Tracking Public Interest in Sustainable Mobility with Google Trends

Gutierrez-Lythgoe, Antonio and Molina, Jose Alberto

University of Zaragoza, IEDIS

November 2025

Tracking Public Interest in Sustainable Mobility with Google Trends[1]

Antonio Gutiérrez-Lythgoe[a]

Jose Alberto Molina[a]

[a] IEDIS, University of Zaragoza, Spain

Abstract: The transport sector remains one of the main contributors to global GHG emissions, making the shift toward more sustainable mobility a key component of climate-mitigation strategies. While previous research has emphasized the role of infrastructure, technology, and behavioral change, less is known about how public attention toward sustainable transport evolves and diffuses across countries. This paper uses Google Trends data as a high-frequency indicator of public interest in sustainable mobility for 38 OECD countries from 2004 to 2025. To ensure comparability across time and space, we propose the construction of log-ratios between sustainable mobility and conventional car-related searches so that the measure is robust to changes in Google's user base. We apply the Phillips and Sul convergence framework to test whether attention levels follow common long-run trajectories. Results show strong convergence in electric-vehicle attention, while hybrid- and public-transport interest remain fragmented. Validation analyses confirm that Google Trends indicators correlate with subsequent electric-vehicle adoption, underscoring their value as dynamic proxies for cultural and behavioral dimensions of sustainable mobility.

Keywords: sustainable mobility, Google Trends, convergence behavior, digital behavior, transportation policy

JEL Classification: R41, C53, Q56

---

[1] This paper has benefitted from funding from the Government of Aragón (Grants S17_24 and S32_23R). Antonio Gutiérrez-Lythgoe also acknowledges financial support from a predoctoral contract funded by the Government of Aragón (Orden CUS/621/2023, Predoctoral Contracts 2023-2027).

Corresponding author at: Department of Economic Analysis. Gran Vía 2. 50005 Zaragoza. Spain. E-mail addresses: agutierrez@unizar.es (A. Gutierrez-Lythgoe).

1. Introduction

The transport sector is one of the main contributors to the global climate crisis, accounting for around 23% of global CO_2 emissions (Shukla et al., 2022) and nearly 30% of final energy consumption (IEA, 2020). In this context, many efforts have been directed towards the implementation of supply-side and demand-side policies to reduce emissions from transport and mobility (Creutzig et al., 2018; Grubler et al., 2018). Among these, interventions targeting travel demand, such as promoting shifts in mobility behavior or reducing car dependency, stand out for their immediate mitigation potential, as they do not rely on large-scale technology (Winkler et al., 2023). At the same time, the rapid diffusion of low-emission vehicle technologies and the expansion of collective transport systems have become central pillars of the transition toward sustainable mobility. This dual focus on behavioral and technological change reflects a broader re-conceptualization of mobility-not merely as a technical or infrastructural issue, but as a socially embedded practice shaped by norms, values, and innovation dynamics (Banister, 2008).

Therefore, mobility behavior is not determined solely by objective factors such as infrastructure, service availability, but also by subjective dimensions including norms, values, and cultural meanings (Anable, 2005; Giménez-Nadal et al., 2025; Haustein & Nielsen, 2016; Klinger et al., 2013; Molina et al., 2020; Nyborg et al., 2016). Increasingly, research points to the importance of context-specific mobility cultures, which shape what forms of travel are seen as acceptable, desirable, or even possible (Klinger et al., 2013; Mattauch et al., 2016; Sheller & Urry, 2006). These cultural frameworks help explain why policy interventions aimed at reducing car use or promoting sustainable modes often produce uneven or inconsistent outcomes across different urban settings (Aldred & Jungnickel, 2014). In other words, the effectiveness of such measures is moderated by the cultural and social context in which they are implemented (Stolze et al., 2025). Understanding mobility thus requires looking beyond behavior to the symbolic and dispositional factors that drive it. This calls for deeper attention to the diversity of mobility cultures and for analytical tools capable of capturing how these cultural contexts influence demand, preferences, and ultimately, the impact of transport policies.

As recent studies have shown, increasing attention has been devoted to understanding the attitudes, contexts, and values that lead individuals to adopt more sustainable mobility patterns (Haustein & Nielsen, 2016; Klinger et al., 2013; Klinger & Lanzendorf, 2016;

Stolze et al., 2025). However, most of this research has relied on survey data collected from static perspectives or at very low temporal frequencies. Yet, mobility attitudes and behaviors are inherently dynamic (Hopkins & Stephenson, 2016), as they are influenced by external shocks such as public health crises (Schaefer et al., 2021), natural disasters (Sheller, 2013), or shifts in social preferences that may alter individuals' perceptions and choices regarding different transport modes. These changes suggest that mobility cultures evolve over time rather than remaining fixed, reflecting continuous adaptation to social, technological, and policy developments. Despite growing evidence on the diversity of mobility cultures, it remains unclear whether these orientations are converging or diverging over time as sustainability discourses and transport innovations diffuse globally. Exploring these long-run dynamics provides new insights into how sustainable mobility awareness spreads across societies and whether cultural change follows a shared global trajectory or remains path-dependent.

Regarding sustainable mobility, we can also distinguish between objective factors- such as infrastructure, sociodemographics, incentives, and the availability of information - which consistently increase willingness to adopt cleaner alternatives (S. Choi et al., 2022; Echeverría et al., 2022; Ito et al., 2019; Webb et al., 2019), and subjective factors - such as attitudes and social dispositions - which also encourage the uptake of greener modes of transport (Giménez-Nadal et al., 2025). Moreover, dynamic long-run shifts, such as the emergence of "peak car"[2] (Webb, 2019), further illustrate that mobility preferences evolve over time in ways that progressively support a transition toward more sustainable mobility.

Against this background, this paper employs Google Trends data to capture the temporal evolution of public attention toward sustainable mobility across countries. By analyzing search volumes for sustainable versus conventional car-related modes, we assess whether distinct patterns of salience emerge and whether countries follow similar or divergent trajectories over time. To this end, we compile monthly Google Trends Search Volume Index (SVI) data for electric cars, hybrid cars, and public transport across 38 OECD countries, using harmonized translations in each country's dominant language. From these data, we construct log-ratios relative to searches for conventional motorized cars,

[2] "Peak car" refers to the stagnation or decline in per-capita car travel and/or car ownership observed in several high-income countries since the early 2000s, often interpreted as evidence of structural shifts in mobility demand linked to urban densification, changing values, demographic transitions, and the growing attractiveness of more sustainable transport modes.

providing a relative measure of attention to sustainable transport alternatives that is robust to changes in Google's user base over time. Based on these indicators, we examine whether countries share common long-run dynamics in the salience of sustainable mobility using the Phillips and Sul (2007, 2009) convergence framework. This method allows us to test for overall convergence in attention levels and to identify potential "convergence clubs" of countries with similar trajectories over the 2004 - 2025 period.

By employing Google Trends as a high-frequency, geographically disaggregated indicator of *issue salience*, we contribute to three strands of literature: (1) comparative research on mobility cultures and transport behavior ; (2) the use of digital trace data, particularly Google Trends, for analyzing sustainability practices and climate-related concerns (Durmuşoğlu, 2017; Kim & Kim, 2023); and (3) applications of Google Trends in the context of urban mobility and transport behavior (Kostakos et al., 2013).

Our results reveal that public attention toward sustainable mobility has evolved unevenly across transport modes and countries. Using the Phillips and Sul (2007, 2009) framework, we find robust convergence in the salience of electric mobility, suggesting that interest in electric vehicles has globally synchronized over the past two decades. In contrast, attention to hybrid cars and public transport remains fragmented, suggesting persistent cross-national differences in policy ambition, infrastructure, and cultural preferences. The club-convergence analysis further highlights the coexistence of convergent and divergent country groups, pointing to multiple diffusion pathways rather than a single global pattern. Finally, validation exercises show that Google Trends indicators are strongly associated with subsequent electric-vehicle adoption, confirming their value as behavioral proxies for mobility-related awareness. Overall, these findings suggest that while digital interest in electric mobility is consolidating as a shared cultural domain, other dimensions of sustainable transport continue to follow context-specific and path-dependent trajectories.

The remainder of the paper is structured as follows. Section 2 presents the conceptual and theoretical background, including literature on mobility cultures, issue salience, and the use of digital trace data. Section 3 describes the dataset, including keyword selection, country sampling, and data collection from Google Trends. Section 4 outlines the methodological approach used to compare patterns of search interest across countries and over time. Section 5 reports empirical results, focusing on temporal dynamics and cross-national differences in modal salience. Section 6 discusses the findings considering mobility culture theory and draws out their implications for transport policy. Section 7 addresses the study's limitations and outlines directions for future research. Finally, Section 8 concludes.

2. Theoretical background

2.1 Mobility cultures and cultural heterogeneity

Mobility culture is an interdisciplinary concept in the academic literature, marked by a diversity of definitions and disciplinary approaches (Stolze et al., 2025). Mobility Cultures refer to mobility patterns that are rooted in specific places and shaped by local socio-cultural features, as well as by spatial, infrastructural and economic conditions (Deffner et al., 2006; Klinger et al., 2013). This perspective links the influence of built environment-most prominently captured by the "3Ds" of density, diversity and design (Cervero & Kockelman, 1997), alongside "soft factors" such as modal attitudes and cultural perceptions of mobility (Haustein & Nielsen, 2016). Therefore, cultural influences on mobility are shaped through the interplay of daily practices, social norms, and material culture (Hopkins & Stephenson, 2016).

Traditionally, transport research has analyzed distinct mobility styles and behavioral segments to classify individuals according to their preferences for particular modes (Anable, 2005). Individual attitudes and preferences may crystallize into collective patterns and social norms, shaped for instance by cross-national differences in environmental awareness (Baiardi, 2023; Haustein & Nielsen, 2016; Pronello & Camusso, 2011). Literature thus highlights persistent discrepancies between objective and subjective (Haustein & Nielsen, 2016; Klinger et al., 2013). For example, while some modes such as private cars or rail are strongly conditioned by infrastructure, active and sustainable mobility, especially cycling, appears more sensitive to subjective and cultural dimensions (Klinger & Lanzendorf, 2016). In this sense, each transport mode carries a culturally shared affective meaning that functions as a predictor of its adoption (Wolf & Schröder, 2019).

Mobility Cultures are dynamic: car-dependency is reproduced when practices, norms, and material culture are aligned, but change in any element can open conditions for transition (Hopkins & Stephenson, 2016). Studies find modal substitution in response to biographical events such as residential relocation (Klinger, 2017; Klinger & Lanzendorf, 2016), or external shocks (Schaefer et al., 2021). Transport disruptions are frequent and diverse, ranging from strikes (Van Exel & Rietveld, 2009) to terrorism (Potoglou et al., 2010), health crises (Schaefer et al., 2021), or natural disasters (Sheller, 2013), but their persistence in shaping modal choice depends on the type of shock (Van Exel & Rietveld, 2009) .

Mobility cultures are also place-specific and shaped by spatial variation. Comparative research shows that cultural orientations toward mobility differ across countries and regions, reflecting not only infrastructural conditions but also norms, values, and levels of environmental awareness (Haustein & Nielsen, 2016; Pronello & Camusso, 2011). At the individual scale, relocation studies demonstrate how moving between cities with distinct mobility cultures can trigger changes in modal practices (Klinger, 2017; Klinger & Lanzendorf, 2016). These findings highlight that mobility cultures are not homogeneous but spatially embedded, which makes cross-national comparison essential.

If mobility cultures are reflected not only in infrastructures but also in attitudes, perceptions, and symbolic meanings, then online search data may provide a complementary window into these cultural dimensions. By analyzing Google Trends indicators of interest in sustainable transport modes across countries, measured on a standardized scale from 0 to 100, we can capture both the *dynamic* nature of public attention (through temporal fluctuations and disruption-driven peaks) and the *place-specific* variation that reflects distinct cultural contexts. This enables a comparative assessment of how mobility cultures differ in their levels of interest in sustainable mobility, and how these interests evolve over time.

2.2 Prior uses of Google Trends

Google Trends (GT) data has gained increasing popularity in social sciences, particularly after 2014, reflecting a broader shift toward the use of internet search data to analyze public interest and behavior (Hölzl et al., 2025). Its most common applications include leading indicators for tourism (Bokelmann & Lessmann, 2019; Havranek & Zeynalov, 2021) , indicators in areas such as the labor market (Mihaela, 2020; Naccarato et al., 2018; Owen & Wei, 2021), uncertainty indicators (Bilgin et al., 2019; Eichenauer et al., 2022; Pratap & Priyaranjan, 2023; Wolozsko, 2020), and consumption (H. Choi & Varian, 2012; Vosen & Schmidt, 2011; Woo & Owen, 2019). Contributions in the areas of well-being (Brodeur et al., 2021) and public health (Ginsberg et al., 2009) also stand out.

GT data presents a number of benefits that have triggered its use in social science (Cebrián & Domenech, 2024; Hölzl et al., 2025; Lolić et al., 2024). Its major advantage lies in its capacity to capture actual search behavior, thereby bypassing some of the limitations of self-reported survey data. Unlike surveys, GT does not rely on respondents' comprehension of questions, memory accuracy, or willingness to provide socially acceptable answers. As such, it avoids cognitive biases and social desirability biases, offering a more unfiltered window into public concerns and interests. For instance, internet search data has been used to study sensitive or stigmatized topics that are often underreported in surveys, including racism (Stephens-Davidowitz, 2014), sexism (Owen & Wei, 2021), and voting behavior (DiGrazia, 2017).

The continuous growth of internet usage has provided researchers with new tools to monitor and evaluate public interest and evolving social trends, particularly in the context of environmental issues (Baiardi, 2023). Google Trends (GT), in particular, has been widely used to track temporal patterns of public concern around climate change and sustainability (Anderegg & Goldsmith, 2014; Kim & Kim, 2023; Nghiem et al., 2016). GT data has also proven valuable for examining socio-technical dynamics related to mobility and transportation. Choi and Varian (2012) demonstrated that search volume data can improve real-time forecasting of automobile sales among other economic indicators. Vergis & Chen (2015) used Google search interest in "electric vehicles" as a proxy for public awareness and found it to be positively associated with the plug-in electric vehicle market share across U.S. states. More recently, Castellacci & Santoalha (2025) developed regional-level indicators of digitalization and EV adoption across 15 countries using Google Trends, showing that digitalization has played a significant role in fostering electric mobility, especially in regions with higher GDP per capita and better digital infrastructure. Complementing these studies, Kostakos et al. (2013) explored the relationship between online search behavior and urban mobility patterns. Their findings suggest that keyword popularity can serve as a proxy for physical movement, as search terms often show strong semantic and spatial alignment with specific locations.

GT has gained increasing attention in recent years as a data source for detecting issue salience, attitudes, and behaviors (Hölzl et al., 2025). In the case of transport, search activity may reflect genuine interest, intention, or attitude, yet for conservative interpretation we treat it primarily as a measure of issue salience-the degree of collective attention devoted to different mobility modes at a given time and place. This perspective positions GT not as a measure of actual usage, but as a cultural indicator of how societies perceive, value, and attend to mobility, capturing variation across individual intentions, collective visibility, temporal fluctuations linked to external shocks, and spatial differences rooted in distinct socio-cultural contexts. While previous research has demonstrated the value of Google Trends data for understanding public attention to environmental and transport-related topics, most studies remain limited in scope-focusing on national-level analyses (e.g., the U.S.), individual technologies (such as EVs), or short-term forecasting of economic indicators. There is a lack of research that systematically examines the cultural dynamics of sustainable mobility across countries over time, particularly in relation to exogenous shocks such as the COVID-19 pandemic or fuel price crises. Moreover, few studies have connected digital interest data to broader conceptual frameworks like mobility cultures, which emphasize the interplay of place-specific material and symbolic factors.

2.3 Convergence dynamics and cross-country heterogeneity

The concept of convergence has long been central in macroeconomic and empirical research, originating from the economic growth literature (Barro & Sala-i-Martin, 1992; Baumol, 1986). Convergence refers to the process whereby differences across countries or regions in a given variable, such as income, productivity, or emissions, decline over time. In this sense, convergence implies that countries with initially lower levels of a variable tend to grow faster, catching up with those at higher levels in the long run. A time-series perspective on convergence emerged from the notion of stochastic convergence (Bernard & Durlauf, 1995, 1996; Carlino & Mills, 1993). In this framework, convergence is assessed through the stationarity properties of the variable under study. Two non-stationary series are said to converge if a stable long-run relationship, i.e., cointegration exists between them.

While this approach represented an important methodological advance, it assumes that all economies follow a common transition path and adjust at a uniform speed, an assumption rarely consistent with empirical evidence. Phillips and Sul (2007, 2009) challenge this view, arguing that traditional convergence tests are inadequate when technological progress, behavioral responses, or institutional dynamics differ across countries and evolve over time. They propose a more flexible framework based on a nonlinear, time-varying factor model that allows for both cross-sectional and temporal heterogeneity. This so-called club convergence approach tests for overall convergence and, when rejected, identifies subgroups of units that share similar transitional dynamics. The Phillips-Sul approach has been widely applied not only in economics and finance, but also in environmental (Belloc & Molina, 2023a, 2023b), energy, and public health studies (Tomal, 2024).

3. Data

Google Trends data

GT data provides information on search activity, capturing the relative popularity of keywords across specific locations and time periods. Rather than reporting absolute search volumes, it normalizes the data into an index ranging from 0 to 100. The construction process follows two main steps: first, GT samples a share of all search queries within a given time and location; second, it computes the frequency of the target keyword relative to the total number of queries in the sample. Finally, this ratio is normalized against the maximum observed value in the time span considered, producing a comparable index (Cebrián & Domenech, 2024; Lolić et al., 2024). Formally, the GT search volume index, which can be defined as:

$$G_t = \frac{GT_t}{M}.100$$

where $GT_t = {}^{m_t}/_{n_t}$, m_t refers to the frequency of a particular term and n_t is the total number of searches, and, consequently, the ratio is normalized to the maximum ratio $M = max\{GT_t, t = 1,2, \dots T\}$ (Lolić et al., 2024).

We are able to extract search volumes either for exact search terms or for broader topics, which bundle related expressions across languages, including acronyms, spelling variations, translations, and conceptually similar terms (Hölzl et al., 2025). However, the procedure by which GT constructs topic-based indices is not transparent, as it remains unclear which terms are included and whether the underlying set of queries has changed over time. Such opacity reduces replicability and may introduce inconsistencies when comparing results across periods. Exploratory evidence further indicates that topic indices can yield lower normalized values than the corresponding exact-term indices, which contradicts the expectation that topic-based measures should subsume all searches for the given keyword plus its variants (Hölzl et al., 2025). For these reasons, our analysis relies on exact search terms, ensuring greater transparency and replicability.

Regarding the spatial dimension, Google Trends provides search volumes at the level of countries, regions, and even large cities. Since GT values are based on sampled data, inconsistencies may arise across samples, especially for less popular keywords, smaller geographical units, and higher temporal frequencies (Cebrián & Domenech, 2024; Eichenauer et al., 2022). For this reason, we restrict our analysis to OECD countries and employ a monthly frequency, to obtain time series that are as stable and reliable as possible. In terms of the time frame, we use data starting in 2004, which marks the earliest year for which GT provides consistent search activity information. Given the large number of countries analyzed, it was decided to use generic terms translated into the main language of each country. This ensures comparability and avoids reliance on national brands or services.

Keyword selection

Table 1 reports the search terms included in this study. Terms were chosen to capture the most widely used transport modes, and-for comparability across countries-we adopted literal translations into the main national languages. We note an inherent limitation related to language use: segments of the population may employ regional synonyms, colloquial expressions, or operator/brand names to describe the same mode. Consequently, the set may not cover every relevant expression, and estimates of interest may be conservative in contexts where alternative labels dominate. Furthermore, there are countries with more than one official language.

[Table 1 about here]

Data pre-processing

We retrieved ten independent downloads for each keyword and country, covering the period from January 2004 to June 2025. To mitigate sampling variability across extractions, we computed the average of the ten series for each keyword in each country. Google Trends data is available starting in January 2004, but important methodological updates in the construction of GT indices were implemented in January 2011, January 2016, and January 2022. Following the standard adjustment procedure (Lolić et al., 2024), observations after each break are rescaled by multiplying them by the ratio between the 12-month average before the turning point and the 12-month average after it.

After averaging samples and scaling each series we apply logarithms to separate each component of the search volume index. Formally, following Lolić et al. (2024), for country *i*, country *c* and month *t*, the Google Trends (GT) index can be expressed as:

$$g_{i,t}^{k} = \log G_{i,t}^{k} = \log m_{i,t}^{k} - \log n_{it} + \log \frac{100}{M_i^k}$$

where $m_{i,t}^{k}$ denotes the GT index for a keyword, n_{it} the index of the conventional benchmark, and M_i^k is the GT scaling constant (time-invariant for a given keyword/country). While $\log m_{i,t}^{k}$ and $\log \frac{100}{M_i^k}$ depend on the input keyword, $\log n_{it}$ does not-it is common to all GT series.

To remove seasonality, we employ the X-13ARIMA-SEATS procedure, which allows for trading day corrections and flexible ARIMA specifications. Google Trends data requires adjustment for structural changes in the population of internet users. Since 2004, the expansion and diversification of Google's user base have introduced a potential downward bias in relative search indices, as the overall search denominator has grown even when interest in a specific term has not declined (Lolić et al., 2024; Wolozsko, 2020).

We transform the preprocessed monthly Google Trends (GT) series into additive log-ratios (LRs) that compare each sustainable-mobility keyword against a motorized baseline. This provides a relative measure of public attention and filters out components that jointly affect all search volumes, such as overall platform growth or algorithmic updates. The motorized baseline is the GT index for conventional cars, excluding searches that explicitly mention "electric" or "hybrid". We define a motorized base as the GT search index for conventional car (without searching for the words 'electric' or 'hybrid'). The log-ratio for mode k is then:

$$LR_{it}^{k} = g_{it}^{k} - g_{it}^{car} = \log m_{i,t}^{k} - \log m_{i,t}^{car} + \left(c_i^k - c_i^{car}\right)$$

with $c_i^k = \log \frac{100}{M_i^k}$, the rescaling constant applied during GT normalization. Log ratio cancels out $\log n_{it}$, the common Google Trend for country *i* during our study period. A keyword/country constant remains, $\left(c_i^k - c_i^{car}\right)$, but it is time-invariant. Log-ratios are also robust to missing data: when either the numerator or the baseline is unavailable for a given country-month, the observation is set to missing; when both are missing, it is excluded. Structural absences (e.g., lack of a subway system) are omitted from group means to preserve comparability across countries.

[Table 2 about here]

Table 3 summarizes the distributional properties of the three log-ratio indicators across OECD countries. Mean values are negative, indicating that searches for sustainable modes remain less frequent than those for conventional cars. The standard deviations-ranging between 0.7 and 1.4 in logarithmic scale-denote substantial temporal and cross-country variability, implying that the relative salience of each mode can differ by more than twofold across contexts. Such magnitudes suggest that public attention to mobility topics is heterogeneous and evolving rather than uniformly stable.

The shape parameters convey additional information about the underlying dynamics of mobility discourse. Electric-car salience exhibits the highest dispersion but an almost symmetric, mesokurtic distribution, consistent with a diffusion process in which countries adopt and normalize electric-vehicle attention at different speeds. Hybrid-car salience shows positive skewness and mild kurtosis, reflecting episodic peaks of interest often linked to policy incentives or product launches, whereas public-transport salience presents negative skewness and higher kurtosis, indicating occasional downward shocks but overall persistence.

These descriptive moments reveal structured rather than random heterogeneity, motivating a closer examination of whether countries are gradually aligning in their attention to sustainable mobility-a sign of convergent mobility cultures-or whether persistent asymmetries remain. In this sense, convergence analysis becomes relevant to identify whether the diffusion of sustainable transport narratives is leading to a shared cultural transition across countries or to differentiated national pathways.

[Table 3 about here]

Figure 1 shows three main emerging patterns. First, public transport consistently attracts the highest relative attention, with log-ratios around -1, indicating that although car-related searches still dominate, collective modes remain a stable component of the mobility discourse. The mild downward drift after 2020 likely reflects pandemic-related disruptions and the subsequent normalization of telework and private travel.

Second, interest in electric cars shows a sustained and pronounced upward trend, especially after 2010. The curve steepens around 2017-2019, coinciding with large-scale policy incentives and major model releases, before stabilizing near -1.5. This trajectory suggests a diffusion process in which public attention toward electrification rapidly expanded and began approaching the salience level of public transport. Third, hybrid-car salience increases modestly during the 2010s but plateaus early and remains below electric-vehicle levels thereafter, consistent with the technological transition from hybrid to fully electric mobility.

The relative slopes of the three series indicate heterogeneous but interconnected dynamics. Public-transport salience is mature and stationary, whereas electric-vehicle attention displays clear catching-up behavior, and hybrid vehicles appear transitional. This pattern provides an initial indication of potential σ- and β-convergence in the discourse on transport electrification: countries with initially low attention to EVs tend to exhibit faster growth, narrowing cross-country gaps. In broader terms, these dynamics may reflect the gradual alignment of public perceptions-a process of cultural convergence in sustainable mobility awareness across OECD societies.

[Figure 1 about here]

Table A1 documents substantial cross-country heterogeneity in public-transport salience. Mean log-ratios range from -0.20 in the United States and -0.34/-0.38 in France and Italy to values below -1.5 in countries such as Chile, Luxembourg, and Slovakia. Several countries (e.g., the United States, Greece, Israel, or Iceland) display occasional months with positive log-ratios-episodes in which public-transport searches temporarily exceed car-related searches-whereas others (Germany, France, Italy, the Netherlands, Spain) remain strictly negative throughout. Dispersion is modest in large economies but markedly higher in small populations (e.g., Iceland, Estonia, Greece), consistent with amplified sensitivity to local shocks. Tail behavior is generally moderate; however, the Czech Republic, New Zealand, and Israel exhibit leptokurtic distributions ($\kappa \geq 10$), suggesting burst-driven attention.

Table A2 shows large cross-country heterogeneity in electric-car salience. Mean log-ratios are least negative in Japan (-0.50), the United States (-1.21); in Italy, Austria, and Australia (≈-1.5); and in Canada, the United Kingdom, and Germany (-1.46 to -1.90), while they are very low in Luxembourg (-3.29), Mexico (-3.02), Estonia (-3.02), and Latvia (-4.01). Dispersion is modest in large economies (e.g., US SD 0.36; CA 0.40) and higher in several smaller countries (e.g., IS 1.45; SI 1.65; KR 1.64), consistent with differing diffusion speeds. Shape parameters are generally well-behaved (κ ≈ 2-6), indicating stable, near-mesokurtic distributions; a notable exception is Costa Rica (skew 3.69; κ 21.3), where attention is dominated by short-lived bursts. Many countries register occasional months with EV salience above cars (max > 0)-including Switzerland, Chile, Colombia, Finland, Greece, Ireland, Iceland, Japan, Korea, Lithuania, Norway, Portugal, and Slovenia-underscoring the breadth of the diffusion process.

Table A3 reveals pronounced cross-country heterogeneity in hybrid-car salience. Mean log-ratios are least negative in Japan (-0.38), the United States (-1.02), and Canada (-1.15), followed by the Netherlands, France, Spain, and Italy (≈ -1.6 to -2.1), while they are very low in small Nordic and Eastern markets (e.g., Norway -4.19, Poland -4.28, Slovakia -4.22). Dispersion is modest in large economies (e.g., US SD 0.36) but high in several small markets (e.g., IS 1.51, DK 1.52, PT 1.31), consistent with episodic policy or model shocks. Tail behavior is often extreme, e.g., CA (κ 23.6), CH (14.7), IL (50.3), LT (54.6), LU (16.8), LV (55.9), NO (157.1), NZ (32.8), SI (50.9), SK (168.7), JP (26.9), indicating news-driven bursts rather than stable attention.

Cross-country comparisons using Google Trends face a fundamental linguistic limitation: the meaning and usage of mobility-related terms vary widely across languages and cultural contexts. A single English keyword may correspond to multiple expressions, regional variants, or brand names in other languages, while in multilingual countries the relative weight of each language group further distorts search proportions. These semantic asymmetries can generate artificial bursts or discontinuities in search intensity that do not correspond to genuine shifts in public attention.

To mitigate this issue, we adopt a cross-linguistic robustness approach. Specifically, we restrict our analysis to countries whose keyword series display approximately mesokurtic and symmetric distributions ($|skew| < 2$, $\kappa < 10$). This criterion identifies cases where search behavior is stable and semantically consistent over time, minimizing the influence of event-driven or language-specific distortions. Rather than attempting to harmonize all linguistic variants *ex ante*, our strategy isolates statistically stable patterns *ex post*, providing a comparable basis for analyzing cross-country convergence in public attention toward mobility across heterogeneous linguistic environments. We also test for common structural breaks in the panel using *xtbreak* estimator (Ditzen et al., 2025). The model allows for fixed effects that may shift across regimes and applies HAC-robust inference with a 15 % trimming factor to avoid spurious breaks at the sample edges. See Table A4 for common structural breaks in panel data.

4. Methods

Phillips & Sul convergence approach

To integrate diverse mobility signals into a single latent measure of issue salience, dimensionality reduction techniques such as principal component analysis, dynamic factor models, or machine-learning algorithms (e.g., XG-Boost) are typically employed (Lolić et al., 2024). As a matter of fact, the starting point of the Phillips & Sul approach is a dynamic factor formulation of the variable of interest:

$\exp\,(LR_{it}^{k}) = \delta_{it}^{k}\,\mu_{t}^{k},$

Where δ_{it}^{k} is a time-varying idiosyncratic component, which measures the deviation of a country *i* at time *t* for interest in keyword *k* from a common trend defined by μ_{t}^{k}. All countries converge in the future to a single steady state if $\lim_{j\to\infty} \delta_{it+j}^{k} = \delta^{k}$ for all i = 1,2,…,N. Within this framework, convergence is a dynamic process in which δ_{it} can vary across countries and time. There is no assumption of a parametric form of μ_{t} and we only focus on δ_{it+j}^{k}. To estimate it Phillips and Sul (2007) adopted the following semiparametric form:

$$\delta_{it+j}^{k} = \delta_{i}^{k} + \sigma_{i}^{k}\xi_{it}^{k}L(t)^{-1}t^{-\alpha}$$

Where δ_{i}^{k} is fixed, ξ_{it}^{k} is weakly dependent over *t,* but *iid(0,1)* across *i*, σ_{i} is the scale parameter and α is the convergence rate, $L(t)$ denotes a slowly varying function, best choice according to Phillips & Sul (2007) is log t. To model δ_{it}^{k} we follow the suggestion by Phillips & Sul (2007), the use of its relative version:

$$h_{it}^{k} = \frac{LR_{it}^{k}}{N^{-1}\sum_{i=1}^{N} LR_{it}^{k}} = \frac{\delta_{it}^{k}}{N^{-1}\sum_{i=1}^{N} \log \delta_{it}^{k}}$$

where h_{it}^{k} is the transition path of unit *i* and keyword *k* in comparison to the panel average at time *t*. There will be convergence if $h_{it}^{k} \rightarrow 1$ for all *i*, as $t \rightarrow \infty$. At the same time, under convergence, cross-sectional variance H_t veers toward zero:

$$H_t^k = N^{-1}\sum_{i=1}^{N} \left(h_{it}^{k} - 1\right)^2 \rightarrow 0 \; as \; t \rightarrow \infty.$$

Testing of convergence across countries in the PS approach is done via the log t regression, applying OLS regression of the form:

$$\log\left(\frac{H_1}{H_t}\right) - 2 \;\log L(t) = \hat{a} + \hat{b}\log t + \hat{u}_t, t = [rT], [rT] + 1, \dots, T$$

where $\frac{H_1}{H_t}$ denotes the cross-sectional variance ratio, $\hat{b} = 2\hat{\alpha}$ is the convergence speed parameter and $\hat{\alpha}$ is an estimate of α, $-2 \;\log L(t)$ is a penalization function to improve the performance of the test under alternative hypothesis and *r* is a parameter designed to remove a certain number of initial observations in order to increase attention to the rest of the sample. According to Phillips and Sul (2009), “data trimming validates the regression equation in terms of the asymptotic representation of the transition distance and ensures test consistency in growth convergence applications”. Best choice for r when T is large (our case) is 0.2 (Phillips & Sul, 2007). A one-sided t-test using $\hat{b}$ and a heteroskedasticity and autocorrelation-consistent (HAC) standard error is used to test the null hypothesis of convergence.

Convergence clubs algorithm

The rejection of null hypothesis of convergence does not mean that there is no club convergence. To analyze convergence clusters, we follow Phillps & Sull (2007) data-driven algorithm. The approach follows five steps. First, the panel units are ordered in descending order according to the most recent values of their series, since convergence is expected to be more evident in the final part of the sample. Next, a preliminary “core group” of at least two countries is identified. The procedure begins with the two highest-ranked series and tests whether their joint evolution satisfies the log-t regression criterion

$t_{\hat{b}} \leq$ -1.65 indicating the absence of convergence clubs in the sample. In the following step, the algorithm checks whether the remaining countries can be incorporated into the previously identified core group. Each remaining unit is added individually, and the log-t regression is re-estimated. If the resulting statistics exceed a critical threshold c* the country joins the club; otherwise, it remains outside. Once all candidates have been evaluated, the full group is re-tested for overall convergence using the 5% critical value (-1.65). If convergence is confirmed, this set defines an initial club. Otherwise, the process is repeated with a higher c* which makes the test more conservative: a higher threshold reduces the probability of including dissimilar members but increases the chance that some units remain unclassified. nce the first convergence club has been formed, the procedure is repeated for the remaining countries that were not included in that group. The log-t regression is again estimated for these residual units to assess whether they display a common convergence path. If the null hypothesis of convergence cannot be rejected ($t_{\hat{b}} \leq$ -1.65), the remaining units constitute an additional convergence club, and the algorithm stops. Conversely, if convergence is rejected, the same iterative process (ordering, core formation, and membership testing) is applied to the remaining subset until all units are classified into one or more clubs. In cases where no valid core group can be identified among the unclassified countries, these units are considered to diverge from the rest of the panel.

Empirical validation: linking search salience to real mobility outcomes

To empirically assess whether the Google Trends indicators reflect actual behavioral changes in sustainable mobility, we estimate a panel data model linking search salience to the adoption of electric vehicles. Specifically, we regress the logarithm of battery electric vehicles (BEV) per capita on the contemporaneous and lagged values (up to two quarters) of Google Trends log-ratios for electric cars, hybrid cars, and public transport. The baseline specification is estimated with country fixed effects, quarterly and yearly dummies, and the following lagged control variables: unemployment rate, consumer price index (CPI), consumer confidence index, COVID-19 stringency index, log GDP per capita, and the log of total EV charging points per capita. The model is estimated using the within estimator with standard errors clustered at the country level to account for serial correlation and heteroskedasticity across panels. Formally, the estimated equation is:

$$\ln(BEV_{it}) = \alpha_i + \gamma_q + \delta_y + \sum_{k=0}^{2} \beta_k lr_{i,t-k}^{EV} + \sum_{k=0}^{2} \theta_k lr_{i,t-k}^{HY} + \sum_{k=0}^{2} \emptyset_k lr_{i,t-k}^{PT} + X'_{i,t-1} + \varepsilon_{it} +$$

where α_i denotes country fixed effects and γ_q and δ_y represent quarter and year dummies, and $X'_{i,t-1}$ is the vector of macroeconomic and infrastructural controls. This specification captures both the short-term and lagged effects of online search salience on real electric-vehicle registrations, serving as a validation exercise for the behavioral relevance of the Google Trends indicators. See control variables used in Table A5.

5. Results

Following Phillips and Sul (2007), convergence is understood as a long-run process; therefore, we isolate the structural component of public attention. Table 4 reports the Phillips-Sul log-t test. In the full OECD sample (Panel A), global convergence is rejected for all three indicators (public transport, electric cars, and hybrid cars). Once we restrict the analysis to linguistically stable series (Panel B; $|$ skew $| < 2,\ \kappa < 10$), global convergence is no longer rejected for public transport ($t = -1.36 > -1.65$), indicating that the lack of convergence may be driven by semantic bursts and noisy series. By contrast, electric and hybrid cars still reject global convergence, consistent with heterogeneous diffusion paths across countries. These results motivate a club-convergence analysis for EVs and hybrids, while public-transport salience behaves as a mature, converging domain in the core sample.

[Table 4 about here]

In Panel A of Table 4, we examine the dynamics of convergence in the relative salience of public transport, electric cars, and hybrid cars across the 38 OECD countries over the full sample period (2004 m1-2025 m6). The results reveal that the null hypothesis of convergence is rejected for public transport (t = -3.6184< -1.65), indicating persistent divergence in collective-mobility narratives across countries. Conversely, the null of convergence is not rejected for electric vehicles (t = 3.4463) and hybrid vehicles (t = 2.6996), suggesting a clear common trend in the salience of private electric mobility.

Panel B restricts the analysis to a linguistically and distributionally stable sample, excluding countries whose salience series exhibit strong asymmetry or kurtosis (|skew| > 2 or κ > 10). Once these unstable cases are removed (IE, IL, LV, CZ, NZ), the public-transport indicator no longer rejects the null of convergence (t = -0.6065 > -1.65), suggesting that the apparent divergence in Panel A may be largely driven by noisy or irregular series. For electric-vehicle salience, excluding Costa Rica and Austria (CR, AT), there is a slightly strengthens evidence of convergence (t = 5.9901), confirming the robustness of the common pattern found in the full sample. For hybrid vehicles, after removing the most unstable series (CA, CH, CR, IL, JP, LT, LU, LV, NO, NZ, SI, and SK), the null of convergence is also not rejected (t = 1.4259), though the statistical support is weaker. Overall, the stability-filtered sample reinforces the view that convergence in electrified-mobility narratives is not an artifact of data irregularities but reflects genuine cross-country synchronization, while public-transport salience becomes more homogeneous once noise is controlled for.

Panel C narrows the temporal focus to the post-2007 regime, following the structural break detected. Under this restriction, the null of convergence is rejected for public transport (t = -7.6949< -1.65), indicating persistent divergence in collective-mobility attention across countries. By contrast, electric-vehicle salience continues to show a strong positive coefficient (t = 2.1506), providing robust evidence of convergence in public interest toward electric mobility. Hybrid vehicles display a negative but only slightly higher than established threshold (t = -1.5009), suggesting near divergent dynamics of cross-country differences after 2007. Taken together, these findings confirm robust convergence in public attention toward electric vehicles across OECD countries, whereas public-transport and hybrid-vehicle salience exhibit persistent divergence, reflecting country-specific differences in mobility policies and cultural preferences.

Panel D combines both adjustments, the post-2007 regime and the linguistically stable subset. The pattern remains consistent: public-transport salience still diverges (t = -4.5747), electric-vehicle salience remains convergent (t = 2.7473), and hybrid-vehicle salience shows significant divergence (t = -4.6059). Altogether, these results suggest that while attention to electric mobility has globally synchronized during the past decade, narratives around public transport and hybrid cars remain fragmented and context-specific.

[Table 5 about here]

Table 5 reports the results of the Phillips-Sul club convergence procedure for public-transport-related mobility salience. For the full sample, the algorithm splits the panel into two clubs. The large core club (N = 36) shows no rejection of within-club convergence, with a beta coefficient of -0.038 and a t-statistic of -1.40, which is above the -1.65 threshold. The small Germany-Greece club (N = 2) is likewise not rejected, with a beta coefficient of -1.064 and a t-statistic of -1.12, although inference is weak given the very small size. In line with the global log-t result (reported earlier as significantly negative), these findings indicate partial convergence, characterized by a dominant convergent core and a peripheral divergent pair. When restricting the analysis to the post-2007 period, the procedure identifies two clubs and one singleton. The main club (N = 31) converges, with a beta coefficient of 0.038 and a t-statistic of 1.22. The second cluster (Austria, Switzerland, Chile, Costa Rica, Germany, and Portugal; N = 6) is not rejected, with a beta coefficient of -0.086 and a t-statistic of -0.64, again with limited statistical power. Greece appears as a non-convergent singleton, flagged by the algorithm as outside any stable group, suggesting greater fragmentation after the 2007 break.

For the post-2007 core-stable sample, the algorithm yields three clubs, all satisfying the within-club convergence condition. The large core club (N = 29) is not rejected, with a beta coefficient of 0.0035 and a t-statistic of 0.085. The Switzerland-Portugal pair has a beta coefficient of -0.610 and a t-statistic of -1.10, while the Costa Rica-Greece pair shows a beta coefficient of 2.449 and a t-statistic of 3.84, both above the -1.65 threshold. Overall, public-transport salience exhibits partial and club-specific convergence, with a stable core of countries following similar long-run dynamics and a small set of persistent outliers, particularly after the 2007 structural break. Results are robust to the core-stable restriction, although interpretation of two-country clubs should be treated with caution due to small-sample limitations.

[Table 6 about here]

Table 6 shows the results for hybrid-car salience after 2007 show a clear pattern of multi-club convergence. The Phillips-Sul algorithm identifies two internally convergent groups and one small non-convergent pair. The largest club (N = 14), which includes mainly Western European and high-income countries, exhibits strong and statistically significant convergence, with a beta coefficient of 0.3366 and a t-statistic of 5.58. The second cluster (N = 10) also satisfies the convergence condition, with a beta coefficient of 0.0802 and a t-statistic of 0.76, suggesting a similar long-run adjustment path at different levels of salience. In contrast, the small Austria-Greece pair (N = 2) is classified as a non-convergent group, showing a beta coefficient of -0.7927 and a t-statistic of -1.68, which falls below the -1.65 threshold. Overall, the results indicate partial but robust convergence in hybrid-vehicle salience after 2007, with a leading convergent core, a secondary convergent bloc, and a minor divergent outlier cluster.

Validation

Table 7 presents the validation exercise assessing whether the Google Trends indicators capture meaningful behavioral signals related to electric-vehicle (EV) adoption. Using a country fixed-effects panel for 2018-2024 at quarterly frequency, we regress the per-capita stock of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) on the corresponding Google search log-ratios, including two lags to account for adjustment dynamics. The models control for macroeconomic conditions (unemployment, CPI, consumer confidence), the COVID-19 stringency index, GDP per capita, and the density of public charging infrastructure, with country-clustered robust errors and full seasonal and annual dummies.

Results show that search attention to electric cars is a strong leading indicator of BEV diffusion. In column (1), the coefficients on the electric-car log-ratio are positive and significant at the 5% level contemporaneously (0.253**) and at the first and second lags (0.359**, 0.157*). Interpreted as elasticities, these results imply that a 10% sustained increase in electric-car search salience over three quarters is associated with roughly a 7-8% higher BEV stock per capita. This effect is consistent with the idea that digital attention reflects both growing consumer awareness and heightened informational diffusion preceding actual purchase decisions. Column (3) confirms that greater attention to electric cars is also associated with an increase in the BEV/PHEV composition ratio (0.219 and 0.288**), indicating that public interest tilts adoption toward fully electric vehicles rather than transitional hybrid technologies.

Cross-mode spillovers behave plausibly. The hybrid-car indicator exerts a negative lagged effect on BEV adoption (-0.124**), suggesting that attention to hybrids and to BEVs may represent substitute narratives within the broader electrification discourse. Similarly, the public-transport log-ratios display negative and significant coefficients at lags one and two (-0.674**, -0.438**), consistent with a mild substitution effect between collective and private mobility attention: when interest in public transport rises, private

EV adoption tends to decelerate. These cross-elasticities underline that Google Trends captures meaningful shifts in the informational competition among mobility modes, not merely noise or seasonality.

Control variables behave as expected. Charging-point density exhibits large and highly significant elasticities for both BEVs (0.665***) and PHEVs (0.842***), confirming that infrastructure availability remains the strongest structural driver of electric-vehicle uptake. A higher Consumer Price Index is associated with greater PHEV adoption (0.049***) but reduces the BEV/PHEV ratio (-0.028**), suggesting that price pressures or inflationary contexts may temporarily favor hybrids over fully electric options. Other macro controls are mostly insignificant, supporting the interpretation that search attention captures a distinct behavioral dimension beyond income or cyclical effects.

Taken together, these findings provide strong evidence of construct validity for the Google-based salience indicators. The positive and lagged relationship between search attention and subsequent BEV growth supports the idea that digital interest precedes and predicts real behavioral change. Google Trends thus offers a timely, high-frequency window into the cultural and informational dynamics underpinning the electrification transition. The results also align with the convergence analysis: while electric-vehicle attention has globally synchronized, consistent with common technological diffusion and policy framing, hybrid and public-transport narratives remain fragmented, reflecting diverse national trajectories within the broader sustainability transition.

[Table 7 about here]

6. Conclusion

This paper examines how public attention toward sustainable mobility has evolved across 38 OECD countries over the period 2004-2025, using Google Trends as a high-frequency indicator of digital interest in electric cars, hybrid cars, and public transport. By applying the Phillips and Sul (2007, 2009) convergence framework, we have investigated whether these patterns reflect a process of global convergence or divergent trajectories shaped by national contexts and policies.

The results provide clear and differentiated evidence. Public attention toward electric mobility shows strong convergence, suggesting that interest in electric vehicles has become increasingly synchronized across advanced economies. In contrast, hybrid cars and public transport exhibit persistent divergence, indicating that collective-mobility narratives and intermediate technologies remain more locally embedded and context-dependent. The club-convergence analysis reinforces this pattern, revealing the coexistence of a large convergent core and several smaller, divergent groups. Validation tests further confirm that Google search attention correlates significantly with subsequent adoption of electric vehicles, supporting the interpretation of digital interest as a behavioral and informational proxy for mobility transitions.

These findings contribute to the growing literature on mobility cultures and digital behavioral indicators by showing that online data can capture meaningful long-run shifts in public awareness. They also highlight the asymmetric diffusion of sustainable-mobility discourses: while electric mobility has achieved global cultural visibility, the salience of public transport continues to depend on national policy priorities, service quality, and social imaginaries. For policymakers, the results suggest that communication and policy strategies promoting sustainable mobility should consider these cross-national differences in public attention and cultural framing.

Future research could extend this approach by combining digital-trace data with survey or mobility-tracking information to explore causal links between online interest, attitudinal change, and behavioral adoption. Further applications could also examine other dimensions of sustainable transport-such as active modes, shared mobility, or telecommuting-to assess whether the convergence observed for electric mobility represents a broader societal shift toward sustainability or a technology-specific trend.

References

Aldred, R., & Jungnickel, K. (2014). Why culture matters for transport policy: The case of cycling in the UK. *Journal of Transport Geography*, *34*, 78-87.

Anable, J. (2005). 'Complacent Car Addicts' or 'Aspiring Environmentalists'? Identifying travel behaviour segments using attitude theory. *Transport Policy*, *12*(1), 65-78. https://doi.org/10.1016/j.tranpol.2004.11.004

Anderegg, W. R. L., & Goldsmith, G. R. (2014). Public interest in climate change over the past decade and the effects of the 'climategate' media event. *Environmental Research Letters*, *9*(5), 054005. https://doi.org/10.1088/1748-9326/9/5/054005

Baiardi, D. (2023). What do you think about climate change? *Journal of Economic Surveys*, *37*(4), 1255-1313. https://doi.org/10.1111/joes.12535

Banister, D. (2008). The sustainable mobility paradigm. *Transport Policy*, *15*(2), 73-80. https://doi.org/10.1016/j.tranpol.2007.10.005

Barro, R. J., & Sala-i-Martin, X. (1992). Convergence. *Journal of Political Economy*, *100*(2), 223-251.

Baumol, W. J. (1986). Productivity growth, convergence, and welfare: What the long-run data show. *The American Economic Review*, 1072-1085.

Belloc, I., & Molina, J. A. (2023a). Are greenhouse gas emissions converging in Latin America? Implications for environmental policies. *Economic Analysis and Policy*, *77*, 337-356. https://doi.org/10.1016/j.eap.2022.11.022

Belloc, I., & Molina, J. A. (2023b). The ecological footprint in Africa: Identifying convergence clubs from 1970 to 2018. *Applied Economics Letters*, *30*(19), 2808-2813.

Bernard, A. B., & Durlauf, S. N. (1995). Convergence in international output. *Journal of Applied Econometrics*, *10*(2), 97-108.

Bernard, A. B., & Durlauf, S. N. (1996). Interpreting tests of the convergence hypothesis. *Journal of Econometrics*, *71*(1-2), 161-173.

Bilgin, M. H., Demir, E., Gozgor, G., Karabulut, G., & Kaya, H. (2019). A novel index of macroeconomic uncertainty for Turkey based on Google-Trends. *Economics Letters*, *184*, 108601.

Bokelmann, B., & Lessmann, S. (2019). Spurious patterns in Google Trends data-An analysis of the effects on tourism demand forecasting in Germany. *Tourism Management*, *75*, 1-12.

Brodeur, A., Clark, A. E., Fleche, S., & Powdthavee, N. (2021). COVID-19, lockdowns and well-being: Evidence from Google Trends. *Journal of Public Economics*, *193*, 104346. https://doi.org/10.1016/j.jpubeco.2020.104346

Carlino, G. A., & Mills, L. O. (1993). Are US regional incomes converging?: A time series analysis. *Journal of Monetary Economics*, *32*(2), 335-346.

Castellacci, F., & Santoalha, A. (2025). Does digitalisation affect the adoption of electric vehicles? New regional-level evidence from Google Trends data. *Regional Studies*, *59*(1), 2358829.

Cebrián, E., & Domenech, J. (2024). Addressing Google Trends inconsistencies. *Technological Forecasting and Social Change*, *202*, 123318. https://doi.org/10.1016/j.techfore.2024.123318

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: Density, diversity, and design. *Transportation Research Part D: Transport and Environment*, *2*(3), 199-219.

Choi, H., & Varian, H. (2012). Predicting the present with Google Trends. *Economic Record*, *88*, 2-9.

Choi, S., Kwak, K., Yang, S., Lim, S., & Woo, J. (2022). Effects of policy instruments on electric scooter adoption in Jakarta, Indonesia: A discrete choice experiment approach. *Economic Analysis and Policy*, *76*, 373-384.

Creutzig, F., Roy, J., Lamb, W. F., Azevedo, I. M. L., Bruine De Bruin, W., Dalkmann, H., Edelenbosch, O. Y., Geels, F. W., Grubler, A., Hepburn, C., Hertwich, E. G., Khosla, R., Mattauch, L., Minx, J. C., Ramakrishnan, A., Rao, N. D., Steinberger, J. K., Tavoni, M., Ürge-Vorsatz, D., & Weber, E. U. (2018). Towards demand-side solutions for mitigating climate change. *Nature Climate Change*, *8*(4), 260-263. https://doi.org/10.1038/s41558-018-0121-1

Deffner, J., Götz, K., Schubert, S., Potting, C., Stete, G., Tschann, A., & Loose, W. (2006). Entwicklung eines integrierten Konzepts der Planung, Kommunikation und Implementierung einer nachhaltigen, multioptionalen Mobilitätskultur. *Frankfurt: Institut für Sozial-ökologische Forschung*.

DiGrazia, J. (2017). Using internet search data to produce state-level measures: The case of tea party mobilization. *Sociological Methods & Research*, *46*(4), 898-925.

Ditzen, J., Karavias, Y., & Westerlund, J. (2025). Testing and estimating structural breaks in time series and panel data in Stata. *The Stata Journal*, *25*(3), 526-560.

Du, K. (2017). Econometric convergence test and club clustering using Stata. *The Stata Journal*, *17*(4), 882-900.

Durmuşoğlu, Z. D. U. (2017). Using Google trends data to assess public understanding on the environmental risks. *Human and Ecological Risk Assessment: An International Journal*, *23*(8), 1968-1977. https://doi.org/10.1080/10807039.2017.1350566

Echeverría, L., Giménez-Nadal, J. I., & Molina, J. A. (2022). Who uses green mobility? Exploring profiles in developed countries. *Transportation Research Part A: Policy and Practice*, *163*, 247-265.

Eichenauer, V. Z., Indergand, R., Martínez, I. Z., & Sax, C. (2022). Obtaining consistent time series from Google Trends. *Economic Inquiry*, *60*(2), 694-705. https://doi.org/10.1111/ecin.13049

Giménez-Nadal, J. I., Molina, J. A., & Velilla, J. (2025). Pro-environment attitudes and worker commuting behavior. *Economic Analysis and Policy*, *86*, 1967-1986. https://doi.org/10.1016/j.eap.2025.05.040

Ginsberg, J., Mohebbi, M. H., Patel, R. S., Brammer, L., Smolinski, M. S., & Brilliant, L. (2009). Detecting influenza epidemics using search engine query data. *Nature*, *457*(7232), 1012-1014.

Grubler, A., Wilson, C., Bento, N., Boza-Kiss, B., Krey, V., McCollum, D. L., Rao, N. D., Riahi, K., Rogelj, J., De Stercke, S., Cullen, J., Frank, S., Fricko, O., Guo, F., Gidden, M., Havlík, P., Huppmann, D., Kiesewetter, G., Rafaj, P., … Valin, H. (2018). A low energy demand scenario for meeting the 1.5 °C target and sustainable development goals without negative emission technologies. *Nature Energy*, *3*(6), 515-527. https://doi.org/10.1038/s41560-018-0172-6

Haustein, S., & Nielsen, T. A. S. (2016). European mobility cultures: A survey-based cluster analysis across 28 European countries. *Journal of Transport Geography*, *54*, 173-180. https://doi.org/10.1016/j.jtrangeo.2016.05.014

Havranek, T., & Zeynalov, A. (2021). Forecasting tourist arrivals: Google Trends meets mixed-frequency data. *Tourism Economics*, *27*(1), 129-148.

Hölzl, J., Keusch, F., & Sajons, C. (2025). The (mis) use of Google Trends data in the social sciences-A systematic review, critique, and recommendations. *Social Science Research*, *126*, 103099.

Hopkins, D., & Stephenson, J. (2016). The replication and reduction of automobility: Findings from Aotearoa New Zealand. *Journal of Transport Geography*, *56*, 92-101. https://doi.org/10.1016/j.jtrangeo.2016.09.005

IEA, I. (2020). World energy balances 2020. *IEA, Electricity Information*.

Ito, N., Takeuchi, K., & Managi, S. (2019). Do battery-switching systems accelerate the adoption of electric vehicles? A stated preference study. *Economic Analysis and Policy*, *61*, 85-92.

Kim, Y., & Kim, Y. (2023). Global regionalization of heat environment quality perception based on K-means clustering and Google trends data. *Sustainable Cities and Society*, *96*, 104710. https://doi.org/10.1016/j.scs.2023.104710

Klinger, T. (2017). Moving from monomodality to multimodality? Changes in mode choice of new residents. *Transportation Research Part A: Policy and Practice*, *104*, 221-237. https://doi.org/10.1016/j.tra.2017.01.008

Klinger, T., Kenworthy, J. R., & Lanzendorf, M. (2013). Dimensions of urban mobility cultures – a comparison of German cities. *Journal of Transport Geography*, *31*, 18-29. https://doi.org/10.1016/j.jtrangeo.2013.05.002

Klinger, T., & Lanzendorf, M. (2016). Moving between mobility cultures: What affects the travel behavior of new residents? *Transportation*, *43*(2), 243-271. https://doi.org/10.1007/s11116-014-9574-x

Kostakos, V., Juntunen, T., Goncalves, J., Hosio, S., & Ojala, T. (2013). Where Am I? Location Archetype Keyword Extraction from Urban Mobility Patterns. *PLoS ONE*, *8*(5), e63980. https://doi.org/10.1371/journal.pone.0063980

Lolić, I., Matošec, M., & Sorić, P. (2024). DIY google trends indicators in social sciences: A methodological note. *Technology in Society*, *77*, 102477. https://doi.org/10.1016/j.techsoc.2024.102477

Mattauch, L., Ridgway, M., & Creutzig, F. (2016). Happy or liberal? Making sense of behavior in transport policy design. *Transportation Research Part D: Transport and Environment*, *45*, 64-83. https://doi.org/10.1016/j.trd.2015.08.006

Mihaela, S. (2020). Improving unemployment rate forecasts at regional level in Romania using Google Trends. *Technological Forecasting and Social Change*, *155*, 120026.

Molina, J. A., Giménez-Nadal, J. I., & Velilla, J. (2020). Sustainable commuting: Results from a social approach and international evidence on carpooling. *Sustainability*, *12*(22), 9587.

Naccarato, A., Falorsi, S., Loriga, S., & Pierini, A. (2018). Combining official and Google Trends data to forecast the Italian youth unemployment rate. *Technological Forecasting and Social Change*, *130*, 114-122.

Nghiem, L. T. P., Papworth, S. K., Lim, F. K. S., & Carrasco, L. R. (2016). Analysis of the Capacity of Google Trends to Measure Interest in Conservation Topics and the Role of Online News. *PLOS ONE*, *11*(3), e0152802. https://doi.org/10.1371/journal.pone.0152802

Nyborg, K., Anderies, J. M., Dannenberg, A., Lindahl, T., Schill, C., Schlüter, M., Adger, W. N., Arrow, K. J., Barrett, S., Carpenter, S., Chapin, F. S., Crépin, A.-S., Daily, G., Ehrlich, P., Folke, C., Jager, W., Kautsky, N., Levin, S. A., Madsen, O. J., … De Zeeuw, A. (2016). Social norms as solutions. *Science*, *354*(6308), 42-43. https://doi.org/10.1126/science.aaf8317

Owen, A. L., & Wei, A. (2021). Sexism, household decisions, and the gender wage gap. *Labour Economics*, *72*, 102062. https://doi.org/10.1016/j.labeco.2021.102062

Phillips, P. C., & Sul, D. (2007). Transition modeling and econometric convergence tests. *Econometrica*, *75*(6), 1771-1855.

Potoglou, D., Robinson, N., Kim, C. W., Burge, P., & Warnes, R. (2010). Quantifying individuals' trade-offs between privacy, liberty and security: The case of rail travel in UK. *Transportation Research Part A: Policy and Practice*, *44*(3), 169-181.

Powell, E., Ellis, J. R., Marcheskie, R. L., & Muhlestein, M. (2025). Trends in Public Interest Towards Car-Free Urbanism: A Decade of Google Trends Analysis (2013–2022). *Electronic Green Journal*, *1*(51). https://doi.org/10.5070/g3.39625

Pratap, B., & Priyaranjan, N. (2023). Macroeconomic effects of uncertainty: A Google trends-based analysis for India. *Empirical Economics*, *65*(4), 1599-1625.

Pronello, C., & Camusso, C. (2011). Travellers' profiles definition using statistical multivariate analysis of attitudinal variables. *Journal of Transport Geography*, *19*(6), 1294-1308.

Schaefer, K. J., Tuitjer, L., & Levin-Keitel, M. (2021). Transport disrupted – Substituting public transport by bike or car under Covid 19. *Transportation Research Part A: Policy and Practice*, *153*, 202-217. https://doi.org/10.1016/j.tra.2021.09.002

Sheller, M. (2013). The islanding effect: Post-disaster mobility systems and humanitarian logistics in Haiti. *Cultural Geographies*, *20*(2), 185-204.

Sheller, M., & Urry, J. (2006). The New Mobilities Paradigm. *Environment and Planning A: Economy and Space*, *38*(2), 207-226. https://doi.org/10.1068/a37268

Shukla, P. R., Skea, J., Reisinger, A. R., & IPCC (Eds.). (2022). *Climate change 2022: Mitigation of climate change*. IPCC.

Stephens-Davidowitz, S. (2014). The cost of racial animus on a black candidate: Evidence using Google search data. *Journal of Public Economics*, *118*, 26-40.

Stolze, D., Klinger, T., & Haustein, S. (2025). Unpacking mobility cultures: A review of conceptual definitions and empirical approaches. *Transport Reviews*, *45*(3), 301-332. https://doi.org/10.1080/01441647.2025.2454414

Tomal, M. (2024). A review of Phillips-Sul approach-based club convergence tests. *Journal of Economic Surveys*, *38*(3), 899-930. https://doi.org/10.1111/joes.12563

Van Exel, N., & Rietveld, P. (2009). When strike comes to town… anticipated and actual behavioural reactions to a one-day, pre-announced, complete rail strike in the Netherlands. *Transportation Research Part A: Policy and Practice*, *43*(5), 526-535.

Vergis, S., & Chen, B. (2015). Comparison of plug-in electric vehicle adoption in the United States: A state by state approach. *Research in Transportation Economics*, *52*, 56-64. https://doi.org/10.1016/j.retrec.2015.10.003

Vosen, S., & Schmidt, T. (2011). Forecasting private consumption: Survey-based indicators vs. Google trends. *Journal of Forecasting*, *30*(6), 565-578.

Webb, J. (2019). The future of transport: Literature review and overview. *Economic analysis and policy*, *61*, 1-6.

Webb, J., Wilson, C., & Kularatne, T. (2019). Will people accept shared autonomous electric vehicles? A survey before and after receipt of the costs and benefits. *Economic Analysis and Policy*, *61*, 118-135.

Winkler, L., Pearce, D., Nelson, J., & Babacan, O. (2023). The effect of sustainable mobility transition policies on cumulative urban transport emissions and energy demand. *Nature Communications*, *14*(1). https://doi.org/10.1038/s41467-023-37728-x

Wolf, I., & Schröder, T. (2019). Connotative meanings of sustainable mobility: A segmentation approach using cultural sentiments. *Transportation Research Part A: Policy and Practice*, *126*, 259-280. https://doi.org/10.1016/j.tra.2019.06.002

Wolozsko. (2020). *Tracking activity in real time with Google Trends* (OECD Economics Department Working Papers). Organisation for Economic Co-Operation and Development (OECD). https://doi.org/10.1787/6b9c7518-en

Woo, J., & Owen, A. L. (2019). Forecasting private consumption with Google Trends data. *Journal of Forecasting*, *38*(2), 81-91.

Table 1. Keywords

subway
train
light rail
public transportation
electric car
hybrid car
car
bus

Note: The keyword ‘car’ excludes queries that jointly search for car + hybrid or + electric.

Table 2. Definition and conceptual meaning of log-ratio indicators

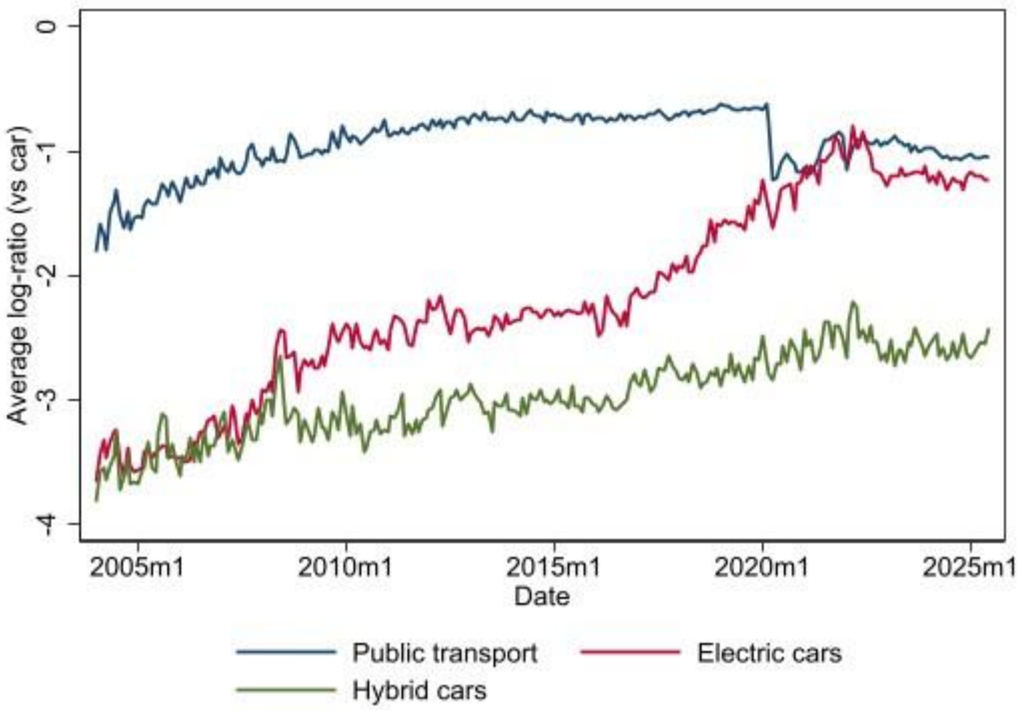
Log-ratio variable	Conceptual meaning
Log ratio: Public transport	Measures the relative public attention to collective transport modes (bus, metro, tram, light rail, public transportation) compared with private car searches. Positive values indicate periods when collective mobility dominates the mobility discourse.
Log ratio: Electric vehicles	Compares search interest in electric vehicles with that in conventional cars. Higher values denote greater prominence of transport electrification within public attention.
Log ratios: Hybrid cars	Measures attention to hybrid vehicles relative to conventional cars, capturing intermediate stages in the technological transition toward full electrification.

Table 3. Summary statistics

VARIABLES	Mean	SD	Min	Max	Skewness	Kurtosis
LR: Public transport	-0.940	0.727	-4.693	1.701	-1.561	6.251
LR: Electric cars	-2.195	1.306	-4.707	4.457	-0.140	1.983
LR: Hybrid cars	-2.973	1.401	-5.175	4.446	0.685	2.137

Note: Authors' calculations using Google Trends data (OECD countries, 2004-2025).

Figure 1. Average evolution of mobility salience across OECD countries



Note: Figure 1 displays the average evolution of mobility salience across OECD countries from 2004 to 2025

Table 4. Phillips-Sul log-*t* test for global convergence in mobility-salience indicators

Panel A. Overall convergence					
Public transport		**Electric cars**		**Hybrid cars**	
b coefficient	t-stat	b coefficient	t-stat	b coefficient	t-stat
-0.1101	-2.7998	0.5834	5.3412	0.1004	2.1800
Panel B. Core sample					
b coefficient	t-stat	b coefficient	t-stat	b coefficient	t-stat
-0.0266	-0.6065	0.6623	5.9901	0.1013	1.4259
Panel C. Post-2007 regime					
b coefficient	t-stat	b coefficient	t-stat	b coefficient	t-stat
-0.2762	-7.6949	0.2153	2.1506	-0.0676	-1.5009
Panel D. Post-2007 regime and stable sample					
-0.2023	-4.5747	0.2816	2.7473	-0.2507	-4.6059

Note: This table reports the results of the Phillips and Sul (2007) log-t convergence test applied to the three Google Trends log-ratio indicators. Panel A refers to the full OECD sample (38 countries), while Panel B restricts the analysis to the core linguistic sample, including only countries whose series display approximately mesokurtic and symmetric distributions ($|skew| < 2$, $\kappa < 10$). The null hypothesis of global convergence is rejected when the t-statistic < -1.65 at the 5% significance level (one-sided test). Each regression uses the standard trimming parameter r = 0.20 and covers monthly data from 2004m1 to 2025m6. Results show that public-transport salience fails to converge in the full sample but does not reject convergence in the core subset, whereas electric- and hybrid-car salience remain strongly divergent across countries.

Table 5. Club convergence - Public transport (Phillips-Sul)

Clubs	2004m1 (N=38)	2007m2 (N=38)	2007m2 + core stable sample (N=33)
Club 1	AT , AU , BE , CA , CH , CL , CO , CR , CZ , DK , EE , ES , FI , FR , GB , HU , IE , IL , IS , IT , JP , KR , LT , LU , LV , MX , NL , NO , NZ , PL , PT , SE , SI , SK , TR US	AU , BE , CA , CO , CZ , DK , EE , ES , FI , FR , GB , HU , IE , IL , IS , IT , JP , KR , LT , LU , LV , MX , NL , NO , NZ , PL , SE , SI , SK , TR , US	AT , AU , BE , CA , CL , CO , DE , DK , EE , ES , FI , FR , GB , HU , IS , IT , JP , KR , LT , LU , MX , NL , NO , PL , SE , SI , SK , TR , US
Club 2	DE , GR	AT , CH , CL , CR , DE , PT	CH , PT
Club 3	-	GR	CR , GR

Note. Club classification obtained using the Phillips and Sul (2007) clustering algorithm as implemented in psecta (Du, 2017). We set parameters kq=0.2 and fr=0. The sample includes 38 OECD countries (33 in the core stable subsample). Clubs are defined according to the sequential log-t procedure; estimated coefficients and t-statistics are omitted.

Table 6. Club convergence - Hybrid cars (Phillips-Sul)

Clubs	2007m2 + core stable sample (N=26)
Club 1	AU , CL , CO , CZ , DK , ES , FI , FR , GB , IE , IT , NL , PT , US
Club 2	BE , DE , EE , HU , IS , KR , MX , PL , SE , TR
Club 3	AT , GR

Note. Club classification obtained using the Phillips and Sul (2007) clustering algorithm as implemented in *psecta* (Du, 2017). We set parameters kq=0.2 and fr=0. The sample includes 38 OECD countries (26 in the core stable subsample). Clubs are defined according to the sequential log-t procedure; estimated coefficients and t-statistics are omitted.

Table 7. Search salience and electric-vehicle adoption: country fixed-effects panel estimates (quarterly, 2018-2024)

VARIABLES	(1) BEV	(2) PHEV	(3) BEV log ratio
Log-ratio: Electric cars	0.253**	0.034	0.219
	(0.117)	(0.171)	(0.143)
Lag 1: Log-ratio: Electric cars	0.359**	0.172	0.187
	(0.151)	(0.159)	(0.138)
Lag 2: Log-ratio: Electric cars	0.157*	-0.131	0.288**
	(0.090)	(0.168)	(0.132)
Log-ratio: Hybrid cars	0.008	0.074	-0.066
	(0.055)	(0.078)	(0.042)
Lag 1: Log-ratio: Hybrid cars	0.006	0.087	-0.081
	(0.072)	(0.107)	(0.056)
Lag 2: Log-ratio: Hybrid cars	-0.124**	-0.100	-0.024
	(0.049)	(0.062)	(0.044)
Log-ratio: Public transport	0.069	-0.197	0.267
	(0.320)	(0.370)	(0.215)
Lag 1: Log-ratio: Public transport	-0.387	-0.674**	0.288
	(0.247)	(0.295)	(0.286)
Lag 2: Log-ratio: Public transport	-0.438**	-0.286	-0.152
	(0.202)	(0.234)	(0.208)
Unemployment rate	0.028	-0.057	0.085
	(0.064)	(0.100)	(0.055)
Consumer Price Index	0.021	0.049***	-0.028**
	(0.014)	(0.016)	(0.011)
Consumer confidence index	0.012	0.055	-0.042
	(0.021)	(0.041)	(0.040)
Stringency COVID-19 index	0.002	0.003	-0.001
	(0.005)	(0.005)	(0.002)
Log GDP per capita	-0.675	-2.354	1.679
	(1.517)	(2.410)	(1.684)
Log of total EV charging points per capita	0.665***	0.842***	-0.178**
	(0.060)	(0.067)	(0.070)
Observations	367	367	367
Number of clusters	22	22	22
R-squared	0.524	0.480	0.327

Note: The dependent variable in columns (1) and (2) is the logarithm of battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) per capita, respectively. Column (3) reports results for the log-ratio BEV/PHEV, capturing changes in the relative composition of the electric fleet. The main explanatory variables are quarterly Google Trends log-ratios measuring relative interest in electric cars, hybrid cars, and public transport. All models include country fixed effects, quarterly and yearly dummies, and control for the unemployment rate, consumer price index (CPI), consumer confidence, the COVID-19 stringency index, GDP per capita, and the logarithm of total EV charging points per capita. Robust standard errors are clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix A. Summary statistics by country

Table A1. Summary statistics for Log ratio of Public transport.

Country	Mean	SD	Min	Max	Skewness	Kurtosis
AT	-0.918	0.404	-2.349	-0.221	-0.839	2.713
AU	-0.445	0.223	-1.033	-0.111	-0.232	2.011
BE	-0.652	0.197	-1.438	-0.204	-1.435	6.150
CA	-0.475	0.325	-1.441	-0.052	-1.096	3.578
CH	-0.848	0.399	-2.245	-0.320	-1.334	4.354
CL	-1.863	0.187	-2.337	-1.520	-0.589	2.400
CO	-1.141	0.239	-1.685	0.014	-0.017	4.219
CR	-1.300	0.453	-2.823	0.823	1.009	8.877
CZ	-1.319	0.266	-2.807	-0.983	-2.480	10.408
DE	-0.631	0.374	-1.454	-0.121	-0.927	2.245
DK	-0.837	0.451	-1.900	-0.200	-1.081	2.990
EE	-1.219	1.011	-4.364	-0.302	-1.652	4.530
ES	-0.617	0.161	-1.042	-0.144	0.319	2.516
FI	-0.709	0.556	-2.546	0.038	-1.119	4.365
FR	-0.344	0.230	-1.026	-0.024	-1.127	2.945
GB	-0.609	0.193	-1.184	-0.186	-0.358	2.418
GR	-1.191	0.940	-4.621	1.701	-1.012	4.776
HU	-0.651	0.445	-2.477	0.080	-1.622	5.606
IE	-0.747	0.596	-2.912	0.000	-2.223	7.841
IL	-0.227	0.400	-2.596	0.281	-2.899	14.550
IS	-2.692	1.369	-4.693	0.212	1.275	3.035
IT	-0.384	0.156	-0.949	-0.089	-0.806	3.672
JP	-0.924	0.231	-1.506	-0.283	-0.084	2.281
KR	-0.805	0.681	-2.383	0.105	-1.044	2.666
LT	-1.471	0.698	-4.418	0.481	-1.654	6.919
LU	-1.815	0.547	-3.673	-0.735	-0.296	2.621
LV	-1.145	0.993	-4.594	-0.268	-2.039	6.017
MX	-1.080	0.168	-1.650	-0.094	0.814	8.098
NL	-0.467	0.251	-1.316	-0.140	-1.239	3.352
NO	-1.045	0.589	-2.805	-0.266	-1.709	5.346
NZ	-0.622	0.422	-2.511	-0.118	-2.732	10.841
PL	-1.075	0.377	-2.153	-0.450	-0.727	2.455
PT	-0.797	0.287	-1.583	-0.056	-0.668	3.569
SE	-0.554	0.307	-1.849	-0.173	-1.905	7.027
SI	-1.293	0.629	-3.406	-0.374	-0.285	2.002
SK	-1.714	0.393	-2.958	-1.130	-0.839	2.661
TR	-0.891	0.762	-2.388	0.231	-0.323	1.619
US	-0.196	0.261	-0.836	0.140	-1.013	2.578

Total	-0.940	0.727	-4.693	1.701	-1.561	6.251

Table A2. Summary statistics for Log ratio of Electric cars.

Country	Mean	SD	Min	Max	Skewness	Kurtosis
AT	-1.542	1.026	-4.517	-0.300	-2.029	5.923
AU	-1.437	0.487	-4.435	-0.158	-0.346	7.332
BE	-2.675	1.029	-4.362	-0.791	-0.288	1.774
CA	-1.464	0.397	-3.024	-0.327	-0.360	3.856
CH	-1.621	1.409	-4.531	0.220	-1.062	2.905
CL	-2.472	1.717	-4.385	0.665	0.641	1.544
CO	-2.835	1.459	-4.286	0.625	1.316	2.993
CR	-3.526	0.688	-4.404	0.961	3.693	21.319
CZ	-1.956	1.263	-4.436	-0.349	-1.242	2.838
DE	-1.901	0.609	-3.710	-0.540	-1.046	3.705
DK	-2.189	1.227	-4.261	-0.043	-0.006	2.169
EE	-3.018	0.960	-4.503	-0.184	-0.098	1.749
ES	-2.097	0.999	-3.699	-0.393	-0.052	1.765
FI	-1.989	1.292	-4.643	0.110	-0.727	2.604
FR	-1.922	0.656	-4.038	-0.502	-0.013	3.055
GB	-1.712	0.715	-2.947	-0.160	0.523	1.982
GR	-2.064	1.331	-4.629	0.350	0.332	1.667
HU	-2.051	1.065	-4.572	-0.797	-1.641	4.171
IE	-1.759	1.357	-4.550	0.254	-0.881	2.776
IL	-3.110	0.969	-4.691	-1.115	0.288	1.928
IS	-2.835	1.450	-4.551	4.457	1.767	5.296
IT	-1.541	0.827	-4.428	-0.047	-1.429	6.546
JP	-0.497	0.463	-1.540	0.477	-0.033	2.216
KR	-1.497	1.640	-4.689	0.713	-0.653	1.974
LT	-1.731	1.672	-4.616	0.354	-0.484	1.473
LU	-3.291	1.451	-4.707	-0.101	1.141	2.456
LV	-4.006	0.204	-4.523	-3.530	-1.049	3.048
MX	-3.023	0.808	-4.196	-0.597	0.642	2.112
NL	-2.474	1.075	-4.442	-0.636	-0.659	2.174
NO	-1.627	1.252	-4.223	0.094	-0.680	2.295
NZ	-1.864	1.045	-4.620	-0.418	-1.689	4.905
PL	-2.272	0.897	-4.375	-0.671	-1.175	3.239
PT	-2.892	0.600	-3.808	0.187	1.179	5.298
SE	-2.061	0.922	-4.095	-0.140	-0.302	2.476
SI	-1.808	1.650	-4.488	0.455	-0.371	1.395
SK	-3.095	0.884	-4.565	-0.766	-0.430	2.050
TR	-2.358	1.174	-4.629	-0.365	-0.190	1.893
US	-1.211	0.360	-2.064	-0.138	0.260	3.414
Total	-2.195	1.306	-4.707	4.457	-0.140	1.983

Table A3. Summary statistics for Log ratio of Hybrid cars

Country	Mean	SD	Min	Max	Skewness	Kurtosis
AT	-3.745	0.998	-4.838	0.119	1.453	4.477
AU	-1.454	0.894	-4.668	0.025	-1.751	7.338
BE	-2.994	0.856	-4.806	-1.326	-0.235	1.781
CA	-1.149	0.490	-4.454	0.040	-3.188	23.642
CH	-4.175	0.743	-5.044	0.279	3.279	14.681
CL	-3.421	0.874	-4.388	-0.321	1.632	4.634
CO	-3.275	0.678	-4.194	1.255	1.869	9.607
CR	-3.513	0.758	-4.542	1.280	3.750	21.157
CZ	-4.014	1.141	-5.175	0.506	2.682	9.058
DE	-1.819	1.111	-4.379	0.437	-0.946	3.219
DK	-2.178	1.520	-4.348	0.014	-0.295	1.276
EE	-4.253	0.083	-4.464	-3.898	0.710	4.547
ES	-2.106	1.440	-3.956	0.343	0.196	1.331
FI	-2.544	1.429	-5.053	0.240	-0.314	1.409
FR	-1.644	0.804	-4.051	0.192	-1.034	4.321
GB	-1.453	0.855	-4.585	-0.180	-1.190	6.081
GR	-2.781	1.183	-4.557	0.279	1.118	3.555
HU	-3.017	1.004	-4.969	0.374	-0.032	2.686
IE	-2.877	1.355	-4.780	-0.916	0.081	1.324
IL	-3.946	0.390	-4.693	0.004	5.276	50.307
IS	-2.816	1.511	-4.563	4.446	1.934	6.428
IT	-2.122	1.052	-4.443	-0.398	-0.905	3.050
JP	-0.377	0.497	-4.151	0.286	-3.913	26.981
KR	-3.704	0.284	-4.635	-3.240	-1.341	4.179
LT	-3.899	0.518	-4.596	0.473	6.983	54.624
LU	-3.956	0.646	-4.512	0.854	3.238	16.812
LV	-3.965	0.426	-4.611	0.083	6.139	55.916
MX	-3.864	0.345	-4.521	-2.997	0.589	2.095
NL	-1.600	1.054	-4.432	-0.171	-1.692	5.090
NO	-4.189	0.307	-4.548	0.164	11.043	157.097
NZ	-4.297	0.557	-4.682	-0.570	5.490	32.840
PL	-4.283	0.156	-4.548	-3.965	0.242	1.851
PT	-2.609	1.307	-4.072	1.016	1.047	2.446
SE	-2.107	1.140	-4.047	0.383	-0.779	2.035
SI	-3.634	0.499	-4.606	1.013	5.421	50.862
SK	-4.217	0.305	-4.756	0.185	11.580	168.729
TR	-3.940	0.331	-4.601	-3.431	-0.467	1.858
US	-1.020	0.358	-1.559	0.232	1.010	3.880
Total	-2.973	1.401	-5.175	4.446	0.685	2.137

Table A4. Structural Breaks in panel data

Structural breaks in Public Transport				
Breaks	Index	Date	[95% Conf. Interval]	
1	38	2007m2	2007m1	2007m3
2	94	2011m10	2011m9	2011m11
3	170	2018m2	2018m1	2018m3

Structural breaks in Electric cars				
Breaks	Index	Date	[95% Conf. Interval]	
1	38	2007m2	2007m1	2007m3
2	139	2015m7	2015m6	2015m8
3	201	2020m9	2020m8	2020m10

Structural breaks in Electric cars				
Breaks	Index	Date	[95% Conf. Interval]	
1	38	2007m2	2007m1	2007m3
2	150	2016m6	2016m5	2016m7
3	207	2021m3	2021m2	2021m4

Note: Common structural breaks in panel data for the whole period (2004m1-2025m6) HAC estimation allowing for breaks in fixed effects.

Table A5. Data description

Variable	Description	Frequency	Period	Database
UNEM_RATE	OECD: Monthly unemployment rate for persons aged 15+, expressed as the percentage of the labor force in the same age group; calendar- and seasonally adjusted, compiled from national Labour Force Surveys.	Monthly	2004-2025	OECD
CPI_ALL	OECD: National consumer price index (CPI/HICP, COICOP 1999); monthly year-over-year growth rate, unit: percent per annum	Monthly	2004-2025	OECD
cci	OECD: Consumer Confidende Indicator (CCI); monthly; amplitude-adjusted index (OECD-harmonized methodology).	Monthly	2004-2025	OECD
ev_total_ev	Number of newly registered electric passenger cars (M1) per month.	Monthly	2018-2025	OECD
ev_phev	Number of newly registered electric passenger cars (M1) per month. (PHEV)	Monthly	2018-2025	OECD
ac_points	Total number of recharging points, according to the AFIR classification.	Quarterly	2020-2025	EAFO
dc_points	Total number of recharging points, according to the AFIR classification.	Quarterly	2020-2025	EAFO
ln_gdp	Log of GDP per capita	Quarterly	2018-2024	OECD
stringency_index	COVID-19 stringency index	Monthly	2020-2022	OxCGRT