19	EV	19.63	0.91	17.84	21.42
Austria	400	0.84	6.59	0.94	8	0.84	8	21	EV	19.88	0.92	18.07	21.69
Austria	400	0.84	6.59	0.94	8	0.84	8	23	EV	20.14	0.93	18.31	21.97
Austria	400	0.84	6.59	0.94	8	0.84	8	25	EV	20.40	0.94	18.56	22.24
Austria	400	0.84	6.59	0.94	8	0.84	8	27	EV	20.66	0.95	18.80	22.52
Austria	400	0.84	6.59	0.94	8	0.84	8	29	EV	20.93	0.96	19.05	22.81
Austria	400	0.84	6.59	0.94	8	0.84	8	31	EV	21.20	0.97	19.30	23.09

Since the CLEWs-EU model adopts technoeconomic assumptions corresponding to passenger car EVs with 400 km driving range, insights are drawn and implemented from this range only to ensure consistency. For the soft-link, the remaining variables are matched to the closest assumptions for each EU member state and for each year across the modelling horizon, so as to identify the corresponding EV adoption share. For instance, in 2025, we examine the assumptions used in the CLEWs-EU model regarding EV purchase price, conventional ICE vehicle purchase costs, diesel and petrol fuel prices in each country and match these with the row that has the closest variable characteristics. This process is repeated for each year and for each country until a table is generated with a range of EV adoption for each point in time.

Subsequently, the estimated ranges of EV adoption are extracted and used as minimum and maximum adoption shares for each country in each year across the modelling horizon from 2025 to 2050. However, as the relevant constraint in the CLEWs-EU model is implemented in terms of capacity additions, results from the DIAMOND baseline scenario protocol are used as a basis to enable this. As such, the projected annual capacity additions of

passenger cars in each year are extracted from this scenario for each country, which are then multiplied by the minimum and maximum EV adoption shares to formulate specific lower and upper capacity additions constraints; these correspond to the number of EV vehicles to be registered annually. These constraints are then implemented for the investigated scenario, so that the rate of electrification of the transport fleet can vary within the defined range. Since both, the DIAMOND baseline scenario with and without the soft-link have net-zero greenhouse gas emission targets implemented for 2050, a lower electrification rate means that the respective residual emissions within the transport fleet must be compensated in other sectors.

4.4.2 First Results

For the evaluation of soft-linking the behavioural module with CLEWs-EU, we focused on three sets of model outcomes relative to the DIAMOND baseline scenario: EV diffusion, system-wide emissions, and the emission-related costs under the EU Emissions Trading System for buildings and road transport (ETS2). We compare the DIAMOND baseline scenario with the same scenario including the soft-link for the 27 modelled countries and the EU27-aggregate. As this is a first, exploratory soft-link, the results should be read as indicative of the direction and plausibility of behavioural effects.

Figure 4.4 shows the effect of the soft-link on EV diffusion. There is a visible split between two types of countries. In countries like Spain, Bulgaria, Hungary, or Slovenia, EV adoption only increases after 2050 in the DIAMOND baseline scenario, while including the soft-link leads to earlier EV adoption and overall higher adoption rates by 2055. In the second group of countries, like Austria, Belgium, Germany, or Denmark, EV adoption increases over time in both scenarios, but at different speeds. While EV adoption is higher in earlier years in the soft-linking scenario, EV adoption in the DIAMOND baseline scenario overtakes it in later years, leading to higher EV adoption rates by 2055 (likely driven by emission targets). This trend can also be observed on the aggregate EU-27 level. Interestingly, even though there is a general positive trend, there are temporary drops in EV adoption in both scenarios (e.g., see Belgium from 2045 to 2050). While this needs further investigation, tentative explanations include increasing electricity costs and the installation of carbon sinks at later points in time.

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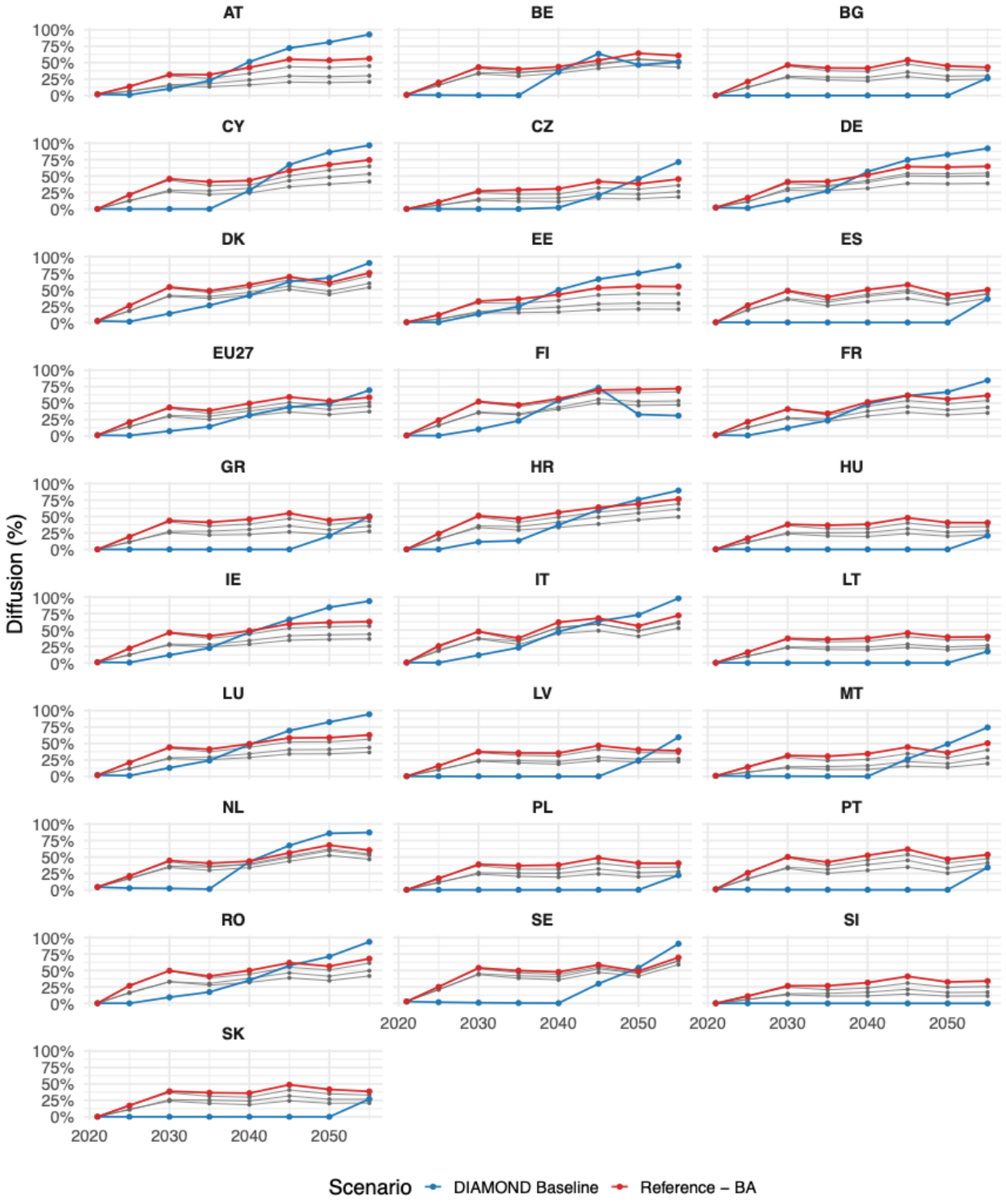

Figure 4.4 EV Diffusion by Country: Baseline vs. Soft-Link. Diffusion refers to the share of EVs in the total passenger car stock. Blue = DIAMOND baseline scenario; red = DIAMOND baseline including the soft-link (Reference – BA). Grey lines show three disruptive-event scenarios that vary the uncertainty in fuel prices and the level of tariffs on EVs.

The EV diffusion pattern between the two scenarios translates into the emission pathways shown in **Figure 4.5**. In all countries, system emissions decline over time in both scenarios, but the soft-link reduces emissions compared to the baseline in the early years in all countries. This emission reduction decreases over time and even flips in the countries where the DIAMOND baseline scenario overtakes the soft-link in terms of EV adoption. In all scenarios and countries, there are residual emissions in the transport sector by 2055, which necessitates that other sectors capture emissions which is most likely through reforestation and carbon capture and storage. Again, the effects

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of the soft-link on other sectors will be investigated in more detail for the planned manuscript.

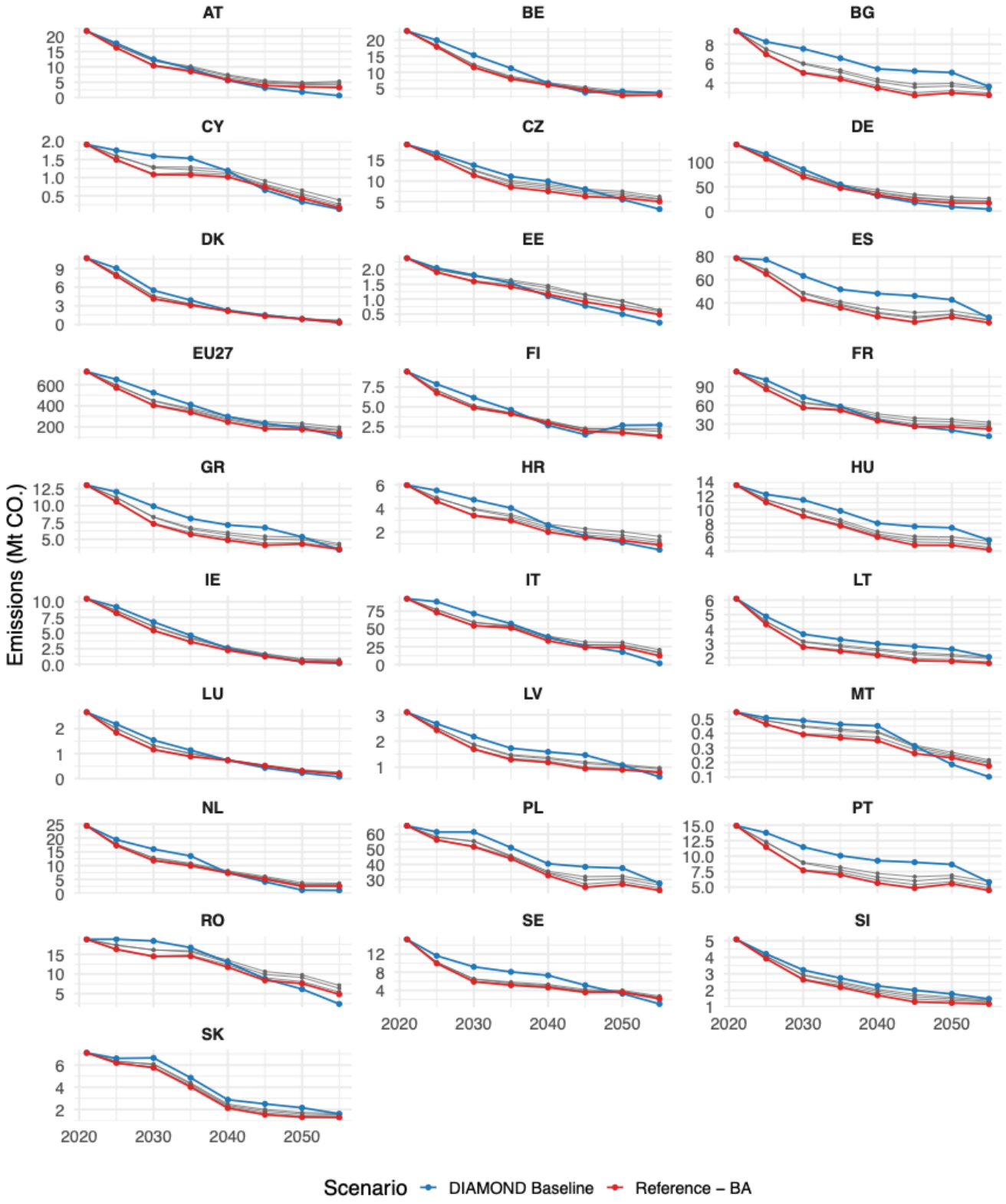

Figure 4.5 Transport Carbon Emissions by Country: Baseline vs. Soft-Link. System emissions (in Mt CO_2) per country over the modelling horizon. Blue = DIAMOND baseline scenario; red = DIAMOND baseline including the soft-link (Reference – BA). Grey lines show three disruptive-event scenarios that vary the uncertainty in fuel prices and the level of tariffs on EVs.

Finally, **Figure 4.6** translates the transport emission differences between the two scenarios into monetary terms by multiplying them by the (rising) carbon price. Because the carbon price increases over the modelling horizon,

even moderate emission differences between the scenarios can correspond to sizeable costs in later years. For most countries, the cost difference stays close to zero, but in some it deviates noticeably in the intermediate years before converging again, mirroring the temporary diffusion and emission gaps seen in the previous figures (e.g., Spain, Poland, Portugal, or Bulgaria). On the aggregate level, the overall pattern is confirmed: the soft-link leads to lower emission costs in early years, while the costs are higher by 2055. Taken together, these first results illustrate that incorporating behavioural heterogeneity through the soft-link can meaningfully shift projected EV diffusion, the associated emission pathways, and their economic valuation, underlining the relevance of behaviourally informed assumptions for IAM-based policy analysis.

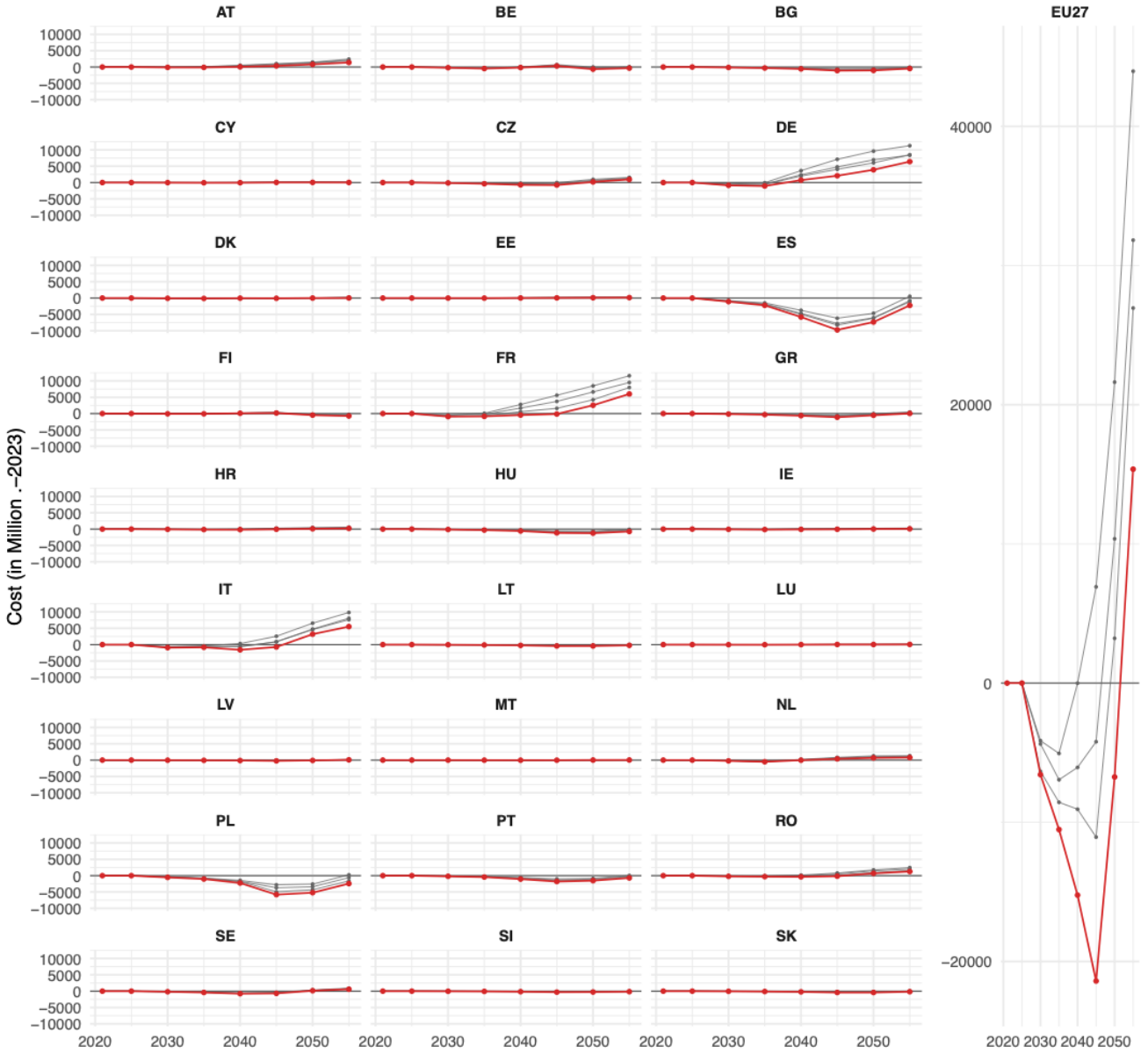

Figure 4.6 ETS2 Cost Difference by Country: Baseline vs. Soft-Link. ETS2 cost (in million €) per country, computed as the difference in transport emissions between the soft-link and the baseline scenario multiplied by the carbon price, which rises over time from 0 €/t CO_2 in 2020 to 520 €/t CO_2 in 2055. Grey lines show three disruptive-event scenarios that vary the uncertainty in fuel prices and the level of tariffs on EVs.

4.5 Soft-Link with OMNIA

4.5.1 Description

The EV-specific soft-link implementation between OMNIA and the behavioural module is one-directional: we provided OMNIA with BEV adoption ranges for the European countries we collected data in for the years the modelling team provided us technological assumptions for. **Figure 4.7A** provides an overview of the specific cost assumptions demonstrating the assumed linear changes in these assumptions between 2025 and 2030, and 2030 and 2040. The resulting country-specific estimated EV adoption shares are presented in **Figure 4.7B**. While in the soft-link, we assume a static EV range similar to CLEWs-EU **Figure 4.7C** showcases how an increase in EV range from 300km in 2025 to 700km in 2040 would affect EV adoption estimates

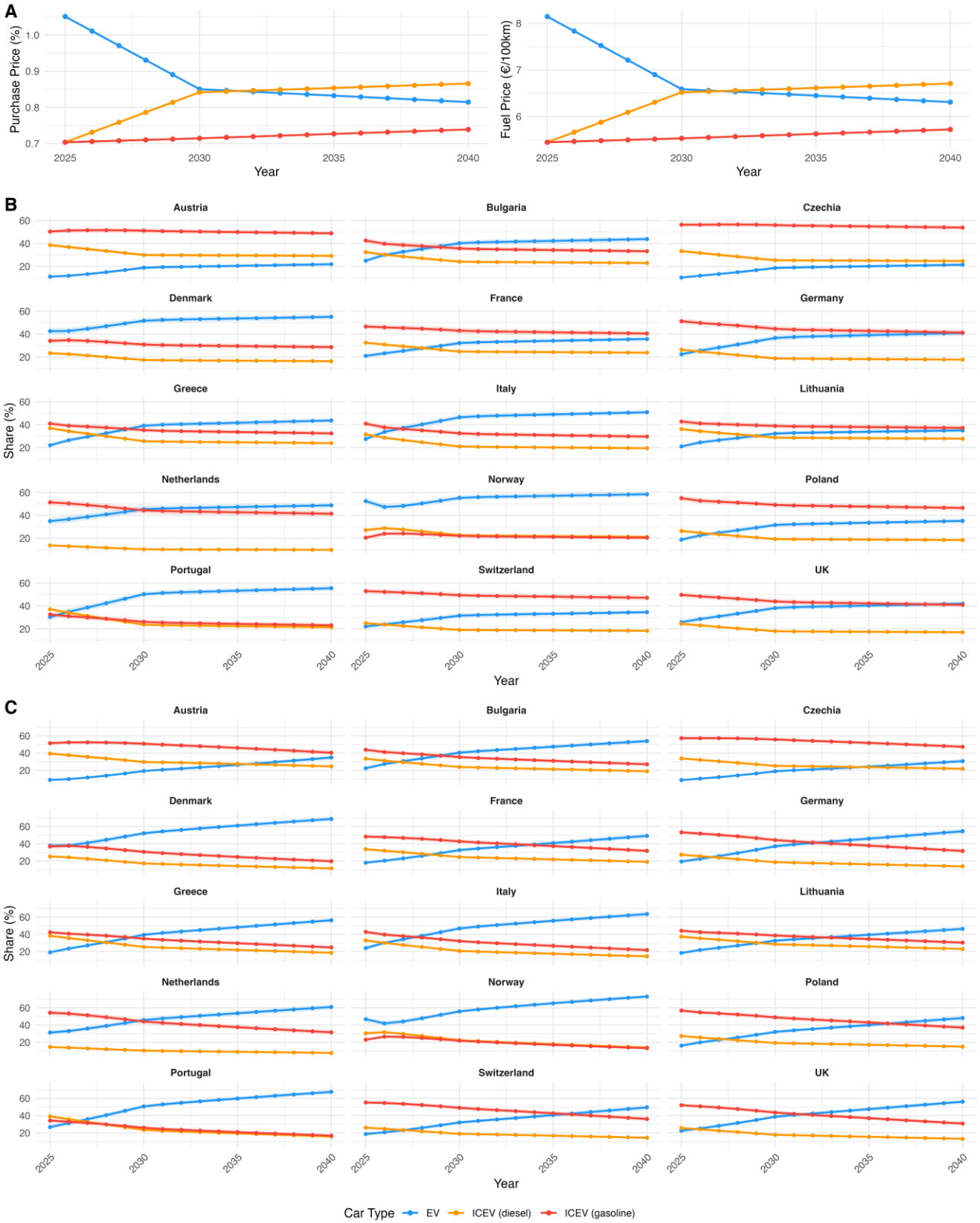

Figure 4.7 Technical Assumptions OMNIA & Corresponding Predicted Annual Adoption Rates. The shaded area surrounding the lines represents the lower and upper adoption bounds and corresponds to 95% confidence intervals. Part A: cost assumptions. Part B: country-specific estimated EV adoption shares based on purchase and fuel price. Part C: same assumptions as in Part B with an increase in EV range from 300km in 2025 to 700km in 2040.

The adoption bounds are first regionalised to align with the OMNIA EU regions, EUE, EUM, and EUW. The dataset includes four or three countries per OMNIA region (see **Table 4.3**), and the lower and upper bounds of EV adoption are aggregated using population-weighted averages. Subsequently, the regionalised data, **Figure 4.8**, are applied as constraints within the model for the OMNIA EU regions. Specifically, the constraints are implemented in the transport sector by directly imposing lower and upper bounds on the annual deployment of new EVs in each EU region.

Table 4.3 Allocation of Countries to OMNIA EU Regions.

OMNIA Regions	Countries considered in the data collection
EUE	Bulgaria, Czechia, Lithuania, Poland
EUW	Denmark, Germany, Netherlands
EUM	France, Italy, Greece, Portugal

This soft-link enables OMNIA to assess the implications of different decarbonisation pathways and net-zero targets within an integrated framework, together with the effects of heterogeneous behavioural reactions on technology adoption, specifically EV adoption. The soft-link helps to identify synergies, trade-offs, and rebound effects from an economy-wide perspective and support the assessment of policies by capturing heterogeneous customer responses to policy signals, societal aspects and energy prices, thereby affecting the timing and extent of EV uptake. Importantly, the soft-link with OMNIA is evaluated based on the DIAMOND baseline scenario including decarbonisation targets.

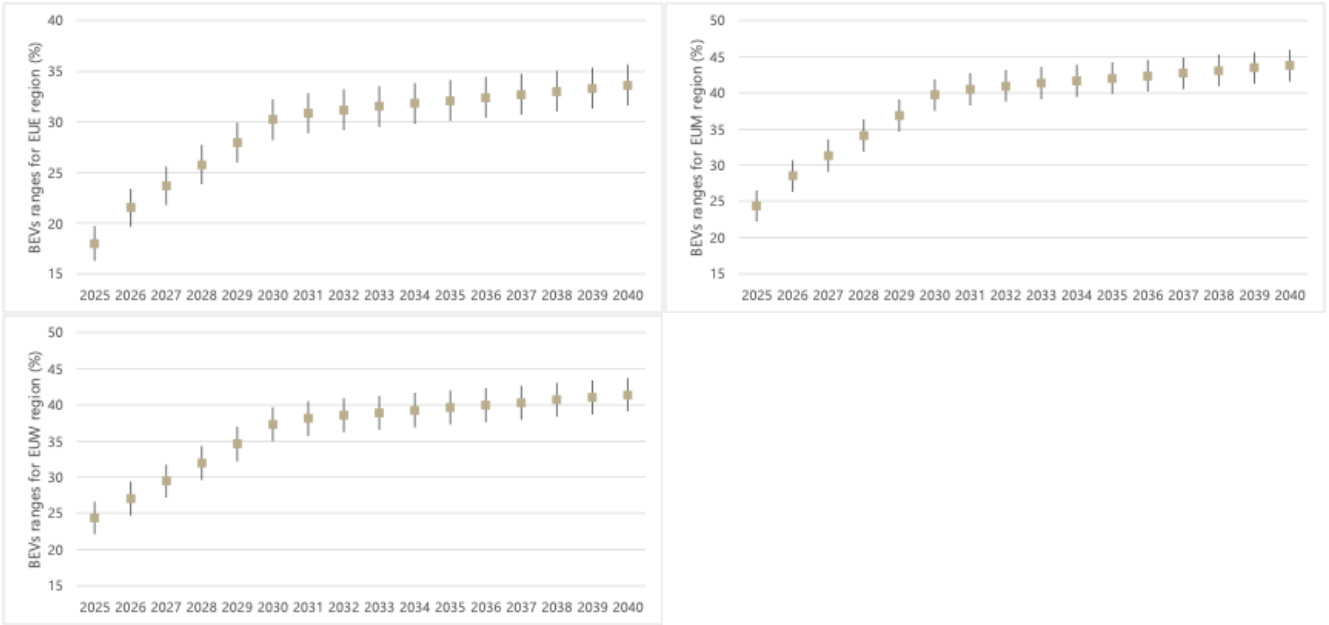

Figure 4.8 EV Adoption Ranges Used in OMNIA Value-Regionalised for EU Regions in the Model. Vertical lines represent 95% confidence intervals, which constitute the lower and upper EV adoption bounds.

4.5.2 First Results

For the evaluation of soft-linking the EV version of the behavioural module with OMNIA, we focus on three sets of model outcomes relative to the DIAMOND baseline scenario: the share of EVs in the car fleet, carbon emissions by source, and the costs in the transport sector. The three IAMs produced slightly different outcome variables, which will be harmonized for the final paper. All results are reported for the three OMNIA macro-regions (EUE, EUM, EUW) and the EU total, comparing the DIAMOND baseline scenario with the same scenario including the

soft-link (labelled Reference – BA in the figures). As for the other IAMs, these are first, exploratory results that indicate the direction and plausibility of behavioural effects rather than final estimates.

Figure 4.9 shows the predicted EV share for the two scenarios. The soft-link changes the timing of EV uptake rather than only its final level: in most regions, the behavioural soft-link produces an earlier and more gradual increase in the EV share, so that it lies above the baseline in the early and intermediate years. The baseline, by contrast, starts from a lower and flatter trajectory but then rises more steeply in the later years, eventually catching up with and overtaking the soft-link so that EV uptake in the DIAMOND baseline scenario is much higher at the end of the horizon. In the DIAMOND baseline scenario, EV adoption reaches 100% by 2050 in all regions. The size and exact crossing point of the two trajectories differ across the macro-regions, reflecting their different starting conditions. Importantly, the adoption rate of alternative fuel vehicles is much larger in the soft-link scenario to meaningfully reduce carbon emissions in the transportation sector.

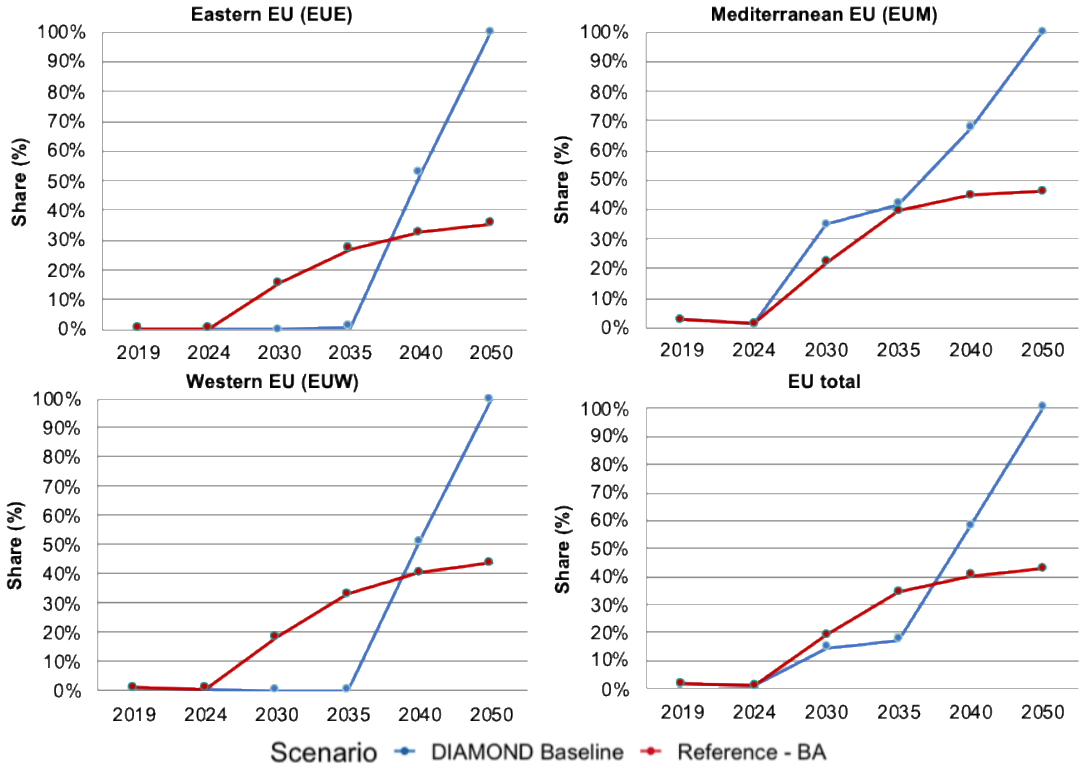

Figure 4.9 Share of EVs by Region: Baseline vs. Soft-Link. Predicted share of EVs in the car fleet per OMNIA macro-region (EUE, EUM, EUW) and the EU total, over the modelling horizon. Blue = DIAMOND baseline scenario; red = DIAMOND baseline including the soft-link (Reference – BA).

Figure 4.10 shows that emissions decline over the modelling horizon in both scenarios and across sources, and that the two scenarios remain close until 2030 in the amount of total system emissions. Overall, there are only small differences in emissions between the two scenarios (maximum difference is around 10Mt), which is expected because both the baseline and the soft-link scenario are constrained by the same decarbonisation targets. The system reaches comparable emission levels regardless of the exact timing of EV uptake. The differences that do emerge are small and concentrated in the intermediate-to-late years, where the earlier EV uptake under the soft-link is reflected in modest emission differences in the transportation sector. As the top panel illustrates, these differences are not uniform across regions. The behavioural soft-link mainly shifts the timing and regional distribution of transport emissions rather than the total emission budget under the binding targets. Higher remaining emissions in the transport sector due to lower EV uptake are partly accounted for by lower emissions from electricity production in the soft-link scenario (see the lower two panels).

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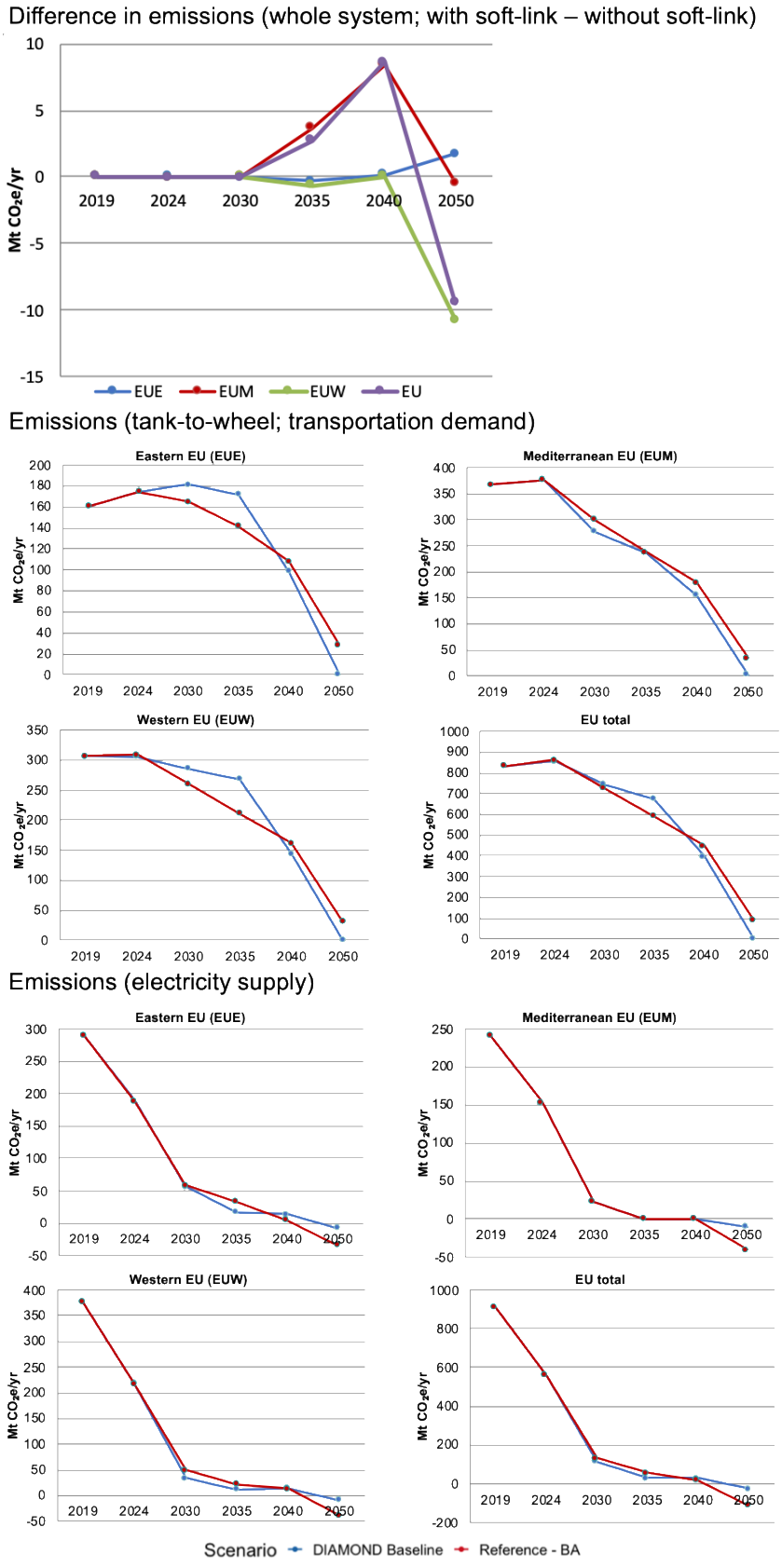

Figure 4.10 Carbon Emissions by Source: Baseline vs. Soft-Link. System emissions (in Mt CO_2eq/yr) by source and macro-region. Blue = DIAMOND baseline scenario; red = DIAMOND baseline including the soft-link (Reference – BA). The top panel shows the emission difference between the two scenarios (soft-link minus baseline) by region (EUE, EUM, EUW, EU).

Figure 4.11 decomposes the transport-sector cost difference between the two scenarios into total, investment,

and FOM (fixed operation and maintenance costs) components. The cost differences follow a clear temporal profile: they are close to zero at the start, rise to a pronounced peak in the intermediate years (in 2035), and end up positive by 2050 (indicating higher costs in the soft-link scenario). This pattern mirrors the earlier EV uptake under the soft-link – bringing forward EV adoption requires additional investment in the intermediate years, which flips later as the baseline DIAMOND scenario catches up. The investment component dominates the total difference and tracks it closely, whereas the FOM component is smaller and smoother. The magnitude of the cost differences varies across the macro-regions, with EUM sticking out as the cost difference first turns negative and only later flips to positive. Taken together, these first OMNIA results suggest that incorporating behavioural heterogeneity mainly changes the timing of EV adoption and of the associated investments, with limited consequences for total emissions under the binding decarbonisation targets.

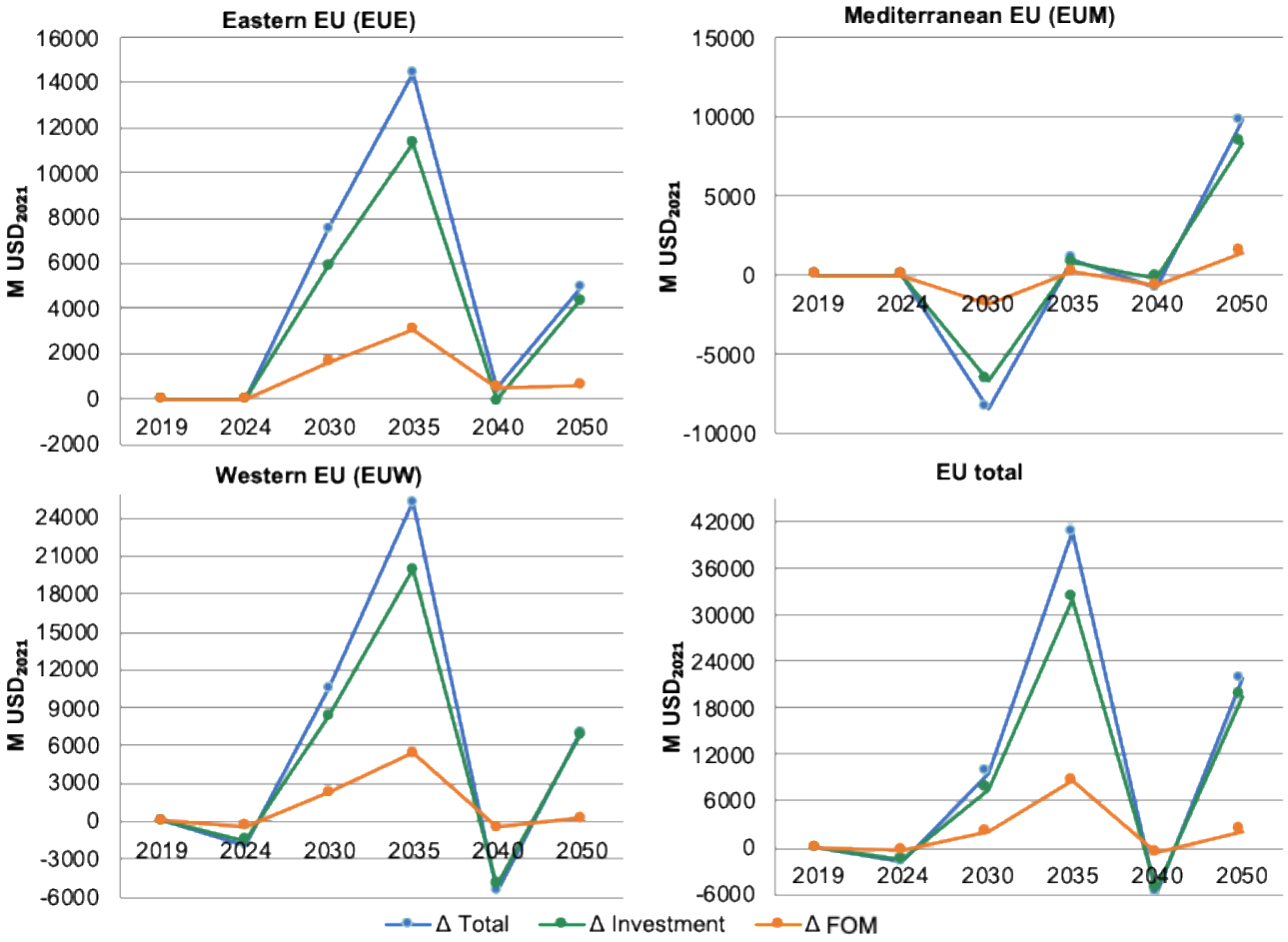

Figure 4.11 Transport-Sector Cost Differences: Soft-Link minus Baseline. Difference in transport-sector costs between the soft-link and the baseline scenario (Reference – BA minus DIAMOND baseline, in M USD_{2021}) per macro-region, shown for three components: total cost, investment cost, and fixed operating and maintenance (FOM) cost.

4.6 Soft-Link with GCAM Europe

4.6.1 Description

Before the soft-link with the EV version of the behavioural module was implemented, the GCAM Europe transport representation was updated based on detailed, country-specific data for all EU-27 member states from the JRC-IDEES database. A detailed description of the JRC data integration and the workflow used to generate the GCAM-compatible transport input is provided in **Appendix 7.1**.

Building on this updated transport representation, the model's interpolation share weights were manipulated to introduce an EV adoption path based on the behavioural module. In GCAM, consumer choices within the passenger transport sector are typically determined through a logit formulation where relative costs, adjusted by non-monetary preferences (share weights), dictate market shares. However, when forcing a predetermined target, such as a specific trajectory for EVs, this endogenous choice must be overwritten by explicitly defining the target market share and forcing GCAM to solve for the unobserved preference parameters required to match that exact path.

Mathematically, the standard logit choice model determines the market share (S_i) of a transport technology i (e.g., EV) within a subsector based on its shareweight (w_i) and its logit exponent (α):

$$S_i = \frac{w_i \times c_i^{\alpha}}{\sum_j (w_j \times c_j^{\alpha})},$$

where C_i represents the generalized cost of technology i. To align this mechanism with the behavioural module's estimates, we transition the target technology from an endogenous logit choice to a fixed share weight interpolation pathway. If the behavioural module specifies a target EV share ($S_{EV,t*}$) for a future year t, GCAM's calibration and interpolation routines can be configured to dynamically scale the shareweights. We establish an implicit anchor share weight for the target year such that:

$$w_{EV,t} = S_{EV,t*} \times \frac{\sum_j (w_{j,t} \times C_{j,t}^{\alpha})}{C_{EV,t}^{\alpha}}.$$

In practice, this is implemented within the GCAM-Europe XML input files using the <interpolation> tag under the target technologies. By setting the interpolation-function to linear or log, we can pass a timeseries of explicit values mapped directly from the behavioural module's estimates. For the policy years where the EV path is actively binding, we set the technology's share weight to match the desired penetration rate relative to competing alternatives, effectively using the share weight as a proxy to absorb the non-cost barriers or hidden incentives calculated by the external tool.

The EV adoption path fed into the model was generated from the behavioural module using country- and year-specific purchase prices and fuel costs supplied by GCAM Europe as five-year anchors (2025, 2030, 2035, 2040, 2045, and 2050) and linearly interpolated to annual values. For the purchase price, GCAM provides a single combined series for conventional vehicles, which was applied to both gasoline and diesel ICEVs (**Figure 4.12**). EV purchase prices and electricity ("fuel") costs were supplied separately (**Figure 4.13**).

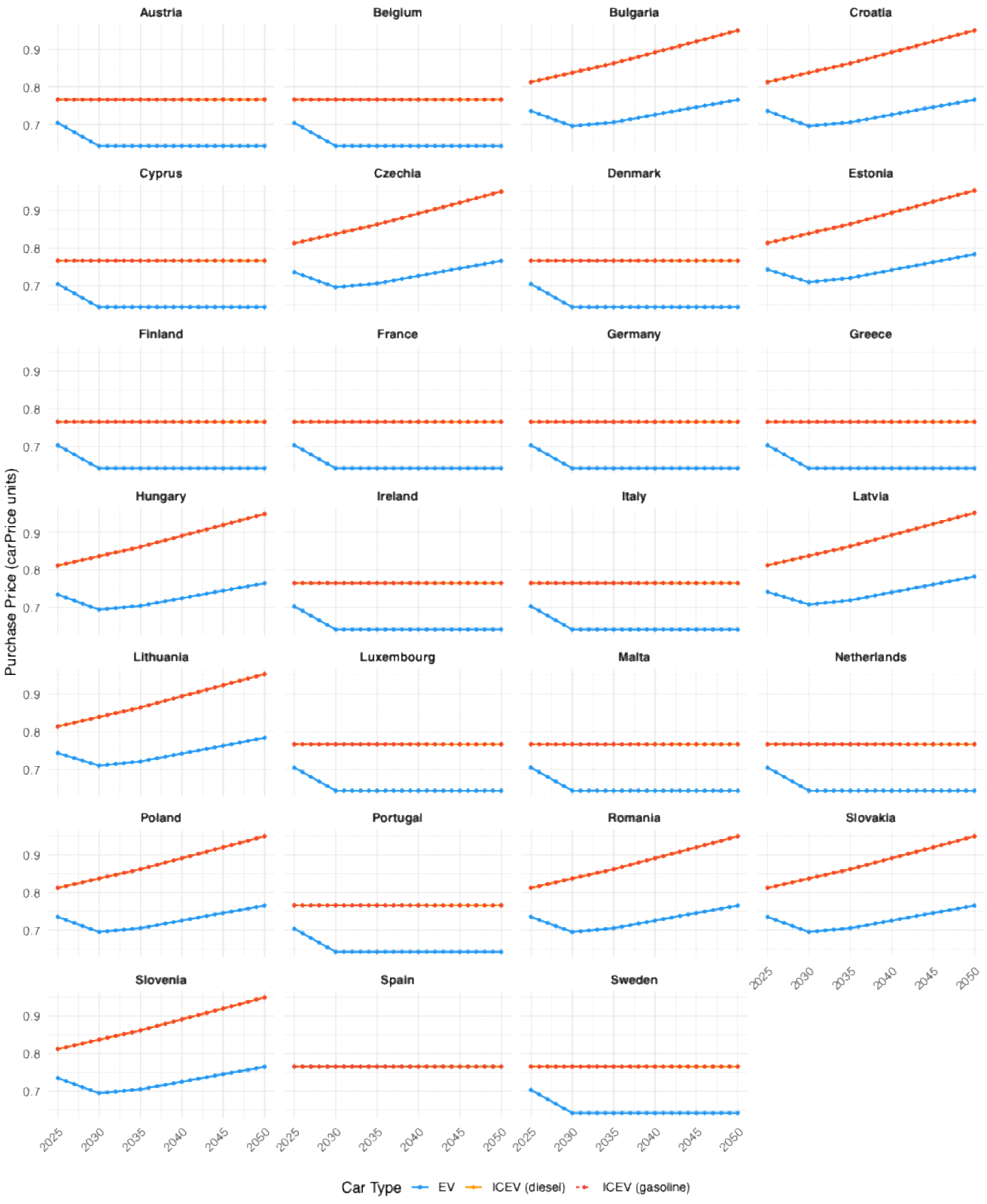

Figure 4.12 GCAM Europe Purchase Price by Car Type and Country. Blue = EV; orange = ICEV (diesel); red (dashed) = ICEV (gasoline). Gasoline and diesel purchase prices are equal. For Spain, purchase prices of all three technologies are equal.

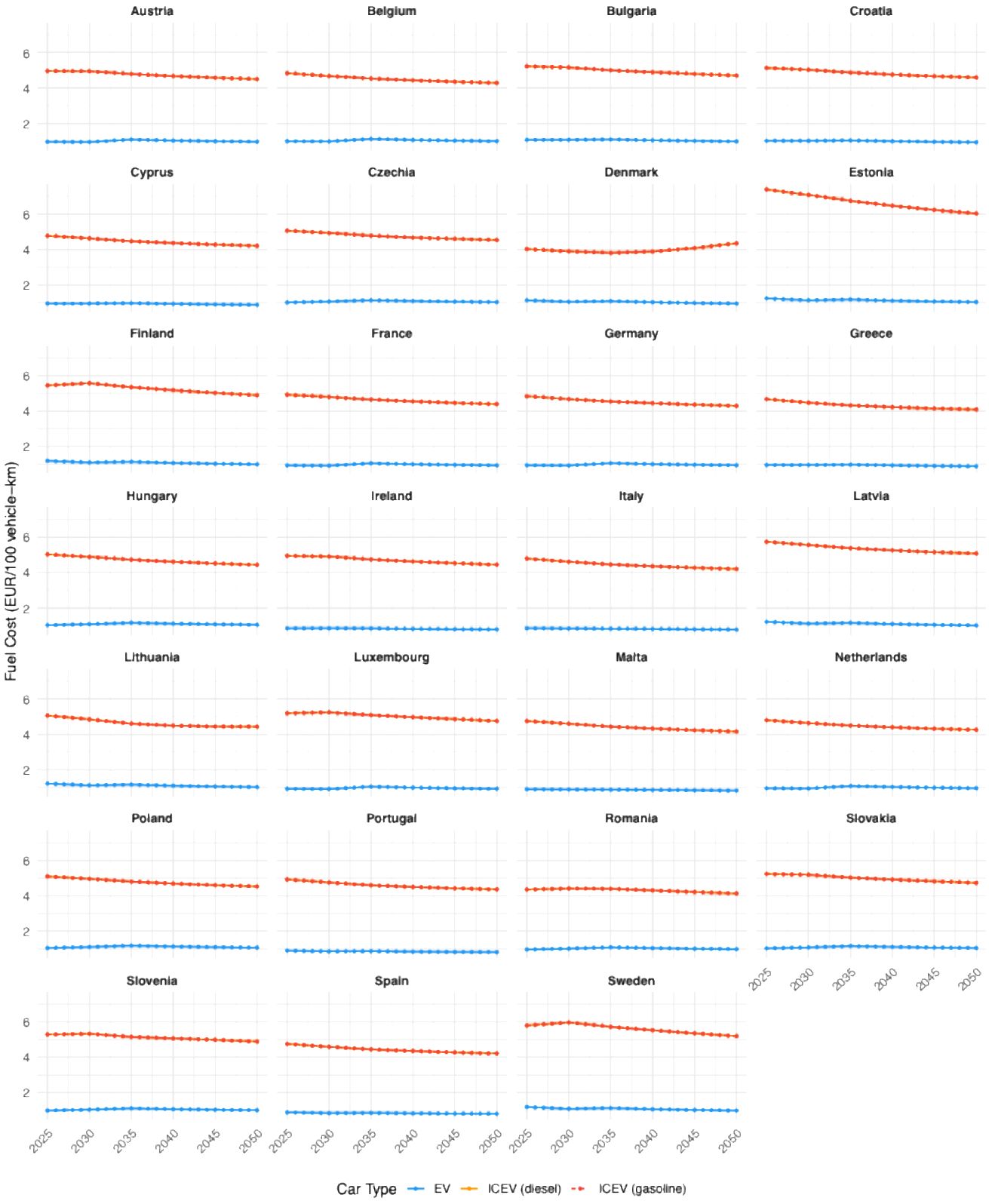

Figure 4.13 GCAM Europe Fuel Cost by Car Type and Country. Blue = EV (electricity); orange = ICEV (diesel); red (dashed) = ICEV (gasoline). Gasoline and diesel fuel costs are equal.

4.6.2 First Results

We tested the effect of the soft-link implementation based on a baseline scenario without climate policies or

targets**. Figure 4.14** shows the effect of the soft-link on the EV share of new car sales for the 27 EU member states. The behavioural soft-link ultimately lifts the EV share above the baseline in all countries. The soft-link produces a steep increase in the EV share up to 2030, after which the share plateaus or even slightly declines. The level of this plateau differs markedly across countries, ranging from about 20% (e.g., Slovenia) to roughly 50% (e.g., Croatia and Cyprus) of new car sales by 2030, reflecting the heterogeneous purchase-price, fuel-cost, and starting-diffusion conditions across the EU-27. Averaged across countries, the soft-link raises the EV share of new car sales from about 17.9% to about 32.7% in 2030, and this gap is robust until 2050 (about 17.3% versus 31.7%).

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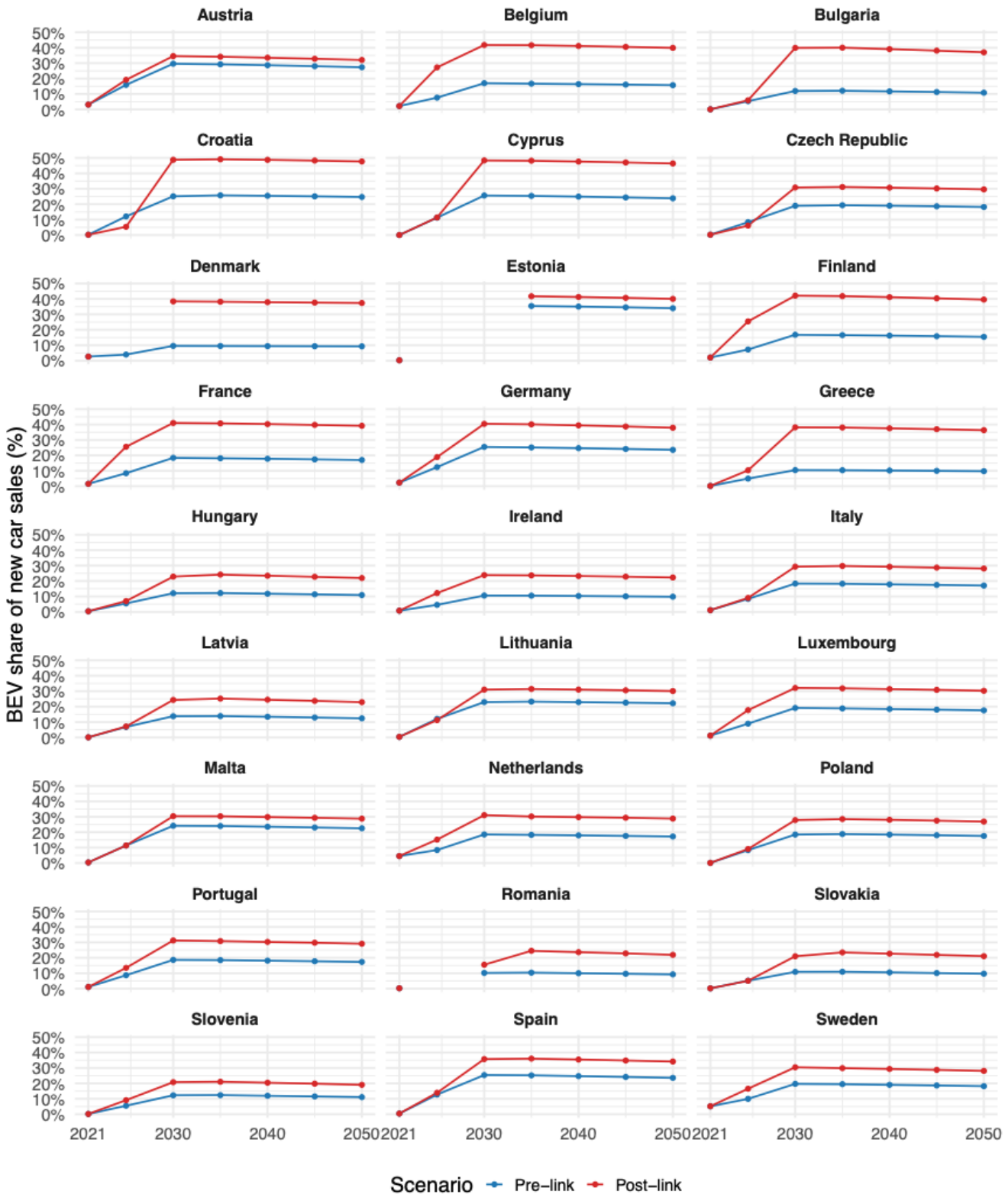

Figure 4.14 BEV Market Share of New Car Sales by Country: Baseline vs. Soft-Link. Blue = pre-link (no-policy baseline); red = post-link (no-policy baseline including the soft-link). BEV = EV. Denmark, Estonia, and Romania show missing early values where total passenger car demand declines compared to earlier years.

The EV diffusion pattern translates into the emission pathways shown in **Figure 4.15**. Total system CO_2 emissions decline over the modelling horizon in both scenarios and across all countries. The earlier and higher EV uptake in the soft-link scenario is reflected in consistently lower transport-related emissions, resulting in lower total system

emissions. Aggregated across the EU-27, the soft-link reduces total system emissions relative to the baseline by 17.87 Mt CO_2 in 2030, which grows to 56.83 Mt CO_2 by 2050.

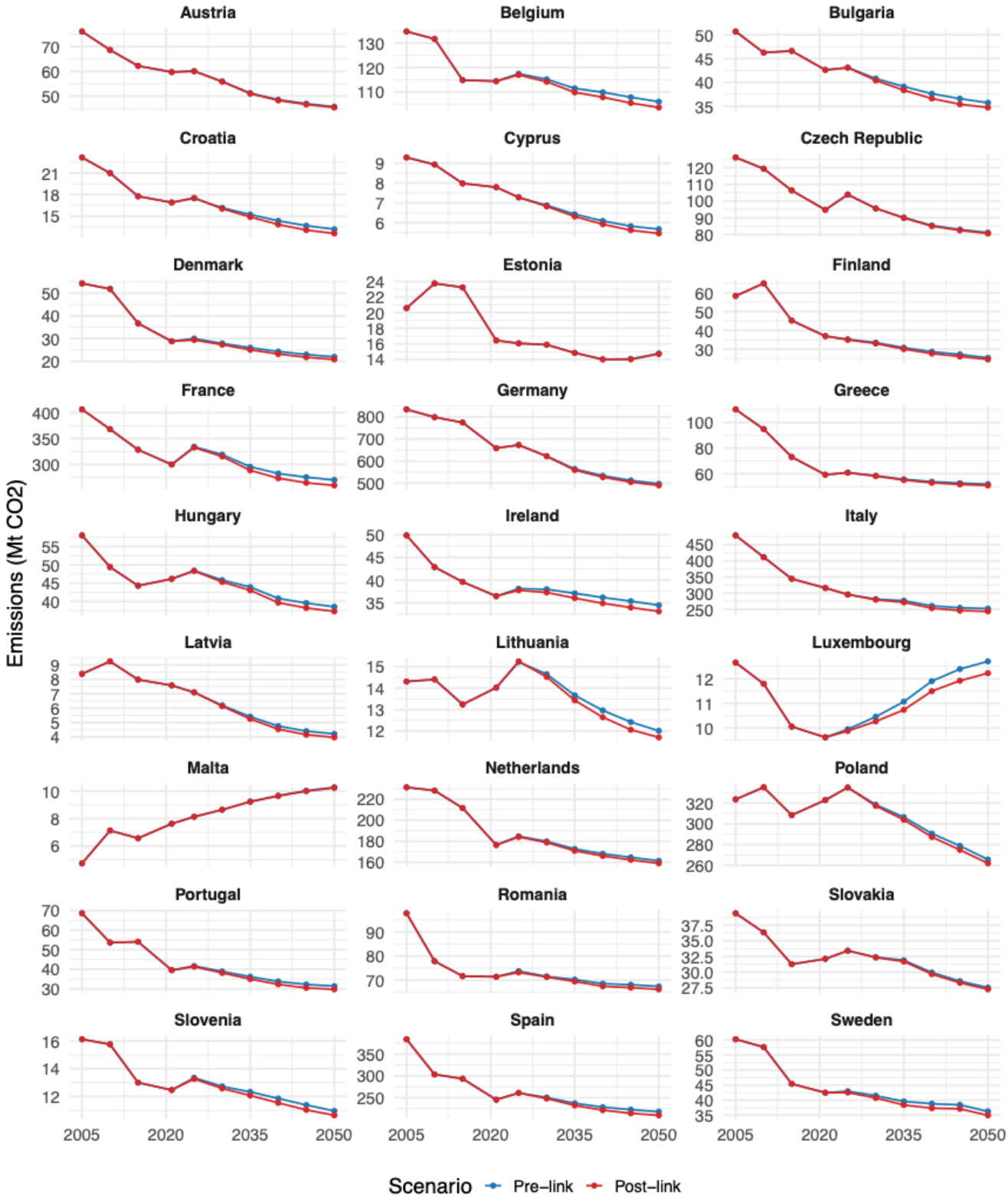

Figure 4.15 Total System CO_2 Emissions by Country: Baseline vs. Soft-Link. Country-specific y-axes. Blue = pre-link (no-policy baseline); red = post-link (no-policy baseline including the behavioural soft-link).

Figure 4.16 shows the corresponding capital investment in four-wheel passenger transport. The absolute difference between the two scenarios is minor. In the early years, capital investment is lower under the soft-link than under the baseline (by 71.73 billion USD_{2020} across the EU-27 in 2030), although this trend is not consistent across countries (e.g., Netherlands). In the intermediate years the difference flips: sustaining higher EV adoption rates seems to require additional investment, so that investment under the soft-link exceeds the baseline by about 38 billion USD_{2020} in 2035.

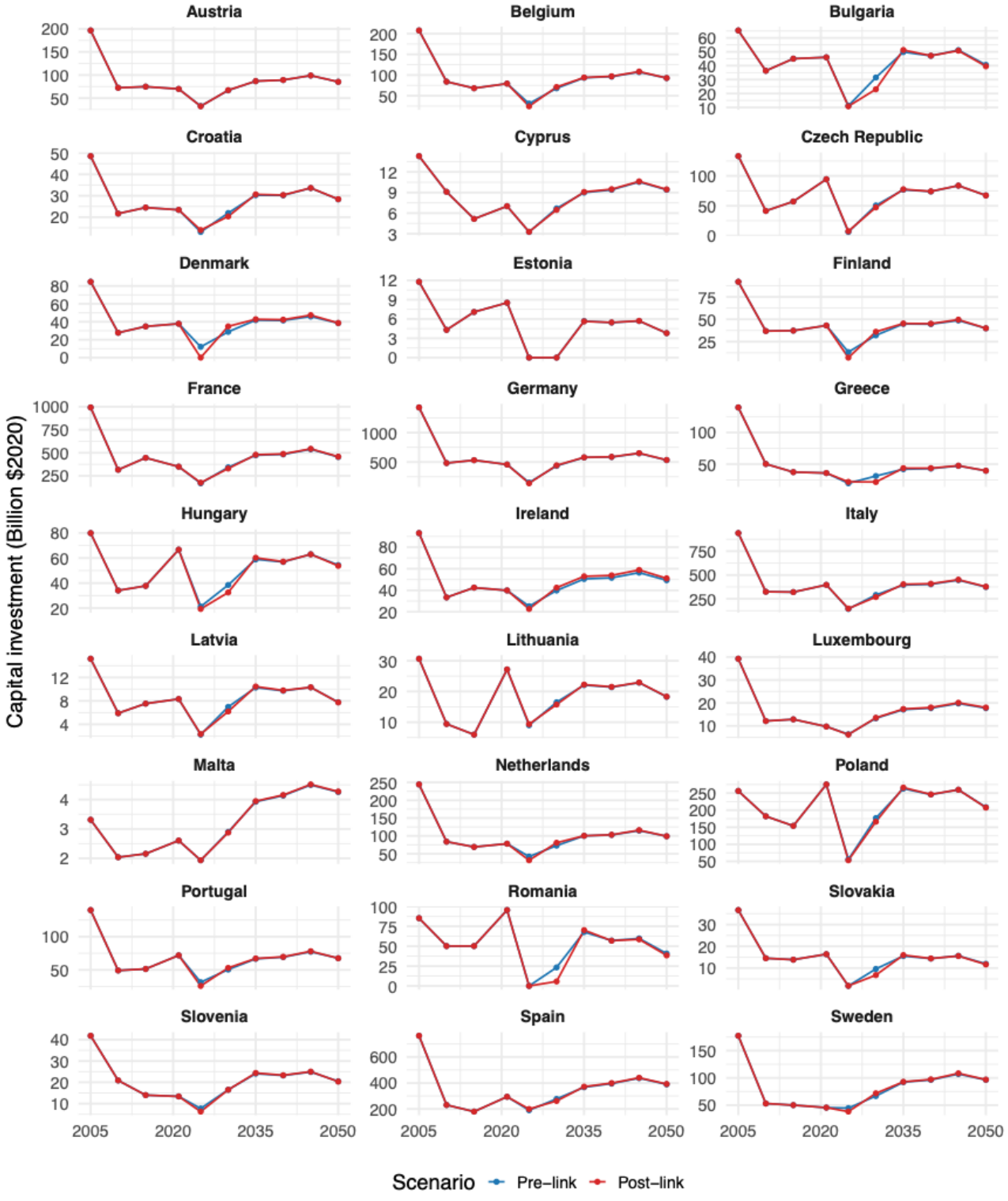

Figure 4.16 Capital Investment in Four-Wheel Passenger Transport by Country: Baseline vs. Soft-Link. Country-specific y-axes. Blue = pre-link (no-policy baseline); red = post-link (no-policy baseline including the behavioural soft-link).

5 Conclusion and Future Research

In this deliverable, we addressed two prominent limitations of IAMs – the lack of actor heterogeneity and the often unrealistic, purely cost-optimising representation of technology diffusion – by developing a behavioural module that was adapted for EV adoption and soft-linking it to three IAMs (CLEWs-EU, OMNIA, and GCAM Europe). The underlying psychological model is grounded in an extensive literature review (Günther et al., 2025) and in an established behavioural theory, the Campbell paradigm (Kaiser, 2021), and was populated with data from a preregistered DCE administered to N = 6,204 participants across 15 European countries.

Regarding the car attributes in the DCE, the results were fully in line with our hypotheses: higher purchase prices and higher operating costs reduced the likelihood that a vehicle was chosen, whereas a longer driving range increased it. The effects of the contextual DCE attributes, by contrast, were more nuanced and did not always behave as expected. For example, emission savings worked in the opposite direction to our hypothesis, with larger emission reductions of EVs being associated with a lower, rather than higher, probability of choosing an EV. Charging infrastructure increased the attractiveness of cars in general, including ICEVs, rather than EVs specifically. Plausible explanations for these counterintuitive patterns include the way the attributes were presented and understood: the charging-infrastructure attribute also conveyed information about the density of the conventional fuelling network, the emission attribute may have been misunderstood or triggered reactance, and the diffusion attribute may have been too abstract a cue to function as an effective descriptive norm, or may even have triggered a contrarian response in some respondents. These interpretations are tentative and should be examined more directly in future work.

At the individual level, the findings were largely consistent with our hypotheses and with the Campbell paradigm. A stronger environmental attitude and more favourable social norms – both injunctive and descriptive – were associated with a higher likelihood of choosing an EV, confirming the central role of personal and social motivation in technology adoption (Kaiser, 2021; Günther et al., 2025). Socio-demographic patterns were also as expected, with higher income associated with a greater likelihood of choosing an EV. The one notable exception concerned temporal discounting. We had hypothesised that stronger discounters would weigh the immediate purchase price more heavily and the temporally distant operating costs less heavily; instead, respondents with stronger temporal discounting weighted both monetary attributes more strongly. One interpretation is that temporal discounting in this context reflects a broader sensitivity to monetary information rather than a specific down-weighting of future consequences; another is that the operating-cost attribute was itself perceived as a relatively immediate and recurring expense rather than a distant one. This finding also adds to a sparse literature on temporal discounting and car purchase behaviour and highlights the importance of including such cognitive processes when investigating technology adoption behaviour. At the country level, the results were mostly in line with our hypotheses and with previous literature. EV diffusion, a supportive policy landscape, and a higher share of renewables in the electricity mix were associated with a higher likelihood of choosing an EV, while higher populist vote share and better public-transport provision were associated with a lower likelihood.

Overall, our empirical findings support the general structure of the behavioural module and were, therefore, subsequently used to populate the EV version of it with data.

Soft-linking the EV version of the behavioural module to the three IAMs produced consistent and interpretable effects relative to the respective baseline scenarios. Across CLEWs-EU and OMNIA, the behavioural soft-link changed the timing and distribution of EV adoption as well as the overall EV share at the end of the model timeline. In general, the soft-link led to a more gradual EV increase and prohibited unrealistically high EV diffusion (i.e., 100%) at later points in time. Because both the baseline and the soft-link scenarios were constrained by the same net-zero targets, the consequences for total system emissions were limited. Instead, a slower or differently timed

EV uptake left more residual emissions in the transport sector in some periods and regions, which had to be compensated elsewhere (e.g., through other sectors or carbon sinks). In OMNIA, these dynamics were reflected in transport-sector costs, where the soft-link produced a temporary, investment-driven increase in the intermediate years that receded or flipped towards the end of the horizon.

Taken together, these results demonstrate that incorporating behavioural heterogeneity and non-cost-optimising decision-making through the soft-link has a tangible impact on model outcomes – on EV adoption trajectories, on sectoral emissions and investment costs, and, through the transport sector, on system-wide emission pathways. This directly addresses the IAM limitations highlighted in the literature (Keppo et al., 2021) and shows that taking realistic assumptions about human behaviour seriously can improve the realism of IAM-based scenarios. At the same time, the whole linking approach points to important caveats. Collecting and integrating behavioural data of this kind is costly in both time and money, and the added realism needs careful, ideally out-of-sample, evaluation: it is not yet established how much closer to reality the behaviourally informed pathways are than the baselines. A further open challenge is the extrapolation of behavioural estimates to future contexts that differ markedly from those observed today. We, therefore, present these results as a proof of concept that behaviourally grounded soft-linking is feasible and consequential.

5.1 Additional Steps with DIAMOND Modelling Teams

Several concrete extensions are planned together with the DIAMOND modelling teams to consolidate and broaden the soft-link. On the methodological side, we intend to apply multi-level regression and post-stratification (MRP; Buttice & Highton, 2017) to produce more accurate, population-representative adoption rates at the country level by combining the individual-level model with known socio-demographic distributions (e.g., from census data). Furthermore, we plan to make the behavioural module more dynamic in two respects: by defining an explicit function for how battery ranges develop over time and feeding it into the adoption estimates (for CLEWs-EU and OMNIA), and by accounting for inter-temporal changes in motivation, ideally by linking our data with existing longitudinal investigations of environmental and social motivation (e.g., Bauske et al., 2022).

On the policy-analysis side, a key next step is to test the effect of specific policy instruments like EV purchase subsidies or carbon taxes with and without the behavioural soft-link in order to quantify how behavioural heterogeneity changes the assessed effectiveness and distributional consequences of these instruments. This includes allowing income-group-specific adoption rates (mainly in GCAM Europe), which our data support and which would let the IAMs incorporate group-specific policies (e.g., income-sensitive subsidies). We further plan to explore the role of the social-motivation component beyond descriptive norms, for example by incorporating the effect of injunctive norms in the soft-linking approach (e.g., by estimating how injunctive norms and their effect change over time depending on EV diffusion).

Finally, several model-specific and exploratory steps are planned. The disruptive-event scenarios (varying fuel-price uncertainty and EV tariffs) will be explored consistently across all three IAMs. For CLEWs-EU, we intend to constrain plug-in hybrid (PHEV) adoption so that the soft-link effect on battery-electric adoption is not simply compensated by a shift towards PHEVs. Another potential step could be to link the behavioural module to the Shared Socioeconomic Pathways (SSPs; O'Neill et al., 2017), embedding our behavioural assumptions within established scenario frameworks.

5.2 Research Outlook

Looking beyond DIAMOND, our work points towards a more holistic integration of psychological data into systems modelling. A central prerequisite is more psychological research on how behavioural drivers are themselves

shaped by time and context: temporal discounting, environmental attitudes, and social norms are not fixed traits but evolve with experience, cohort, and the surrounding social and policy environment, and capturing this dynamic is essential for more credible long-term behavioural estimates. Methodologically, this calls for better ways to extrapolate behavioural estimates to future contexts – for instance, contexts with much higher EV diffusion, different price structures, or shifted social norms – than the current static or recursively updated approaches allow.

The behavioural module is also not specific to EVs. Because it is built on the Campbell paradigm and a multi-level contextual structure, it can be transferred to other climate-relevant behaviours once suitable data are available or collected. Sustainable food consumption is an especially promising candidate, given the large climate footprint of the food system and strong evidence that environmental motivation and behavioural costs jointly shape dietary choices (Poore & Nemecek, 2018; Willett et al., 2019).

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7 Appendix

Table 7.1 Overview of the Purchase Prices Represented in the Discrete Choice Experiment. The Prices are equal across EV, gasoline, and diesel vehicle. Based on the Values in the Table all five Attribute Levels (50%-150%) were computed.

Country	Purchase price (current mean; in €)		
	small	medium	large
Austria	27235	32873	59139
Netherlands	24894	30047	54055
Portugal	25097	30292	54496
Poland	26184	31605	56857
Denmark	25171	30381	54656
Germany	30673	37022	66604
Italy	22470	27122	48792
Switzerland	27945	33730	60680
Norway	29760	35921	64622
France	22452	27099	48752
UK	26820	32372	58238
Bulgaria	26387	31850	57298
Czechia	23899	28846	51894
Greece	19889	24007	43188
Lithuania	26203	31627	56897

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Table 7.2 Overview of the Fuel Prices Represented in the Discrete Choice Experiment. S, M, and L refer to small, medium, and large vehicles.

	Fuel price (in €)								
Level	low			medium			high		
Car size	S	M	L	S	M	L	S	M	L
Country	**ICE (gas)**								
Austria	4.7	5.8	6.8	7.3	9.1	10.6	10.9	13.6	15.7
Netherlands	6.6	8.2	9.6	9.5	11.8	13.7	13.1	16.3	18.9
Portugal	5.9	7.3	8.5	8.4	10.5	12.2	11.7	14.5	16.8
Poland	4.4	5.4	6.3	6.4	7.9	9.2	9.0	11.2	12.9
Denmark	6.1	7.6	8.8	9.2	11.4	13.2	13.2	16.4	19.0
Germany	5.8	7.2	8.3	8.5	10.6	12.3	12.1	15.1	17.5
Italy	5.9	7.4	8.5	8.4	10.4	12.1	11.4	14.2	16.5
Switzerland	5.6	7.0	8.1	8.6	10.7	12.4	12.6	15.6	18.1
Norway	5.9	7.4	8.6	9.2	11.5	13.3	13.6	16.9	19.7
France	5.7	7.0	8.2	8.2	10.2	11.8	11.4	14.2	16.5
UK	5.6	6.9	8.0	8.4	10.5	12.2	12.2	15.2	17.6
Bulgaria	3.9	4.9	5.7	6.2	7.7	8.9	9.2	11.5	13.3
Czechia	4.7	5.8	6.7	7.3	9.0	10.5	10.7	13.3	15.5
Greece	6.0	7.5	8.7	9.0	11.2	13.0	12.9	16.1	18.7
Lithuania	4.7	5.8	6.7	7.3	9.1	10.5	10.8	13.4	15.6
Country	**ICE (diesel)**								
Austria	3.2	4.0	5.5	5.4	6.7	9.1	9.0	11.3	15.2
Netherlands	3.8	4.8	6.5	6.0	7.5	10.2	9.7	12.1	16.4
Portugal	3.7	4.7	6.3	5.7	7.1	9.6	8.9	11.1	15.0
Poland	3.1	3.9	5.2	4.8	6.0	8.1	7.6	9.5	12.9
Denmark	3.7	4.6	6.3	6.0	7.4	10.0	9.8	12.2	16.4
Germany	3.6	4.5	6.1	5.9	7.3	9.9	9.7	12.1	16.4
Italy	3.9	4.9	6.6	5.8	7.3	9.8	9.0	11.3	15.2
Switzerland	4.2	5.3	7.1	6.7	8.3	11.2	10.8	13.5	18.2
Norway	4.0	5.0	6.7	6.5	8.1	10.9	10.7	13.3	18.0
France	3.7	4.7	6.3	5.8	7.2	9.7	9.2	11.4	15.4
UK	4.1	5.1	6.9	6.4	8.0	10.8	10.4	12.9	17.4
Bulgaria	2.8	3.5	4.7	4.6	5.8	7.8	7.8	9.7	13.1
Czechia	3.2	4.0	5.4	5.3	6.6	8.9	8.8	10.9	14.8
Greece	3.6	4.5	6.1	5.7	7.1	9.6	9.3	11.6	15.6
Lithuania	3.1	3.9	5.2	5.2	6.4	8.7	8.7	10.9	14.6
Country	**EV**								
Austria	3.1	3.3	3.9	3.3	3.5	4.2	3.5	3.8	4.5
Netherlands	1.8	2.0	2.4	2.7	2.9	3.5	3.6	3.9	4.6
Portugal	3.0	3.2	3.8	3.0	3.2	3.8	3.0	3.2	3.9
Poland	2.1	2.3	2.8	2.3	2.4	2.9	2.4	2.5	3.0
Denmark	4.0	4.3	5.1	5.4	5.8	6.9	6.8	7.3	8.7
Germany	4.3	4.6	5.6	4.8	5.1	6.2	5.2	5.6	6.7
Italy	3.1	3.3	4.0	4.1	4.4	5.3	5.2	5.6	6.7
Switzerland	2.7	2.8	3.4	3.1	3.3	4.0	3.5	3.7	4.5
Norway	2.2	2.4	2.8	2.6	2.8	3.3	3.0	3.2	3.8
France	2.7	2.9	3.5	2.9	3.2	3.8	3.2	3.4	4.1
UK	3.5	3.7	4.5	4.4	4.8	5.7	5.4	5.8	6.9
Bulgaria	1.4	1.5	1.8	1.5	1.6	1.9	1.6	1.7	2.1
Czechia	2.5	2.7	3.2	3.0	3.2	3.8	3.4	3.7	4.4
Greece	2.3	2.5	3.0	2.8	3.0	3.6	3.3	3.6	4.3
Lithuania	1.9	2.0	2.4	2.8	3.0	3.6	3.7	3.9	4.7

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7.1 GCAM Europe JRC Data Integration

To allow a smooth soft-link implementation, GCAM Europe's model structure and data basis first had to be aligned more closely with the real-world transport and car market. Therefore, default GCAM transport calibration data were overwritten with updated transport data from the JRC-IDEES database.

The integration of the JRC transport dataset substantially improves the accuracy and granularity of the GCAM Europe transport module. By using detailed, country-specific data for all EU-27 member states spanning 2005 to 2023, the model reflects a more realistic and detailed transport landscape. Prior to this integration, historical transport estimates from 2005 onwards relied on a highly aggregated downscaling approach in which data for individual European nations were approximated by extrapolating from the broader GCAM-core macro-regions (Western Europe, Eastern Europe, and the Former Soviet Union). Moving to a bottom-up approach with JRC data allows for a more faithful representation of real-world conditions and, crucially, provides a reliable and empirically grounded timeline for the market penetration of new and disruptive technologies such as EVs.

7.1.1 Workflow

The JRC transport data were pre-processed to generate a transport input file compatible with the GCAM Europe transport module, following five steps.

Data collection and organization. The JRC-IDEES database was downloaded and organised into one directory per EU country. Each country directory contains several Excel workbooks, of which the transport workbook was selected for further processing. This workbook contains multiple sheets covering different transport modes, fuels, energy consumption, load factors, and transport intensities.

Definition of the target structure. The OTAQ/UCD transport input table from the GCAM core database was used as the reference structure, defining the required variables, dimensions, and format of the final dataset.

Mapping between JRC and GCAM transport categories. Each transport variable in the JRC database is associated with a unique identifier code. These codes were manually mapped to the corresponding OTAQ/UCD transport categories, using the transport sector, mode, technology, fuel, and variable type. For example, the combination *UCD_sector = Passenger, mode = LDV_4W, UCD_technology = BEV, variable = intensity* corresponds to the JRC identifier for Austria, *Eff.kgoe_per_kpkm.AT.Tr.Road.Passenger.Car.BEV*, while the equivalent energy and load-factor variables correspond to *FEC.ktoe.AT.Tr.Road.Passenger.Car.BEV* and *Load.passenger_per_movement.AT.Tr.Road.Passenger.Car.BEV*, respectively. The particle AT denotes the country code for Austria and changes for each country (BE, BG, CY, CZ, and so on).

Automated dataset generation. After completing the mapping, a Python workflow automatically generated the final transport dataset for all countries. The workflow loads the mapping table as a template for the output structure, processes each country workbook and scans all relevant transport sheets, extracts the values associated with the mapped JRC identifiers, and assigns them to the corresponding GCAM transport categories. It then merges information from the multiple sheets into a single country-level dataset, creates additional transport categories where required for consistency with the GCAM transport representation, and applies post-processing adjustments (aggregation of selected categories, calculation of derived values, and unit harmonisation). Finally, it converts country codes to GCAM regional naming conventions and retains only the variables required by GCAM: energy use, intensity, and load factor.

Output generation. The processed data for all countries are combined into a single CSV file following the structure of the GCAM transport input database, with metadata describing the file contents, units, and source added automatically.

To illustrate the magnitude of this methodological improvement, representative comparisons for Germany and Spain contrast the output service by technology and vehicle type under the previous regional downscaled estimation versus the new, highly resolved JRC-integrated baseline, for 2021 (calibrated year) and 2030 (modelled year). For an overview of this, see Figure 7.1.

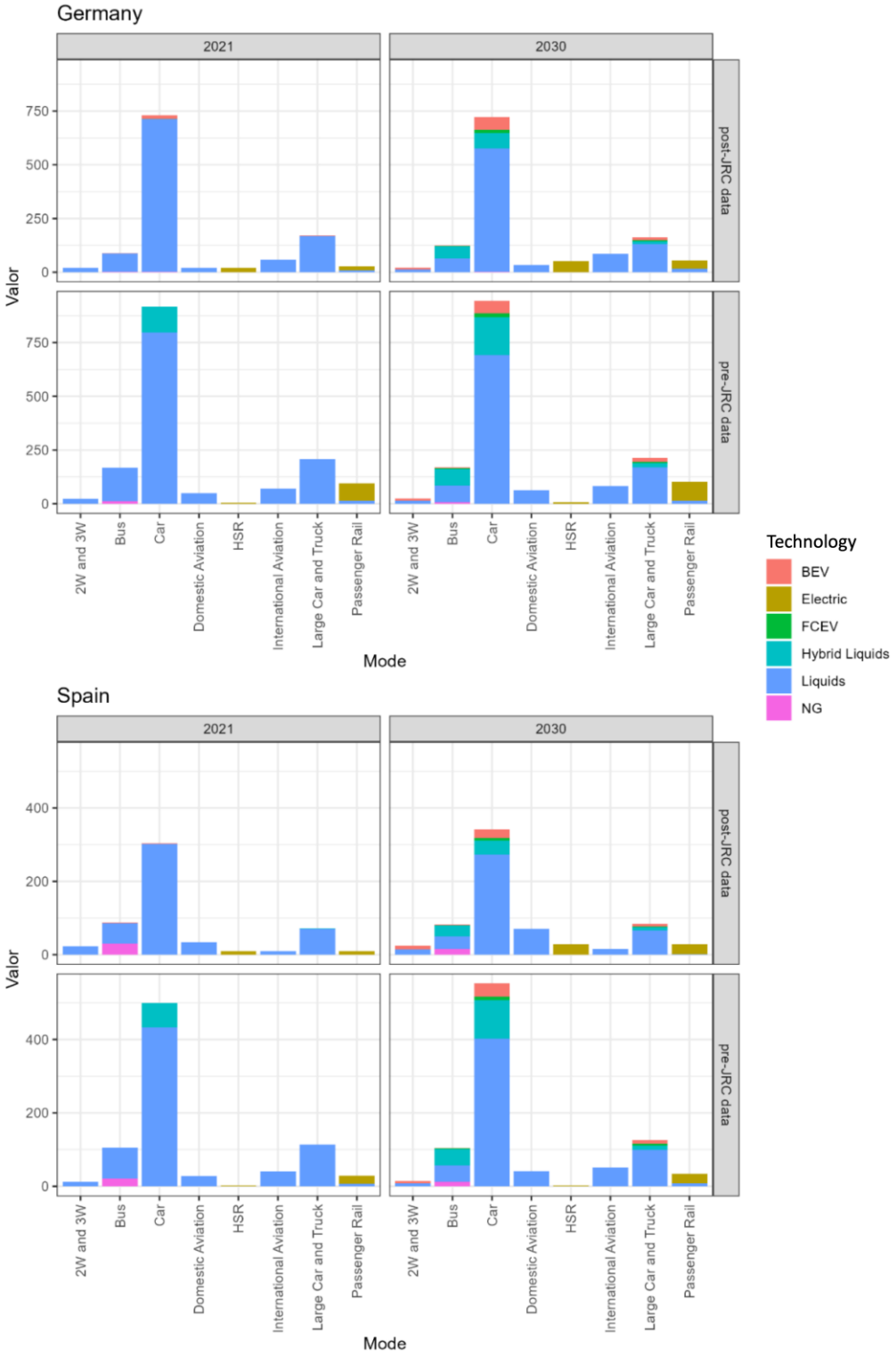

Figure 7.1 Passenger Transport in GCAM-Europe Before and After the Integration of JRC Data, in Germany and Spain, for 2021 (calibrated year) and 2030 (modelled year).