The Green Transition: Regional Vulnerability, Opportunity and Migration Evidence from a Nested Logit Model

Msc in Economics - Master's Thesis

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Abstract

The green transition, the European Union's policy strategy to create a greener and more inclusive economy, is gaining momentum. How this transition unfolds across regions and affects mobility lacks evidence. This thesis investigates whether and how the green transition influences interregional migration within the European Union. By using individual-level data from the 2023 MOBI-TWIN survey and two constructed regional indices, the Green Transition Opportunity Index (GTOI) and the Green Transition Vulnerability Index (GTVI), we examine regional inequalities, realised migration and migration aspirations. The implementation of individual environmental preferences in the analysis gives a new perspective on how individual characteristics affect migration decisions. The results from conditional and nested logit models show that green opportunities tend to attract migrants. The green vulnerabilities show rather mixed results. The alignment between green preferences and migration choices is less straightforward. Environmentally conscious individuals do not always relocate to greener regions, clearly highlighting a potential gap between environmental values and actual behaviour.

JEL Classification: R23, Q56, O15, C25

Keywords: Green transition, Interregional migration, European Union, Environmental preferences, Nested logit model, Regional inequality, Migration aspirations

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1 Introduction

Climate change remains a pressing existential global threat, with severe consequences looming over societies. In response, leaders at the supranational level adopted major agreements to combat climate change, such as the Paris Agreement (United Nations, 2015a). Apart from the United Nations, at a more regional level, the European Union (EU) is taking it's own measures to combat climate change and has intensified climate action through successive strategies. In the early stages, specifically within the first decade of the 21st century, the EU 2020 strategy emphasises "*greener and more competitive economy*"(European Comission, 2010), marking a clear commencement of environmental awareness. Then, under the Juncker Commission, the EU proposed the Circular Economy Package (European Commission, 2015) to promote recycling, improve waste management, and achieve sustainable growth decoupled from excessive resource extraction. In 2019, the EU proposed the European Green Deal (EGD), its "*new growth strategy*" (European Comission, 2019). Its central objective is to make Europe the first climate-neutral continent. From 2020 onward, the term "*twin transition*" began to appear in EU documents, such as the Industrial Strategy (European Commission, 2020b) and Recovery and Resilience Plans (European Parliament and Council of the European Union, 2021), thus, becoming a key pillar of the EU's recovery and long-term competitiveness. The "*twin transition*", as its name implies, is twofold. It consists of both the green and digital transitions. The digital transition focuses on technological factors and the necessary infrastructure, such as the availability of internet access. On the other hand, the green transition focuses on transforming economies and societies toward environmental sustainability. The green transition is constituted of three interrelated dimensions: (i) climate neutrality by 2050, (ii) the promotion of energy and resource efficiency, and (iii) fostering a circular economy with social inclusion (European Comission, 2025a, 2025b). Such a transformation is expected to redistribute economic activities and employment across regions (Fetting, 2020), and its impacts will likely be uneven. Therefore, in the following paper, we begin by analysing how unequal this transformation has been up to the year 2022.

Given that international and national institutions drive the green transition, it is crucial to explore environmental valuation at the individual level. One important question to consider is how much people truly value sustainability and environmental quality when it comes to choosing where to live. In other words, do individuals consider factors such as air quality or local green infrastructure when deciding whether to relocate to another region? Is there a link between expressed environmental preferences and actual relocation behaviour? In other words, do people who claim to value a green environment act on these preferences when choosing where to live? If so, the green transition could become a significant driver of interregional migration as people seek "greener" regions that offer better environmental amenities and economic opportunities in emerging green sectors. This raises the possibility that regional differences in green development will determine new mobility patterns within the EU.

Nonetheless, despite the structural and spatial implications associated with the green transition, the role of regional green transformation in influencing migration needs to be examined. Most empirical research on environmental drivers of migration focuses primarily on temperature changes and rainfall amounts, often within the context of developing countries (Cattaneo & Peri, 2016; Missirian & Schlenker, 2017). In contrast, considerably less is known about how positive, policy-driven environmental change, such as green innovation and investment, influences individual mobility decisions at the regional level within advanced economies, like the EU. In particular, we lack evidence on whether regions that successfully transform into greener economies attract or retain more residents, or, in contrast, whether regions struggling in the green transition experience higher out-migration.

This thesis will assess the differences in opportunities and vulnerabilities by developing the Green Transition Vulnerability Index (GTVI) and the Green Transition Opportunity Index (GTOI) to capture the green transition. We will then examine how these differences, in combination with individuals' environmental preferences, influence migration and migration intentions within the EU.

2 Literature Review

2.1 Migration Decisions and Green Factors

Migration decisions have long been known to be influenced by regional factors such as quality of life, as already highlighted by Roback (1982) and further confirmed by Faggian and Royuela (2010). Wage differentials (Albert and Monras, 2017), income per capita (Beine et al., 2021), education (Handler, 2018) and employment opportunities (Dinbabo and Nyasulu, 2015) as well as cultural similarities such as languages (Bertoli and Fernández-Huertas Moraga, 2015) also are at play. In closer relation to the green transition, most studies on migration flows related to the environment focus on temperature anomalies and the amount of rainfall. Backhaus et al. (2015) studied the influence of temperatures on migration. They find that when the temperature increases in the country of origin by one degree Celsius, bilateral flows increase by 1.9%. Missirian and Schlenker (2017) find that the number of asylum seekers in Europe increases as temperatures in the origin country increase above the "*moderate optimum*" (Missirian & Schlenker, 2017) of 20 degrees Celsius. Furthermore, Cattaneo and Peri (2016)'s results show that in middle-income countries, increasing temperatures lead to higher migration to cities and abroad, whereas, in very poor countries, increasing temperatures reduced emigration, consistent with the concept of "*poverty traps*".

Although traditional migration drivers continue to be important, emerging, but limited, evidence points towards new push and pull factors that may emerge during the green transition. Regions undergoing rapid decarbonisation may experience job losses in traditional, carbon-intensive industries, thereby pushing workers to migrate to areas with more sustainable and resilient economies. This is underscored by Heinisch et al. (2021), who demonstrate that a decrease in Germany's dependency on coal-fired power plants can lead to the reallocation of thousands of workers searching for new jobs in less carbon-dependent regions.

Furthermore, the green transition could unintentionally increase regional inequalities (Hafner & Raimondi, 2020; Rodríguez-Pose & Bartalucci, 2024). Wealthier areas, which are already equipped with advanced technologies, may be in a better position to support displaced workers and attract new labour force. On the other hand, emigration can increase in regions that are less developed and rely heavily on fossil fuel. This could further decrease economic activity in already stagnating regions and create a challenging cycle. García-Riazuelo et al. (2025) found evidence for this cycle by showing that renewable energy plants could lead to population decline in already shrinking regions. Hence, we must further investigate how the green transition affects migration choices in order to create appropriate policies to minimise emigration.

Furthermore, the existing literature addressing migration aspirations and intentions is still limited in its consideration of environmental factors. Aslany et al. (2021) conducted a meta-analysis of papers published after 1990 based on migration aspirations. They show the determinants of migration aspirations, including socioeconomic, institutional, and psychological dimensions. However, the authors note a complete absence of environmental or green transition-related variables in all 49 studies reviewed, despite the growing relevance of climate and sustainability, thus clearly identifying a gap in the literature.

Therefore, this study will contribute to the literature by assessing the influence of the green transition on actual migration and migration intentions.

2.2 Capturing The Green Transition

It is essential to use a precise measure to capture the effects of the green transition. Thus, two indices have been proposed in the recent past: the Green Vulnerability Index (GVI) (Rodríguez-Pose and Bartalucci, 2024) and the Green Transition Index (GTI) (Zhai et al., 2022). The proposal of the GVI, aligns closely with the first pillar of the transition: the reduction of greenhouse gas emissions. By Principal Component Analysis (PCA), the authors built the GVI to capture a region's vulnerability to decarbonisation. They argue, for example, that a carbon tax may affect individuals with lower income to a greater extent, as they have to pay more in relative terms. Six broad categories were considered when building the GVI: "fossil fuel dependency, industry, agriculture and land use, tourism, energy and transportation" (Rodríguez-Pose & Bartalucci, 2024). Thus, the GVI includes a vast range of variables like GHG emissions, the coal transition, wages in quarrying and mining, the gross value added in agriculture, its employment share, tourist arrivals and establishments, cooling degree days, and road freight transport. Using the GVI, Rodríguez-Pose and Bartalucci (2024), reveal that Eastern and Southern European regions are the most vulnerable to the green transition. They say that this is mainly due to their carbon-intensive sectors and lower levels of innovation and human capital. Additionally, the GVI is negatively correlated with regional GDP. Stagnant regions tend to show higher vulnerability. As such, the GVI can be seen as a proxy for push factors of migration. People in highly vulnerable regions may consider relocating to greener areas, particularly if they are young, educated, and mobile, assuming the green transition actually decreases GHG emissions, etc.

In contrast to the GVI, which focuses on regional vulnerability in relation to climate neutrality (i), Zhai et al. (2022) construct an index for pillars (ii) and (iii) of the green transition, with a focus on energy and resource efficiency as well as the circular economy an inclusion. In comparison to the GVI, they ignore GHG emissions, but include expenditures on new technologies, patents, and investments in pollution control. Furthermore, concerning pillar (iii), an additional dimension referred to as social transition has been introduced. Zhai et al. (2022) then use the entropy weight method to construct the GTI. They apply the index to a China case study and get similar results as Rodríguez-Pose and Bartalucci (2024) in terms of divergence. In Europe, development-trapped regions that are already lagging economically may face additional decline due to the green transition. In China, regions that are already performing well show higher values of GTI, and the disparity between these regions is widening. Eastern China outperforms the Central and Western parts in terms of the GTI. The authors then try to identify the reasons that may have caused these inequalities and demonstrate that "*reform and openness, investment capacity, government intervention, and environmental regulation significantly promoted the green transition*" (Zhai et al., 2022), whereas the industrial structure opposes the transition.Moreover, the GTI is heterogeneous in space and spatially dependent. Areas with high GTI scores tend to be clustered together. These spatial differences indicate that more developed regions could become attractive destinations for migrants, particularly those looking for green jobs and improved living conditions. In the European context, similar patterns may emerge in regions surrounding Munich, Stuttgart, and Paris, which are leading hubs of green innovation and skilled labour (Bello et al., 2023). From a migration perspective, we can consider the GTI to reflect pull factors if the regions with increasing GTI actually perform better.

Taken together, the three pillars offer a push-pull scenario as we see it in Table 1. From now on, we refer to pillar (i) as green vulnerability and (ii) collectively with (iii) as green opportunity. One would expect that individuals from highly vulnerable regions have a greater incentive to move to high opportunity regions, as these locations may provide more attractive green employment, amenities, or general future expectations. (Beine et al., 2016). This pattern aligns with the general migration drivers discussed earlier. For instance, people are pulled towards areas with better living conditions (Faggian & Royuela, 2010), which here corresponds to successful green economies.

Table 1: Expected regional migration flow

	Low Opportunity	High Opportunity
Low Vulnerability	ambiguous	+
High Vulnerability	-	ambiguous

In this study, the Green Vulnerability Index will be represented by a green regional attractiveness index, which we will refer to as the Green Transition Vulnerability Index (GTVI), using updated data up to 2022, since Rodríguez-Pose and Bartalucci (2024) used data from 2018 until 2020. This update makes sure that the measure of regional vulnerability reflects the most recent economic and environmental conditions. Inspired by Rodríguez-Pose and Bartalucci (2024) and Zhai et al. (2022), this paper proposes the construction of a Green Transition Opportunity Index (GTOI) that captures pillars (ii) and (iii) of the green transition for the EU NUTS2 regions. This GTOI incorporates region-specific indicators of green progress, including measures of innovation, such as the number of green technology patents and EU funds from the ESIF, Horizon Programme, and RRF, as well as a measure of social progress, housing overburden.

The use of these two indices facilitates an understanding of how regional disparities in the green transition may influence migration patterns across Europe. Specifically, whether regions with greater green opportunities are likely to attract migrants and whether regions that are considered vulnerable tend to repulse migrants.

2.3 Modelling Migration Decisions

From a methodological point of view, there is a rich literature on the approaches and techniques necessary to identify the reasons for migration. Many studies are based on the Random Utility Maximisation (RUM), which models migration as a discrete location choice problem. In the case of individual-level data, researchers often employ discrete choice models such as the logit, multi-level logit (D'Agostino et al., 2019, Sedova and Kalkuhl, 2020), conditional logit (Su et al., 2018) or a nested logit model (Su et al., 2018, Neubecker et al., 2017). In contrast, studies that use aggregate data, where regions or municipalities are treated as the unit of analysis, usually rely on count data models. Negative binomial models or Poisson regressions (Faggian and Royuela, 2010) are common choices. To address issues of heterogeneity and zero flows, Bertoli and Fernández-Huertas Moraga (2015) and Bertoli and Fernández-Huertas Moraga (2012) use a Poisson Pseudo-Maximum Likelihood (PPML) estimator, which offers the option for a richer combination of fixed effects. Bertoli et al. (2013) apply a Common Correlated Effect (CCE) (Pesaran, 2006) estimator with dyadic fixed effects to control for unobserved bilateral factors. Some studies, such as in Mayda (2010), use a panel model with monodic, one-dimensional, fixed effects of origin and destination and time-fixed effects. Others chose simpler, linear models such as OLS models (Dinbabo & Nyasulu, 2015).

Building on the literature, the empirical models in this study are the logit, conditional logit (CL) and nested logit (NL) models. First, the CL and NL models are especially more attractive to the multinomial logit models, due to the possibility of estimating alternative-specific parameters. Thus, you can obtain parameters for every possible option. Additionally, the NL model offers several advantages over the conventional logit and CL models, especially in the context of migration studies. The NL is attractive given the concept of "*multilateral resistance to migration*" (Bertoli & Fernández-Huertas Moraga, 2013). Multilateral resistance refers to the fact that the relative attractiveness of a destination A with respect to a destination B is not only determined by the characteristics of A and B but also by the characteristics of all other possible destinations. In contrast to the standard logit model and the CL model, which assume the Independence of Irrelevant Alternatives (IIA) across all alternatives (Train, 2009), where a change in the characteristics of a third choice equally influences the relative attractiveness of A with respect to B, the NL model relaxes the IIA assumption within designated nests of alternatives. For example, consider a migrant who has to choose between Paris, Berlin, and Rome, with Paris being twice as likely to be chosen as Berlin. If a new destination, Hamburg, is introduced, then the IIA assumption says that the relative attractiveness between Paris and Berlin must remain the same, even though Hamburg is more likely to pull away migrants from Berlin than from Paris since it shares economic and cultural similarities with Berlin. This assumption can lead to misleading results, because it fails to take into account the correlation between destinations with shared characteristics (Beine et al., 2021).

This study makes four main contributions. First, the GTVI is introduced to represent the first pillar of the green transition using updated data. Secondly, we will construct the GTOI to capture pillars (ii) and (iii) of the Green Transition. Then, we use the indices to assess regional differences. Third, it examines how the regional disparities in the GTVI and GTOI impact both migration intentions and realised migration. Finally, the study incorporates individual valuations of the environment within a nested logit framework to highlight how ecological preferences influence mobility decisions. The green preferences will be interacted with the indices to further analyse whether individuals act on their green preferences and move to less vulnerable regions with more opportunities.

3 Case Study

Europe represents the best case for studying the effect of the green transition, given that the EU has defined the green transition as a policy strategy. As mentioned by Rodríguez-Pose and Bartalucci (2024), there are many substantial differences across regions in the GVI in the EU. Reassessing these differences using more recent data allows one to monitor the evolution over the last couple of years and identify which regions remain most exposed. In parallel, the GTOI allows us to further capture differences in terms of the green transition. This is especially relevant from a policy perspective, as it can inform a more equitable allocation of transition-related financial support. Then, for the analysis of migration likelihood, we will concentrate only on Spain, Greece, Finland, the Netherlands, and Italy due to data limitations. Out of approximately 9300 individuals in the survey, 7000 live in the five countries mentioned above. The rich data availability makes this case study of the five countries particularly compelling. The combination of microdata, which is extremely detailed and contains actual migration, migration intentions, the valuation of green factors of individuals, and regional characteristics at the NUTS2 level, allows for flexible econometric specifications. Finally, the EU's free movement possibility makes it an ideal setting to study migration patterns, since it minimises the risk of heterogeneous migration policies. For the logit model, we will consider NUTS2 regions. Afterwards, we will proceed with a cluster analysis to reduce the computational burden of the conditional logit and nested logit models.

3.1 Data

The data applied in this paper comes from several sources. The microdata, which contains individual information, as well as migration aspirations and the green valuation, are from the MOBI-TWIN[1] survey. The data on European funds in reseach and innovation comes from the TEDv from Marques et al. (n.d.)[2]. The data on patents is from the OECD REGPAT database[3].

[1] https://mobi-twin-project.eu/
[2] https://data.jrc.ec.europa.eu/dataset/c4d7603a-f28a-45b1-ba2f-725a535c5697
[3] https://www.oecd.org/en/publications/the-oecd-regpat-database_241437144144.html

3.1.1 Migration Data

The individual-level data was collected from a survey conducted in 2023. The goal was to collect data to assess spatial mobility in relation to the twin transition. The survey was designed to be representative of the EU. In the entire EU, there were around 9000 valid responses. Additionally, there was a particular focus on the five pilot regions: Central Macedonia (775 observations) in Greece, Northern and Eastern Finland (582 observations), Castilla-La Mancha (610 observations) in Spain, Lombardy (915 observations) in Italy, and Groningen (230 observations) in the Netherlands. It was organised into seven core sections, in addition to an introductory note. The sections were the following:

1. Demographics: Socio-economic characteristics, urban/rural status, household composition, and cultural/technological context.
2. Actual migration: Current and past place of residence. If the person relocated in the last 5 years, then we consider it as migration.
3. Intent to relocate: Individuals gave the probabilities to move in the near future. Additionally, if they would like to move, they would have to motivate their answer with a reason.
4. Preferences for traditional mobility factors: Employment, education, amenities, and social networks.
5. Preferences for digitalization-related factors: Access to the internet, digital services, remote work, and online social activity.
6. Preferences for green transition factors: Air and water quality, renewable energy, green infrastructure, and sustainable community behaviours.
7. Life satisfaction and corruption: Societal values, trust, and transparency.

The section on individuals' valuation of green factors is particularly relevant to this paper. The respondents had to value from 1 to 5, with 5 being the highest value, the following factors in the area of residence: Air quality, the use of renewables, affordable energy prices, clean water production, access to green areas, access to water bodies, eco-friendly infrastructure, the use of circular economy waste management and living in a community that values the environment.

Defining Migration and Intentions to Migrate

This analysis will differ between actual migration and intentions to migrate. Thus, we need to define two different dependent variables. We have

$$y_{it} = \begin{cases} 1 & \text{if the person moved in the last 5 years} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{it} = \begin{cases} 1 & \text{if the person expresses high or very high probability of moving} \\ 0 & \text{otherwise} \end{cases}$$

Table 2: Comparison of Intended Moves vs Actual Moves: Full Dataset

Category	Value	Frequency	Percent	Cumulative %
Intend to Move	0	4,265	45.71%	45.71%
	1	5,066	54.29%	100.00%
Actual Move	0	6,633	71.09%	71.09%
	1	2,698	28.91%	100.00%
Total Observations		9,331	100%	

Note: An individual is added to the "Intend to move" category if that individual expresses a high probability or a very high probability of moving in the next 6 months, 1 to 2 years, 5 years or 10 years.

Table 3: Probability of Changing Residence Over Time: Full Dataset

Probability of Moving	6 Months	1–2 Years	5 Years	10 Years
Very low probability	6,878 (75.02%)	4,445 (48.67%)	2,739 (30.13%)	2,172 (23.84%)
Low probability	884 (9.64%)	1,501 (16.43%)	1,202 (13.22%)	906 (9.95%)
Moderate probability	573 (6.25%)	1,401 (15.34%)	1,844 (20.28%)	1,665 (18.28%)
High probability	382 (4.17%)	919 (10.06%)	1,613 (17.74%)	1,439 (15.80%)
Very high probability	451 (4.92%)	867 (9.49%)	1,693 (18.62%)	2,927 (32.13%)
Total	9,168	9,133	9,091	9,109

From Table 2, we observe a significant difference between the number of actual movers and the number of people considering moving. We are short of nearly twice the intended movers compared to the actual movers. From Table 3, we see that the probability of relocation increases with the timespan into the future.

3.1.2 Regional Data

In addition to the individual-level data, the Mobi-Twin Dataset (D1.2) (Väisänen et al., 2024) includes data on regional characteristics from 2005 to 2023. The data is split into seven categories: social fabric, living conditions, economy and labour, access and connectivity, digitisation, landscape and environment, and regional typologies. Of particular interest to this study is the traditional regional attractiveness index and digital regional attractiveness from Royuela et al. (n.d.), which enables us to capture a broad set of variables in a single measure. The exact computation of the indices can be found in Appendix A. Given that the indices are at the regional NUTS2 level, and we switch to a cluster analysis, we will use the variables, except those included in the GTVI and GTOI, of the latter two indices mentioned to build principal components that control for the traditional factors of migration at the cluster level[4]. Considering the significant computational power required to estimate conditional and nested logit models, the use of principal components lightens the burden.

[4]See Appendix B.1 for details on clustering and B.2 for information on what each component captures.

3.1.3 Green Transition Vulnerability Index and Green Transition Opportunity Index

We defined the green transition by three pillars: (i) reduction/dependency on GHG emissions, (ii) efficiency and (iii) the promotion of the circular economy and inclusion. The variables used for the GTVI and GTOI are listed below in Table 4. All the variables are from the Mobi-Twin dataset (Väisänen et al., 2024), except the EU funds and the patent applications.

Table 4: Variables for the Green Transition Indices

Pillar	Indicator	Reasoning
(i) Emissions Dependency	GHG emissions	Higher levels indicate greater vulnerability since these regions need to cut back emissions more relative to other regions
	Wages in mining	Proxy for economic reliance on extractive, fossil-heavy industries
	Agriculture share	Dependence on resource- and emission-intensive primary sectors
	Tourism share of GDP	Reflects potential unsustainable consumption and mobility patterns
(ii) Efficiency	Environmental technology patents	Measures propensity to innovate
	EU R&I funding	Reflects institutional and financial commitment to R&D
(iii) Circular Economy and Inclusion	Circular economy employment	Labour market orientation towards recycling, reuse, and sustainable sectors
	Housing overburden	Measures housing affordability, the more affordable the more inclusive

The dataset for the funds is the Territorial Economic Data Viewer (TEDv). It is built by Marques et al. (n.d.) under the initiative of the European Commission's Joint Research Centre. Its goal is to help policymakers observe and compare the distribution of EU research and innovation (R&I) funds across European regions. It summarises data from three funding programmes: the European Structural and Investment Funds (ESIF), which support development at the regionally level and are managed nationally or regionally, the Horizon Programme (Horizon 2020 and Horizon Europe), which funds scientific research and innovation at the EU level, and the Recovery and Resilience Facility (RRF), which supports post-COVID recovery and the green and digital transitions.

Then, we will use data from the OECD for the patents. The database contains the number of patent applications for each NUTS2 region. The patents are filtered to only be patents related to environmental technologies. The patents are summed to cover the period from 2013 to 2017 for the 2017 indices and from 2018 to 2022 for the 2022 indices. Both patents and funds are used in per capita terms to make them comparable.

The GTVI rises with increased vulnerability. As outlined in pillar (i), all variables increase the vulnerability. Thus, we need to apply the following normalisation to all variables:

$$n_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \times 100 \tag{1}$$

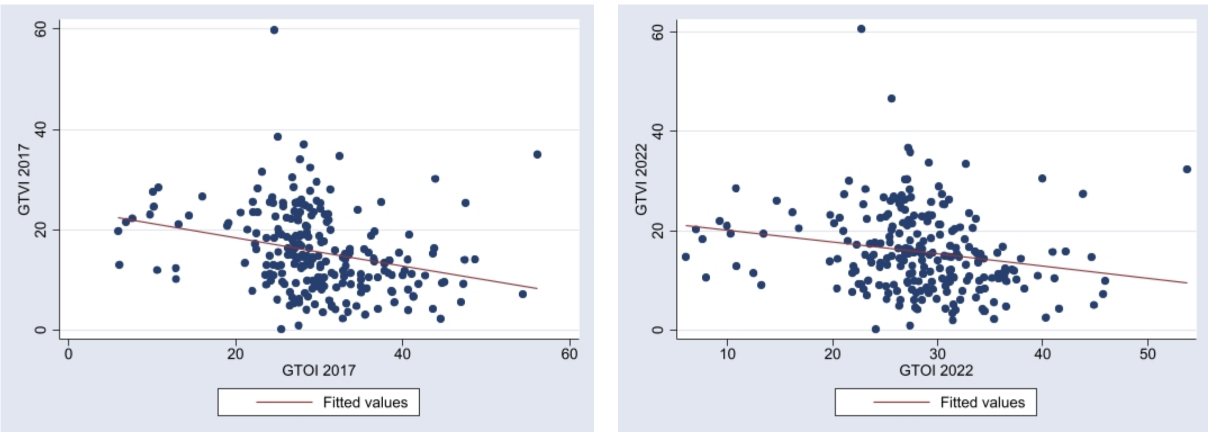
Where $x_{\min}$ and $x_{\max}$ are the minimum and maximum of the variable and n_i is the normalised value.

The GTOI increases with more opportunities. All the variables from pillars (ii) and (iii) increase the opportunities except housing overburden. For the ones that increase with opportunity, we use Equation 1, for housing overburden, we use:

$$n_i^{\text{rev}} = \frac{x_{\max} - x_i}{x_{\max} - x_{\min}} \times 100 \tag{2}$$

Then the normalised values are taken to calculate the indices. They are defined as follows:

- $GTVI = \frac{1}{4} \cdot \text{GHG} + \frac{1}{4} \cdot \text{Mining} + \frac{1}{4} \cdot \text{Agriculture} + \frac{1}{4} \cdot \text{Tourism}$
- $GTOI_{EFF} = \frac{1}{2} \cdot \text{Patents} + \frac{1}{2} \cdot \text{Funds}$
- $GTOI_{CE} = \frac{1}{2} \cdot \text{CE} + \frac{1}{2} \cdot \text{Housing-Overburden}$
- $GTOI = \frac{1}{2} \cdot GTOI_{EFF} + \frac{1}{2} \cdot GTOI_{CE}$



(a) Relation between GTVI and GTOI in 2017 (b) Relation between GTVI and GTOI in 2022

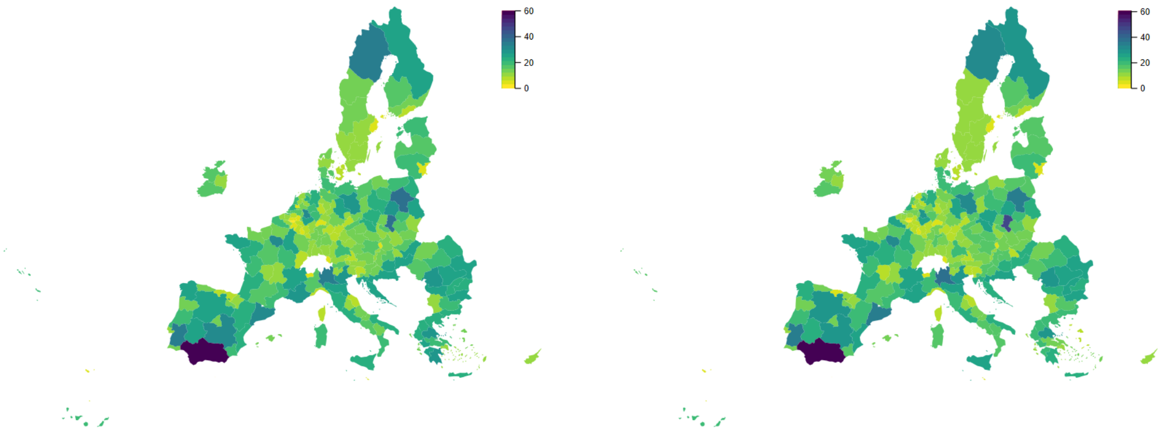
Figure 1: Scatterplots: GTVI and GTOI

Tables with the values for the GTOI and GTVI for the years 2017 and 2022 for the five main countries of interest can be found in Appendix C. A table for the average values for the five countries is provided as well as a table for the values for each of the 70 regions in the five countries.

Figure 1 presents two scatterplots that shows the relationship between the GTVI and the GTOI for every NUTS2 region in Europe for the years 2017 and 2022. The plot 1a shows that there is a negative correlation, with a correlation coefficient of -0.2743, between a region's vulnerability and its green transition opportunity in 2017. In other words, the vulnerable regions were also worse performers in terms of green innovation, investment, circular economy, and inclusion. This pattern raises concerns about potential regional inequalities.

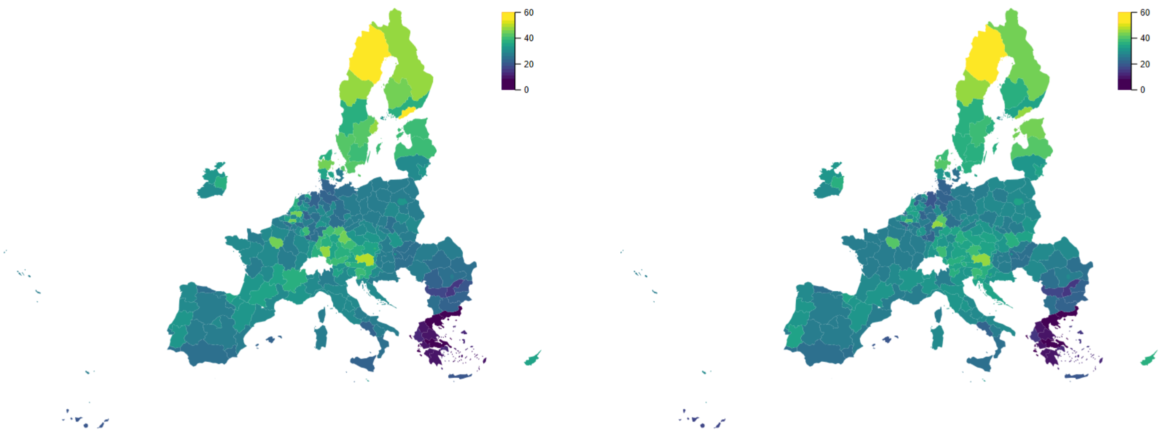
From the plot 1b we observe that the pattern changed slightly in 2022. The correlation coefficient is equal to -0.2053, thus less strong. There seems to be a slight convergence in terms of opportunities and vulnerability. Some regions may have improved in opportunities while staying structurally vulnerable, or vice versa.

Both graphs are of policy relevance, given that there is still regional inequality. The regions with the fewest opportunities and higher vulnerability need the necessary investment to properly catch up.



(a) GTVI in 2017 (b) GTVI in 2022

Figure 2: The GTVI mapped



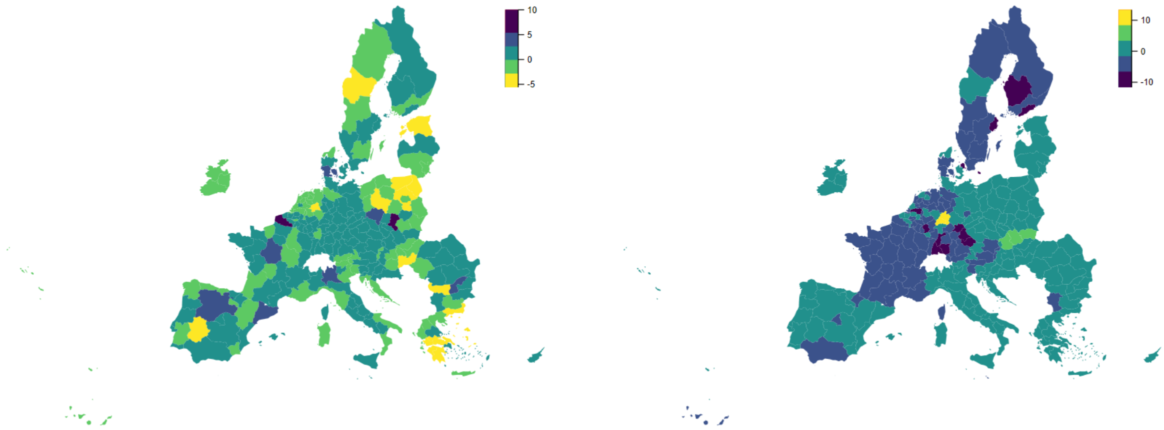
(a) GTOI in 2017 (b) GTOI in 2022

Figure 3: The GTOI mapped

All the maps are constructed in such a way that the lighter colour is associated with the positive outcome. The maps in Figure 2 of the Green Transition Vulnerability Index for 2017 and 2022 reveal clear and persistent spatial disparities across Europe. Regions, notably in Eastern and Southern Europe, including Poland, Bulgaria, Romania, Greece, Italy, and parts of Spain, France and Portugal. Especially Andalusia (Spain) performs really bad. In contrast, Western and Northern European regions, particularly in Germany, Denmark, Belgium and the Netherlands, are less vulnerable. Importantly, the comparison between 2017 and 2022 shows little overall change.

These findings align closely with those of Rodríguez-Pose and Bartalucci (2024) and reach nearly identical conclusions. They showed the same geographic locations of vulnerability, notably Eastern and Southern Europe and warned that such places risk becoming further marginalised in the green transition.

The maps in Figure 3 show the spatial allocation of the GTOI across Europe in 2017 and 2022. Regions depicted in lighter colours signify higher opportunities, indicating better innovation capability, higher green employment, and availability of green investment. These regions include innovation hubs such as Île-de-France, Stuttgart, and Bavaria. Sweden and the Netherlands are performing well too. These findings are in line with Bello et al. (2023). On the other hand, darker regions signify low green opportunity. They are largely found in Southern and Eastern Europe. Greece seems to lack the most opportunities with Andalusia.



(a) Change in the GTVI from 2017 to 2022

(b) Change in the GTOI from 2017 to 2022

Figure 4: Changes of the GTVI and GTOI over the past 5 years

The third map, Figure 4 visualises the change in GTVI and GTOI between 2017 and 2022, offering insights into how regions have evolved in terms of vulnerability and opportunity. In terms of vulnerability, most of the regions in central Europe experience little change. This change, however, tends to be on the negative side as the dark green colour indicates an increase in vulnerability. One may ask oneself to what extent people actually observe these changes. The region that made the most progress in terms of vulnerability is the region in yellow. These are in Greece, Poland, Sweden and one in Spain.

On the other hand, interestingly, when we consider the change in the GTOI, we observe that the largest positive change was in Germany in Giessen and Kassel. Furthermore, most regions in central Europe see their green opportunities deteriorating. France, Sweden and Finland suffer greatly. Southern and Eastern Europe have a rather marginal evolution, with some experiencing small changes above zero an some below zero.

4 Empirical Approach

4.1 Basic Logit: Binary Choice

In this section, I will provide the theoretical background to understand the implementation of the nested logit model. Following Bertoli et al. (2013), we are starting with the Random Utility Model (RUM), where an individual i's utility from moving to location j is given by:

$$U_{ij} = V_{ij} + \epsilon_{ij} = \mathbf{X}'_{ij}\beta + \epsilon_{ij} \tag{3}$$

V_{ij} is referred to as the deterministic component of the utility that is common to all individuals. ϵ_{ij} is the random part of the utility that is specific to each individual.

Furthermore, V_{ij} can be interpreted as a function of amenities and economic factors: $V_{ij} = f(E_{ij}, A_{ij}) = \mathbf{X}'_{ij}\beta$. In the case of a binary choice, e.g. moving ($y_i = 1$) or staying ($y_i = 0$), it is common to use a logit model. By using the logistic link function, we get the usual:

$$\Pr(i \text{ migrates}) = \frac{e^{V_i}}{1 + e^{V_i}} \tag{4}$$

4.2 Conditional Logit

The above case was a binary choice case. Let us now assume that we have multiple possible destinations $j \in J$. In general, if the data includes alternative-specific variables for the chosen destination, as well as the other options (not chosen), then one should opt for the conditional logit. Let $k \in J$ be a destination such that $k \neq j$, then, assuming that ϵ follows an Extreme Value Distribution (McFadden, 1974), we get the following probabilities:

$$\Pr(i \text{ chooses } k) = \frac{e^{V_{ik}}}{\sum_j e^{V_{ij}}} \tag{5}$$

4.3 Nested Logit and Independence of Irrelevant Alternatives (IIA)

The problem arises when we take ratios:

$$\frac{\Pr(i \text{ chooses } k)}{\Pr(i \text{ chooses } l)} = \frac{e^{V_{ik}}}{\sum_j e^{V_{ij}}} \frac{\sum_j e^{V_{ij}}}{e^{V_{il}}} = \frac{e^{V_{ik}}}{e^{V_{il}}} \tag{6}$$

We see that the ratio is constant even if characteristics in destination j change. This issue arises in the cases of the logit and conditional logit. It is the Independence of Irrelevant Alternatives (IIA) assumption. The IIA states that the "*elasticities due to a change in one destination's attributes are identical for all alternatives*" (Beine et al., 2021).

To overcome the obstacle of independence from third options, we can use the nested logit model, which allows decisions to be made in sequential steps. Following Train (2009), all possible destinations can be split into G non-overlapping nests $N_1, N_2, \ldots, N_G$. For example, i has to decide in the first level whether to move to the nest French-speaking countries (France, Belgium, Luxembourg, Monaco) or the nest any other country in the EU, for example. In the second level, if i chose the nest French-speaking countries, he then has to decide to which French-speaking country he wants to move. In general, individual i still gets $U_{ij} = V_{ij} + \epsilon_{ij}$ from destination j in a nest N_g. Assuming that ϵ_i follows a generalised extreme values distribution (GEV) (McFadden, 1974) with cumulative distribution function (CDF):

$$exp\left(-\sum_{g=1}^{G}\Big(\sum_{j\in N_g} e^{-\varepsilon_{ij}/\tau_g}\Big)^{\tau_g}\right) \tag{7}$$

In this case, we allow correlation among error terms within each nest, thus if $France$ and $Luxembourg$ belong to $N_{French-speaking}$, then $Corr(\varepsilon_{France}, \varepsilon_{Luxembourg}) \neq 0$. However, the correlation of alternatives that belong to different nests is zero; $Corr(\varepsilon_{France}, \varepsilon_{Other}) = 0$. τ_g is a "*dissimilarity parameter*" (Bertoli & Fernández-Huertas Moraga, 2013) that dictates the degree of independence between the destinations within nest g. The measure $1 - \tau_g$ can be used as a guidance of correlation, but Bertoli and Fernández-Huertas Moraga (2015) show that the correlation of alternatives belonging to the same nest is $\sqrt{1-\tau_g^2}$. Finally, we get the following probabilities for destination $d \in N_g$:

$$P(i \text{ chooses } d) = \frac{e^{V_{id}/\tau_g}\left(\sum_{j\in N_g} e^{V_{ij}/\tau_g}\right)^{\tau_g - 1}}{\sum_{l=1}^{G}\left(\sum_{j\in N_l} e^{V_{ij}/\tau_l}\right)^{\tau_l}} \tag{8}$$

and the ratio if $d \in N_g$ and $m \in N_l$:

$$\frac{P(i \text{ chooses } d)}{P(i \text{ chooses } m)} = \frac{e^{V_{id}/\tau_g}\left(\sum_{j\in N_g} e^{V_{ij}/\tau_g}\right)^{\tau_g - 1}}{e^{V_{im}/\tau_l}\left(\sum_{j\in N_l} e^{V_{ij}/\tau_l}\right)^{\tau_l - 1}} \tag{9}$$

From Equation 9, we observe a change in the IIA. $\frac{P_{id}}{P_{im}}$ is not anymore independent from all third options. In fact, the ratio is affected by all the possible destinations in N_g and N_l. Train (2009) also mentions that in this case we have "*independence of irrelevant nests (IIN)*".

To make the estimation of the conditional logit and the nested logit model tractable and empirically meaningful, we reduced the initial set of destination alternatives by clustering spatial units into broader regional types. The original specification included over 70 potential destinations, which proved too granular and computationally demanding. More critically, many of these spatial units received only a handful of migration flows, making it unfeasible to estimate reliable choice-specific parameters for each region. Sparse data at the regional level can introduce considerable noise and instability in discrete choice models, especially when the number of alternatives is large relative to the sample size. To address this, we imposed a minimum threshold of approximately 15 migration observations per spatial unit, using this as a guideline to merge regions with insufficient flows.

The clustering process was based on structural and economic similarities, informed by variables such as GDP per capita, employment rates, service provision and other traditional drivers of migration flows. In particular, we identified a total of 12 clusters[5] shown in Figure 6. Two for Finland, Greece and the Netherlands. Three for Spain and Italy. This approach is consistent with the nesting logic of the model, which allows for correlation in unobserved utility components within nests. Importantly, clusters were constructed independently of realised migration flows, thus avoiding endogeneity. By merging destinations in a theoretically grounded manner, we preserved the interpretability and policy relevance of the model while improving its empirical robustness. Overall, this approach allowed us to balance spatial detail with estimation feasibility, enhancing both the reliability and the policy relevance of the results.

When deciding to migrate, a crucial aspect is first whether to migrate within the same country or not. Domestic migration typically entails lower linguistic, institutional, and cultural barriers, leading to greater similarity among regional destinations within the same country. Thus, we would have defined the nests for each country with its respective regional clusters. However, due to sample size limitations and few observations within some clusters, such a structure was not empirically feasible. Thus, we proceeded as follows. We argue that people who move are deciding between leading regions, such as those with larger cities like Madrid, Barcelona, Athens, Amsterdam, and Helsinki, or opting instead to move to the more traditional, slower-paced regions, like the south of Spain and Italy. Thus, we define the nest according to the principal components that capture the control variables, which are all the variables included in the traditional RAI and digital RAI, except those included in the GTOI and GTVI, as defined in Appendix A. The nest structure is depicted in Figure 5. From Figure 5, we see that the second cluster of Greece is in the group of Clusters 2, however, one may consider Greece's second cluster to perform rather poorly, thus the 12 main specifications for the nested logit will also be presented in Appendix G following the alternative nest structure with Greece's second clusters belonging to the nest Clusters 3.

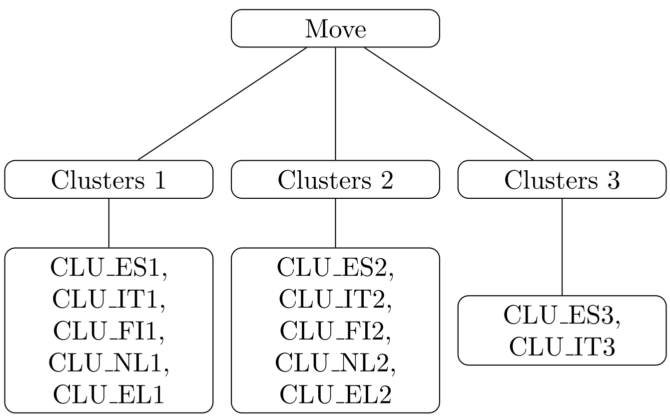


Figure 5: Nest Structure

[5]See Appendix B.1 for more details

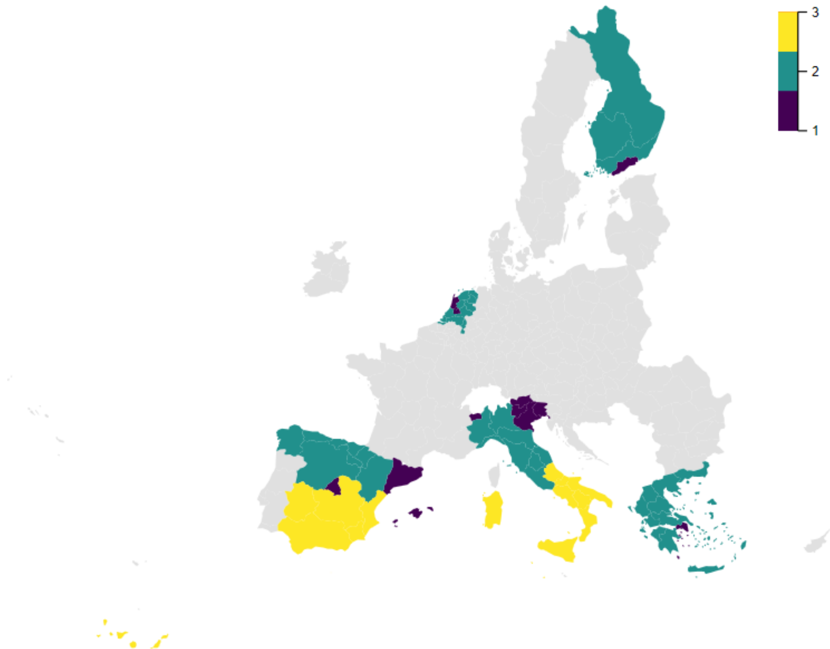


Figure 6: Nests and Clusters Mapped

4.4 Green Preferences

The granular details of the Mobi-Twin survey allow the construction of an index to capture the green valuation of the individuals. The answers related to the nine questions are summarize in Table 5.

Table 5: Descriptive Statistics for Environmental Valuation (Ranked by Mean)

Description	**Obs**	**Mean**	**SD**
Clean water production	9,297	4.437	0.804
Access to green areas	9,314	4.277	0.887
Air quality	9,319	4.156	0.916
Affordable energy prices	9,311	4.134	0.921
Access to water bodies	9,308	3.965	1.019
Circular economy / waste management	9,313	3.792	1.047
Community values the environment	9,315	3.791	1.069
Eco-friendly infrastructure	9,298	3.761	1.048
Use of renewables	9,311	3.754	1.058

Note: All items are based on a Likert scale from 1 (low) to 5 (high importance).

The use of polychronic PCA[6] is particularly useful for summarizing information from multiple survey items into a single index. Given that the variables are not continuous but rather discrete, it is advised to calculate polychoric correlations to more accurately capture the relationships between ordinal variables (Kolenikov, Angeles, et al., 2004).

The Green Preference Index (GPI) is a continuous measure ranging from 0 (no environmental

[6]See Appendix B for more details

Table 6: Descriptive Statistics of Green Preference Index by Group

Group	Q1	Median (Q2)	Q3	Mean
Total Sample	0.635	0.769	0.893	0.750
Age 20–29	0.635	0.750	0.884	0.747
Age 30–39	0.629	0.751	0.887	0.742
Age 40–49	0.653	0.774	0.912	0.761
Age 50–59	0.652	0.803	0.952	0.768
Age 60+	0.633	0.795	0.941	0.753
Female	0.667	0.800	0.924	0.779
Male	0.605	0.743	0.860	0.719
Low Education	0.611	0.750	0.895	0.739
High Education	0.647	0.773	0.892	0.757
No Remote Work	0.635	0.770	0.912	0.751
Remote Work	0.636	0.767	0.888	0.748

concern) to 1 (strong concern). Table 5 shows the GPI and reveals a population that is generally highly inclined toward environmental values. The mean GPI is 0.750, and the median is 0.769, suggesting that environmental concern is widespread.

Even among the least environmentally inclined individuals, the data shows at least a moderate concern for the environment. The 25th percentile value sits at 0.635. Thus, even though people have different levels of environmental preferences, it's pretty uncommon to find complete indifference or denial. This distribution shows positive environmental attitudes are common and widely spread in the community.

Breaking down the data by age reveals a nonlinear pattern when it comes to environmental concern among different age groups. Individuals aged 20 to 29 have a mean GPI of 0.747, nearly identical to the overall mean. However, in the 30 to 39 age group, the mean GPI declines slightly to 0.742. From the age of 40 onward, environmental preferences increase again. For individuals aged 40 to 49, the mean of the GPI climbs to 0.761, and continues to increase for those aged 50 to 59, reaching a maximum of 0.768. It is the highest average observed across all age categories. For individuals aged 60 and over, the mean declines marginally to 0.753 but is still above the values in the younger age brackets.

These patterns indicate that environmental concern peaks in middle adulthood, then slightly declines in later life. This inverted-U relationship could originate from the cycle of life. Middle-aged individuals are often rather stable in life, politically aware, and usually have children, which heighten the importance of environmental awareness.

Gender differences in green preferences are among the most pronounced in the dataset. Women report a mean GPI of 0.779, which is higher than the male mean of 0.719. The interquartile range further backs this disparity. The 25th percentile for women is 0.667 compared to 0.605 for men, and the 75th percentile reaches 0.924 among women but only 0.860 among men. This consistent and large gap across the entire distribution indicates that women are systematically more environmentally oriented.

Education also plays a meaningful role in shaping environmental preferences. Individuals with higher levels of education have a mean GPI of 0.757, whereas those with lower education levels average 0.739. The median and interquartile values reflect a similar pattern. Education is likely to influence environmental valuation through multiple channels. One of these may be exposure to scientific knowledge and critical reasoning.

Remote work status does not appear to be meaningfully associated with differences in environmental attitudes. Individuals who do not work remotely have a mean for the GPI of 0.751, while those who do work remotely report a mean of 0.748. These figures are basically identical. Remote work decisions may be driven by sectoral factors, job flexibility, or lifestyle considerations that are independent of environmental concerns.

In summary, Table 5 shows that a population with generally strong environmental concern, albeit with variation across socio-demographic characteristics. Table 5 gives comparisons at the individual level. Interestingly, we can examine the averages within the clusters, which we can use to define a baseline group for running the models. When running a CL or a NL model, one must indicate a baseline alternative. In our case, we have to indicate a cluster to which we compare the other clusters. We chose cluster ES3, located in southern and central Spain, mainly for two reasons. First, it is the cluster with the most observations, thus serving as a reliable reference. Secondly, the average green preference is the third highest, following closely the highest average in Southern Italy (IT3) and the second highest in the cluster around Athens (EL1). The geographical distribution of the average green preference is shown in Map 7.

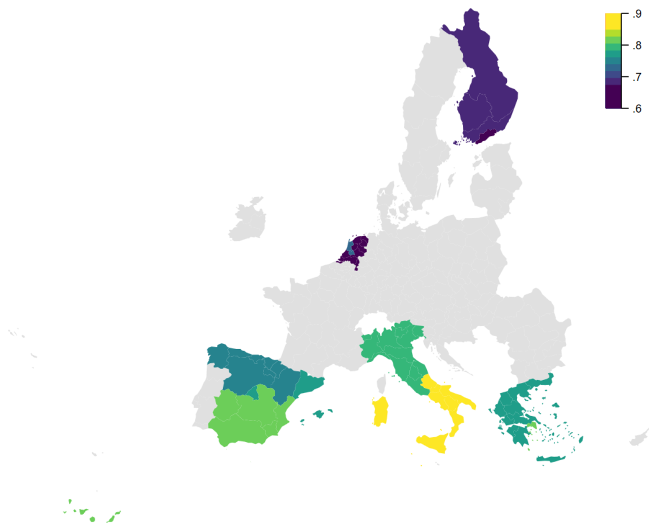


Figure 7: Green Preference by Cluster

5 Results

We now present the results of our analysis. We begin by examining the decision to migrate or not using separate push and pull modelling in a logit framework. This separation is necessary due to high multicollinearity in the case of a combined analysis. Next, we apply the same modelling approach to individuals' intentions to move, comparing realised behaviour with aspirations. Starting with the binary choices gives us an initial intuition about the driving factors. For individuals who moved, the destination variables are those from their current residence in 2022, and the origin characteristics are those of their past residence in 2017. For the stayers, the origin is the same as their current residence, so we replaced the values from 2017 in the origin characteristics. We will show why the basic logit model using the binary variable of migrating or not is not perfect. Then we will provide results using the conditional and the nested logit model for the individuals who actually moved.

5.1 Logit

Table 7: Logit Estimates - Push

Variable	O1	O2	O3	O4	O5
RAI_traditional_origin	-0.0031				-0.0035
GTVI_origin		0.0165***		0.0165***	0.0148***
GTOI_origin			-0.0007	0.0007	0.0062
Green_Preference	0.5107*	0.4346	0.5701*	0.4378	0.4099
Age	-0.0008	-0.0017	-0.0013	-0.0017	-0.0010
Gender	0.0417	0.0472	0.0493	0.0476	0.0421
Remote Work	0.0867	0.0780	0.0750	0.0766	0.0798
Higher Education	-0.6235***	-0.6025***	-0.6133***	-0.6004***	-0.5989***
Constant	-1.4217***	-1.8445***	-1.5853***	-1.8712***	-1.8248***
Observations	5,600	5,600	5,600	5,600	5,600
AIC	4,702.50	4,688.22	4,705.31	4,690.18	4,690.94

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used.
All models are weighted using probability weights (Stata `pweight`) to account for the survey design.
Gender is a dummy equal to 1 for everyone but males. Remote Work is a dummy equal to one if the working arrangement is (i) part remote, part onsite, (ii) mostly remote, or (iii) freelancer. Higher Education is a dummy equal to one if the respondent has tertiary education.

Table 7 and Table 8 report the push and pull estimates. The RAI in the tables serves as control. In Table 7, the GTVI does influence the decision-making. The parameters are positive and significant, thus consistent with expectations. The likelihood of moving increases with the vulnerability in the region of origin. People do not appear to act on the GTOI, as all the coefficients are insignificant. The individual green preference is only significant at the 10 % level in two of the models, showing a negligible influence of the green preference. Thus, people who express a higher environmental valuation do not show a higher likelihood of moving. Additionally, Table 7 indicates that gender, age and the job arrangement do not seem to matter. Unexpectedly, higher qualification seems to decrease the likelihood of migration. In Table 8, we observe that, contrary to expectations, the GTVI is highly significant but with a positive sign.

Table 8: Logit Estimates - Pull

Variable	**D1**	**D2**	**D3**	**D4**	**D5**
RAI_traditional_destination	-0.0021				0.0093**
GTVI_destination		0.0169***		0.0171***	0.0238***
GTOI_destination			-0.0070*	-0.0076*	-0.0210***
Green_Preference	0.1555	0.0351	0.1782	0.0150	0.0948
Age	0.0011	0.0003	0.0006	0.0001	-0.0015
Gender	0.0190	0.0151	0.0199	0.0113	0.0202
Remote Work	0.0973	0.0932	0.1010	0.1059	0.0939
Higher Education	-0.5552***	-0.5361***	-0.5677***	-0.5547***	-0.5611***
Constant	-0.7761***	-1.1528***	-0.7068**	-0.9210***	-1.2481***
Observations	6,170	6,170	6,170	6,170	6,170
AIC	6,577.86	6,547.02	6,575.74	6,544.69	6,534.04

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used.
All models are weighted using probability weights (Stata `pweight`) to account for the survey design.
Gender is a dummy that is equal to 1 for everyone but males. Remote Work is a dummy that is equal to one if the working arrangement is (i) part remote, part onsite, (ii) mostly remote, or (iii) freelancer. Higher Education is a dummy that is equal to one if the education is tertiary.

Thus, people are more likely to migrate when the destination is vulnerable to the green transition. Additionally, the GTOI also follows an unexpected pattern. The likelihood of moving decreases with the availability of more opportunities at the destination. These results are counterintuitive, but we will discuss this issue further below. Age, gender, remote work, and the green preference do not impact the likelihood of moving. Again, more education significantly decreases the likelihood of choosing to migrate. This may be due to the fact that the more educated are well established in their region of residence.

Table 9: Logit Estimates for Intention to Move - Push

Variable	**IO1**	**IO2**	**IO3**	**IO4**	**IO5**
RAI_traditional_origin	0.0070***				0.0081**
GTVI_origin		-0.0097**		-0.0098**	-0.0042
GTOI_origin			0.0056	0.0058	-0.0061
Green_Preference	1.3046***	1.2468***	1.1758***	1.2667***	1.3453***
Age	-0.0577***	-0.0567***	-0.0568***	-0.0566***	-0.0579***
Gender	0.0004	-0.0127	-0.0122	-0.0094	0.0006
Remote Work	0.2070**	0.2375**	0.2301**	0.2260**	0.2123**
Higher Education	0.2681***	0.2420**	0.2676***	0.2564***	0.2504***
Constant	0.6026**	1.2406***	0.9274***	1.0598***	0.7787***
Observations	6,170	6,170	6,170	6,170	6,170
AIC	6,312.86	6,320.98	6,328.49	6,320.38	6,312.56

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used.
All models are weighted using probability weights (Stata `pweight`) to account for the survey design.
Gender is a dummy that is equal to 1 for everyone but males. Remote Work is a dummy that is equal to one if the working arrangement is (i) part remote, part onsite, (ii) mostly remote, or (iii) freelancer. Higher Education is a dummy that is equal to one if the education is tertiary.

Turning to the intention to migrate, Table 9 and Table 10 represent the push and pull models of

Table 10: Logit Estimates for Intention to Move - Pull

Variable	**ID1**	**ID2**	**ID3**	**ID4**	**ID5**
RAI_traditional_destination	0.0122***				0.0064
GTVI_destination		-0.0142*		-0.0139*	-0.0095
GTOI_destination			0.0214***	0.0209***	0.0121
Green_Preference	1.3676***	1.2198***	1.1719***	1.2953***	1.3678***
Age	-0.0567***	-0.0556***	-0.0552***	-0.0548***	-0.0556***
Gender	0.0703	0.0407	0.0544	0.0533	0.0632
Remote Work	0.0375	0.0881	0.0566	0.0489	0.0373
Higher Education	0.2212*	0.1778	0.2531**	0.2363*	0.2310*
Constant	-0.7557**	0.3680	-0.5384	-0.3284	-0.5864
Observations	4,250	4,250	4,250	4,250	4,250
AIC	3,465.77	3,480.99	3,474.14	3,466.08	3,465.02

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used.
All models are weighted using probability weights (Stata `pweight`) to account for the survey design.
Gender is a dummy that is equal to 1 for everyone but males. Remotework is a dummy that is equal to one if the working arrangement is (i) part remote, part onsite, (ii) mostly remote, or (iii) freelancer. Higher education is a dummy that is equal to one if the education is tertiary.

migration aspirations. Table 9 again shows disappointing results, with decreased likelihood of aspiring to migrate if the origin is more vulnerable and possesses fewer opportunities. However, now, the green preference is highly significant and positive. Thus, people who prefer living in a green area are more likely to aspire to migrate. This is again contradictory, as the GTOI and GTVI indicate the opposite. Age is also highly significant now. The younger you are, the more likely you are to aspire to migrate. Further, working under flexible working arrangements increases the likelihood of intentions. Interestingly, higher education also switched signs, as did the realised migration. Thus, higher educated individuals express, on average, a higher aspiration to migrate.

From Table 10, the vulnerability plays a marginal role with a 10% significance in two models. The sign aligns with expectations, as the destination's vulnerability decreases its attractiveness. The GTOI also matches the expected sign in two of the models, but is not significant in the last specification. The green preference is significant for all the specifications, confirming its important role in migration aspirations. The same is true for age. Gender and remote work lost significance in the latter table. Tertiary education is impacting aspirations in all but one specification at the 10% to 5 % level.

We highlighted a fact in the analysis of Table 7 and Table 8 that the more vulnerable the destination is, the higher the likelihood of moving, which, of course, is a counterintuitive result. However, Table 11 helps to understand the phenomenon. In fact, movers initially resided in regions that were, on average, slightly more vulnerable than those of non-movers. They also relocated to destinations with even higher average vulnerability than their origins. In contrast, stayers only suffered from a moderate increase in their region's vulnerability over time, but remained in relatively less vulnerable areas overall. Regarding the GTOI, both groups saw a decline in the average opportunity levels of their regions over the five-year period. However, the drop was more pronounced for movers. The overall evolution of the indices is in Appendix 31.

Table 11: Summary Statistics: GTOI and GTVI by migration status

Variable	**Mean**
GTVI_origin (Moved)	23.94
GTVI_origin (Did not move)	22.35
GTVI_destination (Moved)	25.52
GTVI_destination (Did not move)	22.75
GTVI: Change (Moved)	**1.58**
GTVI: Change (Did not move)	**0.40**
GTOI_origin (Moved)	27.89
GTOI_origin (Did not move)	27.23
GTOI_destination (Moved)	26.14
GTOI_destination (Did not move)	25.88
GTOI: Change (Moved)	**-1.75**
GTOI: Change (Did not move)	**-1.35**

Nonetheless, one should be cautious when interpreting these findings due to the time dimension in the green transition indicators. The indices for the origin and destination regions are measured at two different points in time, with a five-year difference. The origin reflects conditions before the move, and the destination reflects conditions after relocation. If people relocated five years ago, they likely selected their destination based on the circumstances at that time, which could have been favourable. Over time, however, these destination regions may have become more vulnerable independent of the migrants' choices. This temporal difference may create a bias when including the characteristics of origins and destinations. It may appear that individuals relocate to less desirable locations, even if they actually chose better places at the time of their decision.

Therefore, from now on, to analyse the destination choices of movers, while avoiding time-related issues, we will focus exclusively on individuals who relocated, utilising data solely from 2017

5.2 Conditional Logit

Following the issues mentioned, we present conditional logit estimates. We are only considering individuals who actually moved, so we are excluding those who did not. One caveat is that we have only around 1,500 individuals in this case. For the intentions, we follow the same pattern. We only consider individuals who express an aspiration to move (around 1100 individuals). This large decrease in individuals is due to a lack of data. Often, when a person relocated, we only have country data, not regional data. A further distinction will be made from now on, using clusters instead of the NUTS2 region to reduce computational burden.

Due to space constraints, we will not report the entire specifications for the conditional logit model, but only the global parameters. The estimates for the individual characteristics are evaluated for every possible cluster. Thus, the full tables would be too large to report. We will only summarise the estimates for the individual characteristics for model M12 in a graph to save space. The full tables are in Appendix D, and all the results will be commented. We follow the same procedure with the intention to move. The full tables for aspirations are in Appendix D.

Table 12: Conditional Logit Estimates - Realised Move

Cluster	**Variable**	**M1**	**M2**	**M3**	**M4**
Global	GTOI_2017	0.492***	0.785***	1.318***	1.157***
	PC1_2017		-1.072***		-0.202*
	PC2_2017			14.044***	10.202***
Cluster	**Variable**	**M5**	**M6**	**M7**	**M8**
Global	GTVI_2017	-0.465***	-0.595***	-0.796***	-0.927***
	PC1_2017		-0.709**		0.711***
	PC2_2017			7.111***	13.396***
Cluster	**Variable**	**M9**	**M10**	**M11**	**M12**
Global	GTVI_2017	-1.362***	2.391***	-0.383***	1.919***
	GTOI_2017	-1.400***	4.099***	0.413***	3.466***
	PC1_2017		-3.148**		-2.593***
	PC2_2017			10.143***	1.763***

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SEs used. All models are weighted using probability weights (`pweight`) to account for the survey design.

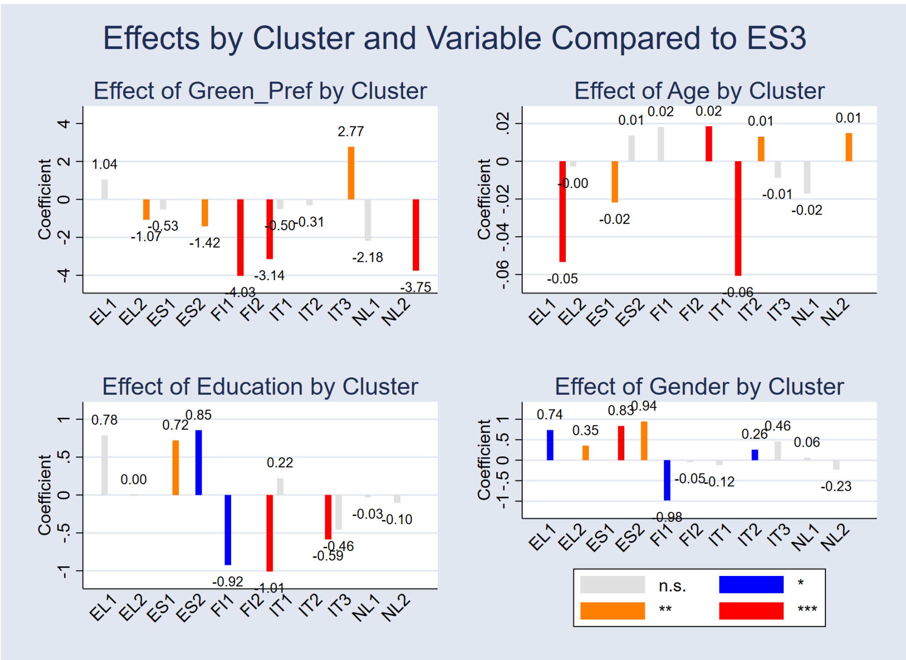


Figure 8: Estimates for individual characteristics: M12

Table 12 presents the global parameters, which capture the general effect of the GTOI, GTVI, and the principal components, serving as control variables. Table 12 is divided into three parts, with part one capturing the combinations of the principal components with the GTOI, the second part with the GTVI and the last with both.

The GTOI is consistently highly significant and positive in models M1 to M4, meaning that people actively choose destinations with higher GTOI values. Furthermore, the GTVI is highly significant and negatively correlated with the choice of a destination. Thus, overall, the higher the vulnerabilities, the lower the likelihood of choosing that destination. Nonetheless, by including both GTVI and GTOI in a specification, the implications become less evident. The coefficients actively switch signs by trying different combinations, clearly indicating problems. The GTOI shows more consistency by switching signs only once. GTVI switches signs, especially after including PC1 as a control. Given the small sample size, even slight changes in the specification can significantly alter the convergence process of the maximum likelihood estimation. One possible explanation could be the added multicollinearity by combining GTOI and GTVI. During the estimation process, we faced several issues with convergence, especially for models M10 and M12. Keeping in mind that the third part of Table 12 clearly shows issues, when we consider the segregated analysis, we obtain the anticipated results of a positive effect of the GTOI on the likelihood of choosing a destination and the reverse for the GTVI.

When we focus on individual characteristics, such as green preference, age, higher education, and gender, we refer to the tables in Appendix D and Figure 8. We compare all the individual characteristics with respect to southern Spain, ES3.

Individuals with stronger green preferences are significantly less likely to choose clusters such as FI1, FI2, and NL2 in comparison to ES3. The green valuation is significant and positive for IT3, indicating that environmentally conscious individuals actively prefer this cluster compared to ES3.

Younger individuals are significantly more likely to choose clusters such as EL1 in Greece and IT1 over ES3. The consistently negative and significant coefficients indicate that these clusters are more attractive to the younger population. On the other hand, older individuals are more likely to prefer clusters like IT2, FI2, and NL2, where the coefficients are positive and significant.

Individuals with tertiary education are significantly more likely to choose ES1 and EL1 over ES3 across all models. On the other hand, higher education is negatively associated with choosing FI2 and IT2.

FI1 consistently suffers a negative coefficient for gender, indicating that females, transgender women, transgender men, and non-binary individuals are less likely to select this cluster in comparison to ES3. In Model 12, females appear more likely to prefer clusters such as EL1, ES1, and ES2, with positive and significant gender coefficients.

We now move from realised migration to migration aspirations. From Table 13 we can observe the same patterns for the global parameters as for the actual migration. In the separate analysis, the GTOI is positively associated with the likelihood of choosing a region, while the GTVI is negatively associated with choosing a region. Then, in a combined analysis, the parameter signs start to switch, highlighting the same issue as before.

People with higher green preferences are less likely to choose clusters NL2 and FI2. IT3 emerges as a preferred destination for green-minded individuals. Age remains relatively insignificant, but older people prefer IT3 over ES3. The more educated prefer ES1, ES2, to ES3 but do not prefer FI1, FI2, IT2 and IT3. For gender, we identify Greece as attractive, while the Netherlands is in some specifications.

Table 13: Conditional Logit Estimates Intentions

Cluster	Variable	Int1	Int2	Int3	Int4
Global	GTOI_2017	0.492***	0.785***	1.318***	1.157***
	PC1_2017		-1.072***		-0.202*
	PC2_2017			14.044***	10.202***

Cluster	Variable	Int5	Int6	Int7	Int8
Global	GTVI_2017	-0.560***	-0.762***	-1.055***	-0.935***
	PC1_2017		-1.034***		-0.279
	PC2_2017			10.618***	7.129***

Cluster	Variable	Int9	Int10	Int11	Int12
Global	GTVI_2017	-2.087***	0.999***	-1.283***	0.807***
	GTOI_2017	-1.912***	2.599***	-0.424***	2.342***
	PC1_2017		-2.573***		-2.347***
	PC2_2017			8.295***	0.728

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SEs used. All models are weighted using probability weights (`pweight`) to account for the survey design.

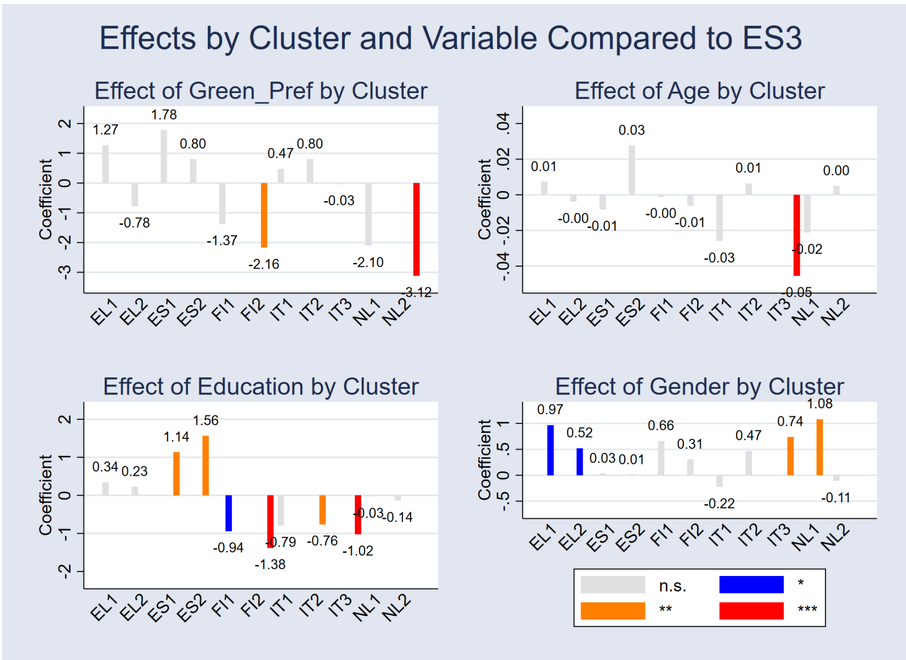


Figure 9: Estimates for individual characteristics: Int12

In summary, in both migration and aspirations, individuals prefer destinations with higher GTOI and avoid those with high GTVI. When both indices are combined, sign instability and convergence issues emerge. At the individual level, people with high green preferences avoid FI1, FI2, and NL2, and prefer IT3. Younger individuals are more drawn to EL1 and IT1, while older people favour IT2, FI2, and NL2. Higher education is associated with a preference for ES1 and EL. Overall, aspirations closely match actual migration patterns.

5.3 Nested Logit

Following the conditional logit estimates, we now present the results from the nested logit, which relaxes the assumption of Independent Irrelevant Alternatives. The conditional logit is a special case of the nested logit model, where the dissimilarity parameters are assumed to be equal to one. The full tables will be in Appendix E. Here, we report the results in an abbreviated manner, following the same format as in the latter section. We present the global parameters and the parameters for the individual characteristics for the last model.

Table 14: Nested Logit Estimates - Realised Move

Cluster	**Variable**	**NL21**	**NL22**	**NL23**	**NL24**
Global	GTOI_2017	0.657**	0.862***	1.094***	0.866***
	PC1_2017		-1.787		-0.454
	PC2_2017			9.930***	10.665***
Cluster	**Variable**	**NL25**	**NL26**	**NL27**	**NL28**
Global	GTVI_2017	-0.455	-3.505***	-0.709	-3.601***
	PC1_2017		-5.040***		-3.740**
	PC2_2017			3.774	12.452***
Cluster	**Variable**	**NL29**	**NL30**	**NL31**	**NL32**
Global	GTVI_2017	0.401	-13.769	-0.545	-12.214
	GTOI_2017	-0.648	0.990	0.699*	2.014
	PC1_2017		-26.635		26.769
	PC2_2017			8.759***	-0.511

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SEs used. All models are weighted using probability weights (`pweight`) to account for the survey design.

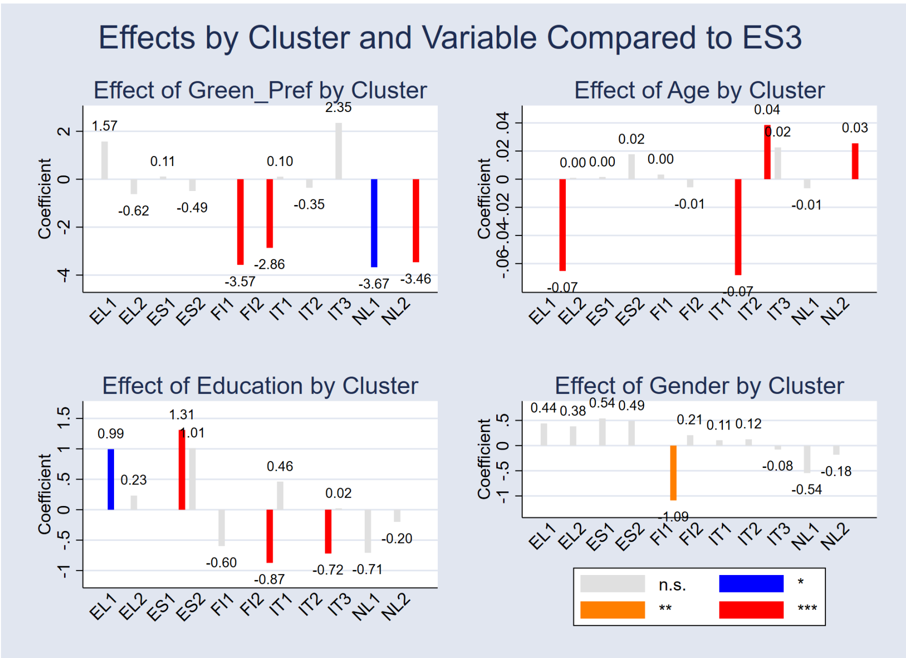


Figure 10: Estimates for individual characteristics: NL32

In Table 14, we identify the global parameters of all the estimated models. The GTOI is associated with a positive parameter in all the models except NL29. From the eight positive parameters, it is significant five times. Hence, the GTOI has a marginal but positive influence on the destination choice. The GTVI is negatively associated with the likelihood of choosing a destination in every specification but one. However, in terms of significance, we cannot identify a clear pattern that questions the role of green vulnerability in migration choice.

Shifting the analysis to individual characteristics, we now compare all the estimates in relative terms with respect to the baseline ES3. The expressed environmental valuation from survey responses yields negative and significant coefficients in clusters such as FI2, NL2, ES2, EL2 and IT2, depending on the specification. The common negative effects are among NL2, FI2, ES2, and EL2, which are interestingly the clusters in group 2. Thus, environmentally conscious individuals tend to avoid certain destinations, which is surprising for NL2 and FI2, as one might expect that the more you value your green environment, the more likely you are to move to regions in Finland that are abundant in nature compared to cluster three of Spain. For the other clusters, we cannot observe a significant difference with respect to ES3.

Age plays an important role. We can identify various differences across clusters. In specification NL28, younger individuals tend to avoid closely to all the other clusters compared to ES3. These are ten clusters. Thus, we can observe that, on average, people are more likely to move to ES3 if they are the oldest. Across all models, this consistency is maintained for NL1, NL2, IT3, ES2, and EL1.

Higher education is no longer a significant factor, so we cannot identify any differences in terms of education. This is extremely interesting as it means that the highly educated are homogeneously choosing the clusters. The effects of gender vary. In many of the specifications, for clusters NL2, IT2, IT3, FI2, ES2, ES1, EL2, gender has a large positive effect, indicating possible gendered inclusion in these clusters. Most of the significance is lost in model NL32.

Up to this point, we have only analysed realised migration choices in the nested logit case. Shifting the focus to migration intentions comes with certain challenges. Although we have a large number of observations from individuals expressing a desire to migrate, information on their desired destinations is often missing, resulting in a limited dataset with around 1100 observations. The conditional logit model can still be estimated across all specifications. However, the added complexity of the nested logit model did not allow for converge. Thus, for the intentions, we have to rely on the conditional logit estimates.

5.4 Independence of Irrelevant Alternatives

The primary reason for making the effort to estimate a nested logit model as opposed to a conditional logit model is the IIA. To check whether the nested logit model is the appropriate model to use, it is important to test for the IIA. This test comes with certain caveats. The use of robust standard errors and probability weights to account for the survey design does not allow for testing for the IIA. Henceforth, we test for the IIA without these options. We will test the IIA nine times, always using the full specification of each table, specifically for NL24, NL28 and NL32. We will test the IIA for all the clusters.

Table 15: Hausman Test for IIA

Model Specification	Cluster 1	Cluster 2	Cluster 3
GTOI only (NL24)	$\chi^2(3) = 139.26^{***}$	$\chi^2(7) = 122.05^{***}$	$\chi^2(7) < 0$
GTVI only (NL28)	$\chi^2(7) = 0.6990$	$\chi^2(7) = 189.61^{***}$	$\chi^2(7) = 351.22^{***}$
GTOI + GTVI (NL32)	$\chi^2(8) = 99.35^{***}$	$\chi^2(8) = 194.75^{***}$	$\chi^2(8) = 136.66^{***}$

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 9 gives us a 3×3 matrix. If we examine row one, column one, we can determine whether the odds of going to one of the clusters in cluster group 2 relative to going to one of the clusters in cluster group 3 change when we include cluster group 1 as alternatives. Clearly, the use of a nested logit model is necessary given that seven out of the nine different tests do show extremely high significant levels.

6 Mechanisms

To further delve into the analysis and identify potential mechanisms for providing policy guidance, we interact the indices with the green preference. Technically, the higher the green preference or the index value, the greater the interaction. If green preferences are accurately reported and not biased, meaning individuals who claim to value the environment also act accordingly, then introducing this interaction should not significantly alter the results. Furthermore, we also run the nested logit for the change in the indices interacted with the green preference between 2017 and 2022. Finally, we show estimates for the change in the overall GTOI and GTVI, without interaction, to assess whether increasing opportunity or decreasing vulnerability alone affects migration decisions, independent of individuals' green preferences. In all the estimates, we control for general attractiveness factors using PC1 and PC2. The base category stays ES3.

Table 16 presents the results for the global parameters. In model NL33, the interaction term with GTOI is negative and significant. This result is counterintuitive, as one would expect individuals with strong environmental preferences to be more likely to move to regions with greater green economic opportunities. In model NL34, the interaction with GTVI is positive and significant. This again runs contrary to expectations. People with strong green preferences are more likely to move to vulnerable regions.

These findings suggest that the interaction between green preferences and structural green indicators does not reinforce the expected alignment, indicating a possible perception gap or other trade-offs that influence decisions. The findings indicate that individuals who report stronger environmental preferences are significantly less likely to relocate to regions with high GTOI values in 2017.

Models NL35 and NL36 assess whether changes over time in the alignment between individuals' green preferences and regional green transition indicators influence migration choices. Specifically, they estimate the effect of the change in the interaction between green preferences and the

Table 16: Nested Logit Estimates - Realised Move

Cluster	Variable	NL33	NL34	NL35	NL36
Global	GTOI_GP_2017	-0.607***			
	GTVI_GP_2017		0.380***		
	Δ GTOI_GP			2.001****	
	Δ GTVI_GP				1.527***
	PC1_2017	-12.582	-2.078***	-21.428	-2.268***
	PC2_2017	-13.582	-14.711***	-17.037	-14.843***
Cluster	**Variable**	**NL37**	**NL38**		
Global	Δ GTOI	-2.003***			
	Δ GTVI		-1.771		
	PC1_2017	-0.582	0.501		
	PC2_2017	2.927	4.064*		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SEs used. All models are weighted using probability weights (`pweight`) to account for the survey design.

GTOI in NL35, and the GTVI in NL36. The results from NL35 show a positive and statistically significant coefficient for the change in the GTOI–green preference interaction. This suggests that individuals who value environmental sustainability are more likely to move to regions where green economic opportunities have improved between 2017 and 2022. Importantly, this dynamic effect contrasts with the earlier model, NL33, where the interaction was negative. This implies that while high levels of green opportunities alone may not be sufficient to attract environmentally conscious individuals, improvements over time in these opportunities may be the driving force.

In contrast, model NL36 shows that green preference interacted with the change in GTVI is positive and statistically significant. Hence, an increase in vulnerability in the cluster seems to attract more environmentally conscious migrants, which contradicts intuition.

In models NL37 and NL38, the main variables of interest are the change in GTOI and GTVI. In NL37, the change in GTOI is significant and negative, implying that regions where green opportunities have increased over time are significantly less attractive. NL38 shows a negative but statistically insignificant effect for the change in GTVI, indicating no influence.

7 Policy Implications

The findings have significant implications for the European Union's broader green transition strategy, including the European Green Deal. The green transition should be an equitable process, where no one is left behind. However, the model's evidence shows that high-GTVI regions tend to be negatively associated with people being attracted in contrast to the GTOI. Although this pattern weakens in the more complex models that include both indices simultaneously (Tables 12 and 14), the underlying issue of regional inequalitiy persists. Both vulnerability and opportunity are unequally distributed and must be actively addressed. The maps 3 and 2 further confirm the existence of spatial differences across Europe in terms of vulnerability and opportunity.

We recall that the GTVI is linked to pillar (i), which involves reducing GHG emissions. It highlights the vulnerability to the stringent emissions reduction policies. The effectiveness of the EU policies in reducing GHG emissions is astonishing. In fact, GHG emissions fell by 8.3% in 2023 in one year (European Commission, 2025b). One big drop occurred in electricity production and heating, with a decrease of 24% of emission under the EU Emissions Trading System. Even with the significant decrease, further cuts to emissions may be necessary, as current policies are insufficient, particularly since air transport emissions increased in 2023, rebounding after the COVID-19 pandemic with an 8.5% rise (European Commission, 2025b). The 55% reduction and ultimately net-zero will require accelerating emissions cuts in the rather resilient sectors. Therefore, regions that are vulnerable must be monitored and supported, as they may be at risk of further intensification of policies aimed at reducing emissions. This is a direct reflection of the regional disparities the EU wants to eliminate. It justifies the EU's Just Transition Mechanism (European Commission, 2020a), which is designed to support the most affected, vulnerable regions so that the shift to a climate-neutral economy occurs in an equitable way. If regions with high vulnerability indices also are subject to population outflows, they may fall into economic decline, thereby failing to meet the Green Deal's equity goals. EU policies using the Just Transition Fund (European Commission, 2020a) and related investments target such areas to create new jobs, re-skill workers, and diversify economies. By doing so, the EU can reduce the factors captured by the GTVI that drive labour away. We can say that the model's output validates the EU's approach of channelling funds to regions at risk. Without such intervention, the green transition could accelerate internal migration and regional inequality.

Moving to energy efficiency, thus addressing pillar (ii) of the green transition. We associated pillar (ii) with patents and funds for research and innovation. The R&I is especially important for the efficiency in renewables and the creation of better technologies and storage options (European Comission, 2025c). The EU managed to use 24.5% renewable energy in its total energy consumption (EEA, 2025). This large surge to the highest level it has ever reached was due to a significant investment in wind and solar energy plants (EEA, 2025). However, as before the transport sector lags behind, with a renewables energy share of only 10.8%, highlighting an area for policy intervention. Under the REPowerEU plan (European Commission, 2018) and the Fit for 55 package (Erbach & Jensen, 2022), the EU sets new targets in renewable energy use. The REPowerEU plan specifically targets the transport sector. It increases fuel constraints and requests that all new vehicles sold by 2035 be zero-emission. Fit for 55 raises the Union's overall renewable energy target to a minimum of 45% by 2030. To achieve these goals, investments must be made in a fair and equitable manner, particularly given that the findings regarding GTOI show that individuals are drawn to areas with increased innovation, competitive funding, circular economy jobs, and inclusion. This clearly demonstrates the necessity of distributing green opportunities throughout Europe.

In pillar (iii), the circular economy, the EU's progress remains limited. In 2022, only 11.5% of materials used came from recycled sources. Each citizen produced about half a tonne of waste annually (EIB, 2024). Hence, substantial investment in recycling and reuse is needed. Nevertheless, the potential is significant. Up to 2.5 million new jobs could be created in circular economy sectors by 2030 (OECD, 2025). These jobs, however, must be made accessible to regions currently low in GTOI. As Map 3 shows, most green opportunities are concentrated in a handful of innovation-rich areas. If uncorrected, this could further diverge spatial inequality, as workers migrate to these hubs.

In summary, EU-level averages indicate steady progress in the green transition. However, they may mask regional disparities in both risks and benefits. Our findings, although limited, provide evidence that such imbalances can affect migration patterns, as individuals are drawn to greener opportunities or pushed away from vulnerable regions. To balance out the opportunities and vulnerabilities, action is needed.

The EU should enforce its support for vulnerable areas, particularly regions in Southern and Eastern Europe. These areas often face the highest costs of decarbonisation while lacking the green opportunities. EU climate and innovation funding should be distributed, ensuring that disadvantaged regions receive proportionally more support.

At the same time, a just transition requires preparing the workforce for the green economy. Reskilling programs should be expanded, particularly for workers transitioning out of fossil fuel sectors, such as coal mining and oil and gas, given the rapid growth of the renewable energy industry.

To enhance regional implementation and accountability, annual reporting on green transition outcomes (emissions, employment, investment, and migration) should be integrated, utilising common indicators such as the GTVI and GTOI.

8 Conclusion

This thesis set out to explore whether and how the green transition influences interregional migration within the European Union. Using the MOBI-TWIN dataset, we introduced two region-level indices, the GTOI and the GTVI to show the existence of regional inequality. Then we examined their relationship with both actual migration choices and stated migration intentions. A key factor of the analysis was the incorporation of individual-level environmental preferences to investigate whether personal values around sustainability align with regional mobility patterns. Given the likely violation of the IIA assumption, the nested logit model is appropriate.

The results show certain patterns that should be interpreted, keeping in mind the convergence issues. First, more consistently, green opportunity appears to be positively associated with migration and migration intentions. In contrast, vulnerability did not yield consistent effects, despite the majority of models showing a negative effect. Surprisingly, interactions between individual green preferences and regional green characteristics show counterintuitive tendencies, with individuals who expressed a high environmental preference being more likely to relocate to regions with fewer opportunities and greater vulnerability. This highlights the existence of a gap between “stating and acting”.

These results do have important implications for European green transition policies. If regions with greater green vulnerability and lower opportunities fail to retain or attract people, it could enlarge existing inequalities, clearly missing the principle of a just transition. Policymakers should support these areas not only through investment but also by ensuring that the workforce experiences the necessary training to switch to a greener economy.

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A Computation of RAI's

A.1 Traditional RAI

Table 17: Traditional factors of regional attractiveness

Component	**Indicator**
Economy	Gross Domestic Product per capita
Labour market	Employment rate
Sectoral composition	Industry share; High value-added private services share
Visitor Appeal	Tourist arrivals at accommodation establishments per 100,000 inhabitants
Residents Well-Being	Tertiary students; Physicians per 100,000 inhabitants
Housing affordability	Housing over burden rate
Regional Safety	Robbery rates
Institutional Quality	Quality of Government Index (EQI)
Environment	Cooling degree days index; Heating degree days index; Air quality index

$$
\begin{aligned}
RAI_{\text{traditional}} = {} & \frac{1}{9}\,\text{GDP}_{pc} + \frac{1}{9}\,\text{Employment rate} + \frac{1}{9}(0.5 \cdot \text{Industry\%} + 0.5 \cdot \text{Services\%}) + \\
& \frac{1}{9}\,\text{Tourists} + \frac{1}{9}(0.5 \cdot \text{Tertiary stud} + 0.5 \cdot \text{Physicians per 100K}) + \frac{1}{9}\,\text{Housing aff} + \\
& \frac{1}{9}\,\text{Robbery rate} + \frac{1}{9}\,\text{EQI} + \frac{1}{9}(0.33 \cdot \text{Cooling} + 0.33 \cdot \text{Heating} + 0.33 \cdot \text{Air qual})
\end{aligned} \tag{10}
$$

Table 18: Digital factors of regional attractiveness

Component	Indicator
Connectivity	Broadband access
ICT employment	High-tech employment
Digital skills	Internet used between individuals; Internet used with public authorities; Internet selling; Internet banking

A.2 Digital RAI

$$
\begin{aligned}
RAI_{\text{Digital}} = &\frac{1}{3} \cdot \text{Broadband access} + \frac{1}{3} \cdot \text{High-tech employment} \\
&+ \frac{1}{3} \cdot (0.25 \cdot \text{Internet private} + 0.25 \cdot \text{Internet public} \\
&+ 0.25 \cdot \text{Internet selling} + 0.25 \cdot \text{Internet banking})
\end{aligned} \tag{11}
$$

B Principal Component Analysis (PCA)

Principal Component Analysis (Kolenikov, Angeles, et al., 2004) is a method used to capture the maximum amount of information from a dataset using a smaller number of variables. The PCA thus creates new variables called principal components, which are linear combinations of the original variables. Additionally, these new variables are uncorrelated.

Suppose we apply the PCA to a set of five variables, then, five principal components will be generated. Most of the information will be captured by the first principal components, especially the first principal component. Formally, following Kolenikov, Angeles, et al. (2004), we have a vector $\mathbf{x}$ of dimension 5, with a 5×5 variance-covariance matrix $\mathbb{V}[\mathbf{x}]$. The PCA will maximise the variance of the linear combinations of the x's. It finds the weights $\mathbf{a_1}, \ldots, \mathbf{a_5}$ such that:

$$\mathbf{a_1} = \arg \max_{\mathbf{a}:\|a\|=1} \mathbb{V}[\mathbf{a}'\mathbf{x}] \tag{12}$$

$$\ldots$$

$$\mathbf{a_5} = \arg \max_{\mathbf{a}:\|\mathbf{a}\|=1, \mathbf{a} \perp \mathbf{a_1}, \ldots, \mathbf{a_5}} \mathbb{V}[\mathbf{a}'\mathbf{x}] \tag{13}$$

B.1 Clusters

To determine the clusters within each country, PCA was applied to the variables included in the $RAI_{\text{traditional}}$ and RAI_{digital} except those included in the GTOI and GTVI to avoid including variables twice. The resulting principal components capture the most relevant variation in the regions' characteristics. Based on these components, we applied Ward's hierarchical clustering method, which groups regions by minimising the variance within each cluster. This approach allowed us to identify distinct regional clusters that share similar characteristics within each country.

B.1.1 Spain

- Cluster 1: ES30, ES51, ES53
- Cluster 2: ES11, ES12, ES13, ES21, ES22, ES23, ES24, ES41
- Cluster 3:ES42, ES43, ES52, ES61, ES62, ES63, ES64, ES70

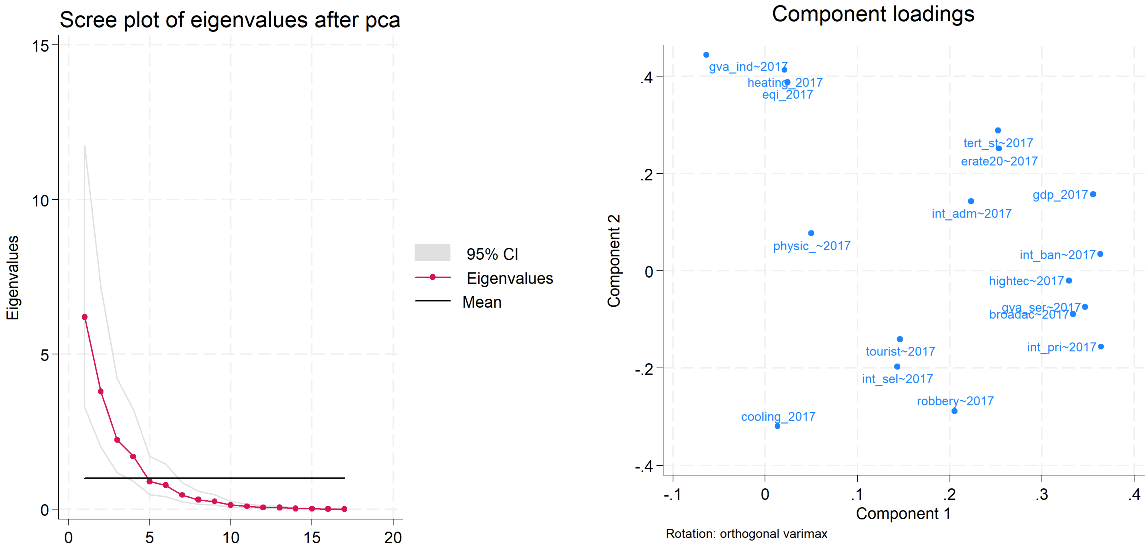
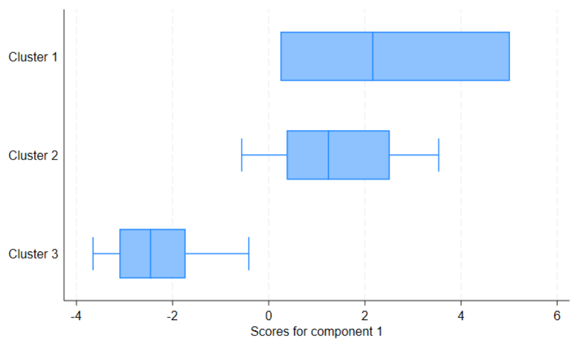
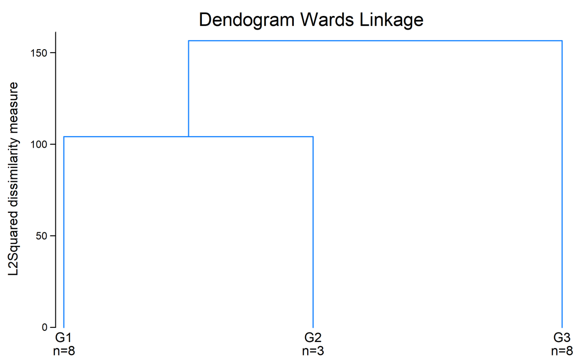


Figure 11: PCA



(a) First component scores by cluster



(b) Identification of number of regions per cluster

Figure 12: Cluster Analysis: Spain

B.1.2 Italy

- Cluster 1: ITC2, ITH1, ITH2, ITH3, ITH4
- Cluster 2: ITC1, ITC3, ITC4, ITH5, ITI1, ITI2, ITI3, ITI4
- Cluster 3: ITF1, ITF2, ITF3, ITF4, ITF5, ITF6, ITG1, ITG2

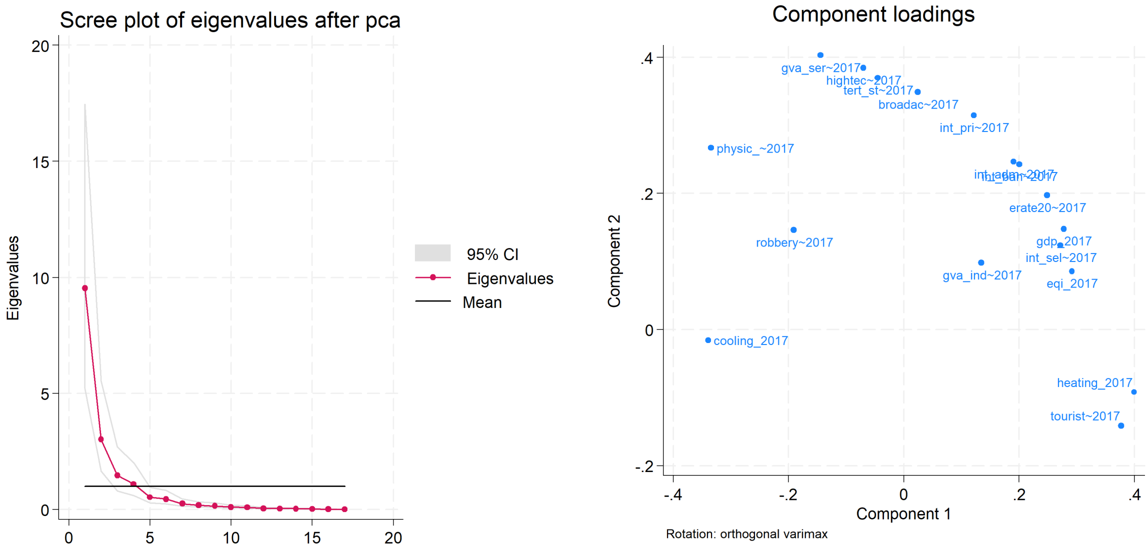
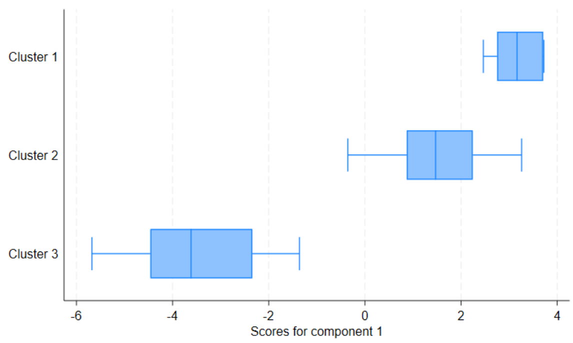
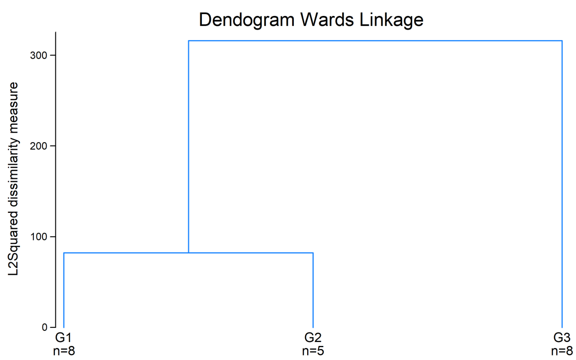


Figure 13: PCA



(a) First component scores by cluster



(b) Identification of number of regions per cluster

Figure 14: Cluster Analysis: Italy

B.1.3 Finland

- Cluster 1: FI1B
- Cluster 2: FI19, FI1C, FI1D, FI20,

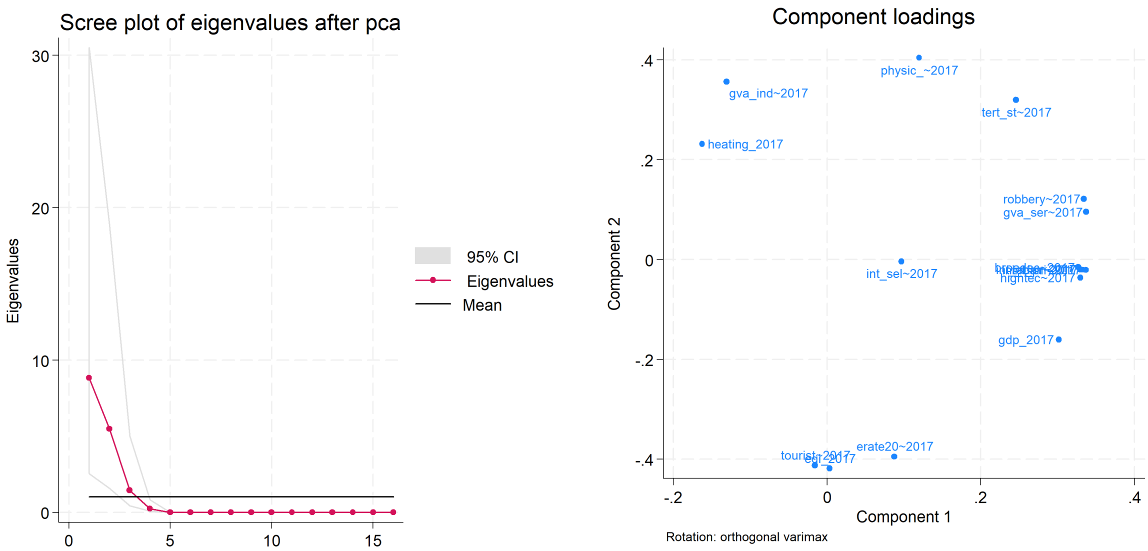
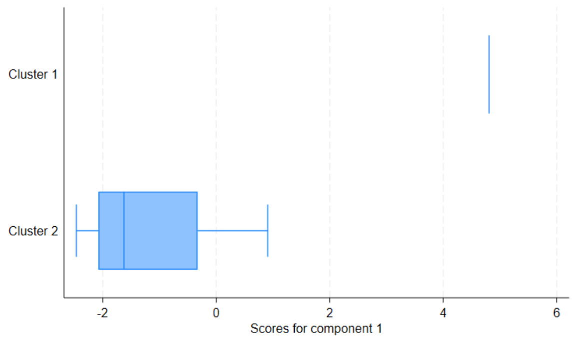
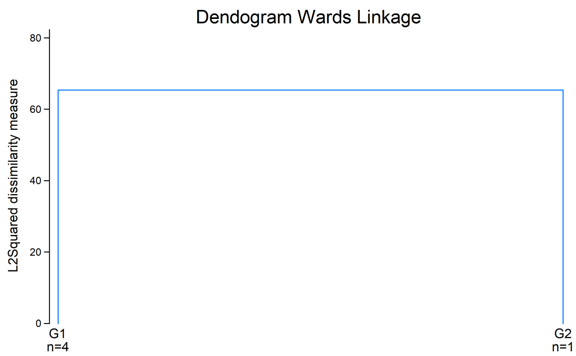


Figure 15: PCA



(a) First component scores by cluster



(b) Identification of number of regions per cluster

Figure 16: Cluster Analysis: Finland

B.1.4 The Netherlands

- Cluster 1: NL31, NL32
- Cluster 2: NL11, NL12, NL13, NL21, NL22, NL23, NL33, NL34, NL41, NL42

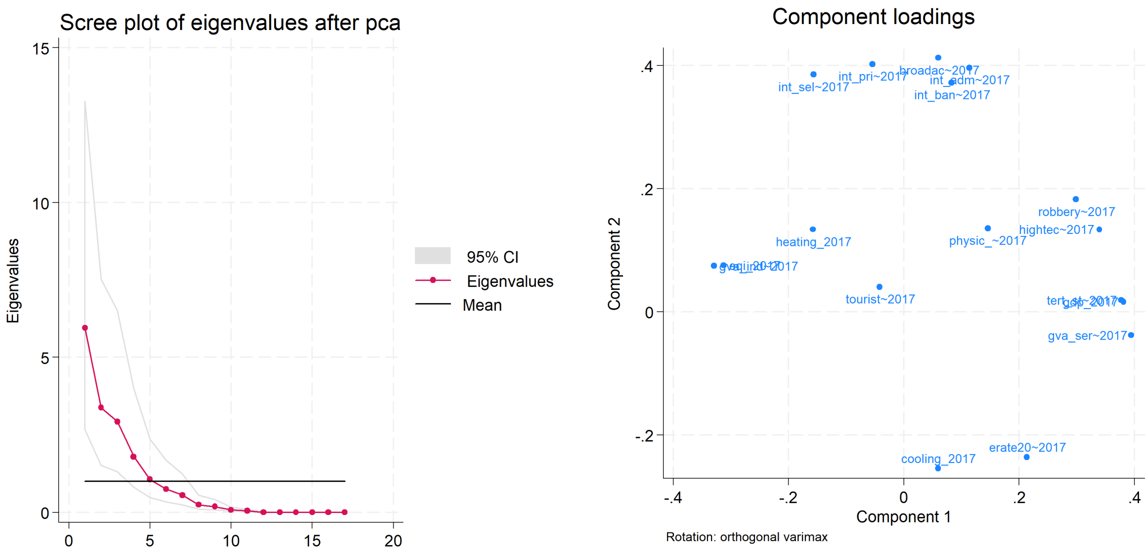
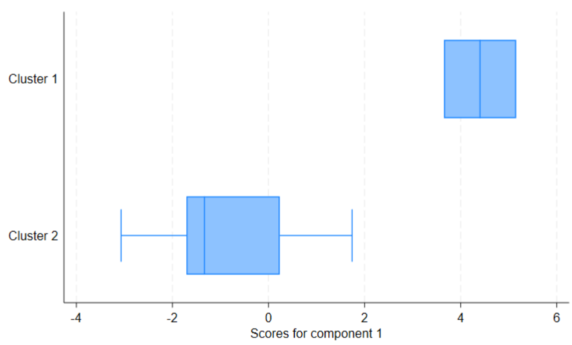
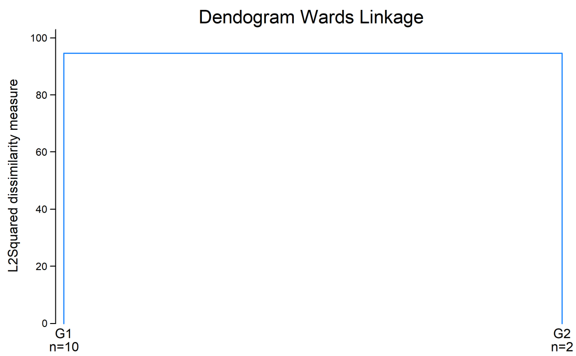


Figure 17: PCA



(a) First component scores by cluster



(b) Identification of number of regions per cluster

Figure 18: Cluster Analysis: The Netherlands

B.1.5 Greece

- Cluster 1: EL30
- Cluster 2: EL41, EL42, EL43, EL51, EL52, EL53, EL54, EL61, EL62, EL63, EL64, EL65

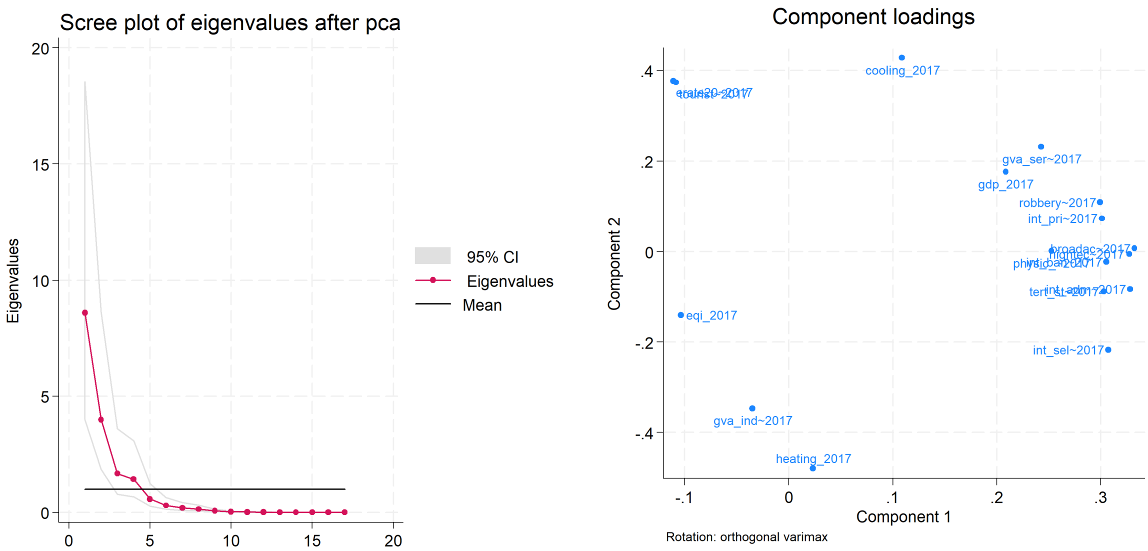
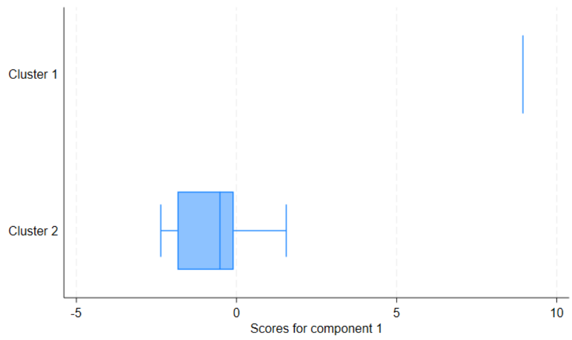
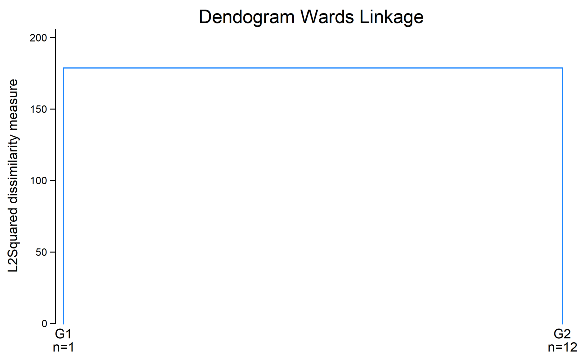


Figure 19: PCA



(a) First component scores by cluster



(b) Identification of number of regions per cluster

Figure 20: Cluster Analysis: Greece

B.1.6 What do the principal components capture?

Table 19: Component 1 from PCA by Country (2017)

Variable	Spain	Italy	Netherlands	Finland	Greece
gdp_2017	0.3783	0.3063	0.3653	0.3280	0.2306
erate20_2017	0.3541	0.3167	0.1239	0.1669	-0.0591
gva_ind_2017	0.2190	0.1658	-0.2867	-0.2012	-0.0817
gva_ser_2017	0.2301	0.1545	0.3598	0.3103	0.2717
tourist_2017	0.0307	0.1925	-0.0265	0.0694	-0.0567
physic_2017	0.0868	-0.0779	0.1819	0.0341	0.2503
tert_st_2017	0.3757	0.2077	0.3626	0.1751	0.2882
robbery_2017	-0.0119	-0.0488	0.3416	0.3019	0.3111
eqi_2017	0.2549	0.2764	-0.2705	0.0895	-0.1218
cooling_2017	-0.1834	-0.2670	-0.0276	–	0.1658
heating_2017	0.2676	0.2414	-0.1053	-0.2066	-0.0421
broadac_2017	0.2114	0.2463	0.1917	0.3230	0.3304
hightec_2017	0.2495	0.1986	0.3640	0.3301	0.3236
int_adm_2017	0.2645	0.3050	0.2371	0.3264	0.3141
int_ban_2017	0.3096	0.3099	0.2003	0.3299	0.2994
int_pri_2017	0.1945	0.2978	0.0807	0.3339	0.3082
int_sel_2017	-0.0059	0.2863	-0.0216	0.0953	0.2752

Table 20: Component 2 from PCA by Country (2017)

Variable	Spain	Italy	Netherlands	Finland	Greece
gdp_2017	0.0905	-0.0700	-0.1094	-0.0952	-0.1463
erate20_2017	-0.0461	-0.0141	-0.2932	-0.3685	-0.3885
gva_ind_2017	-0.3917	-0.0140	0.1784	0.3216	0.3392
gva_ser_2017	0.2696	0.3991	-0.1648	0.1628	-0.1963
tourist_2017	0.2003	-0.3537	0.0522	-0.4070	-0.3849
physic_2017	-0.0313	0.4204	0.0804	0.4201	0.0330
tert_st_2017	-0.0758	0.3089	-0.1055	0.3632	0.1289
robbery_2017	0.3536	0.2354	0.0751	0.1877	-0.0674
eqi_2017	-0.2939	-0.1262	0.1738	-0.4092	0.1253
cooling_2017	0.2622	0.2104	-0.2599	–	-0.4095
heating_2017	-0.3158	-0.3308	0.1784	0.1931	-0.4787
broadac_2017	0.2731	0.2478	0.3703	0.0522	0.0380
hightec_2017	0.2157	0.3362	0.0153	0.0323	0.0498
int_adm_2017	0.0215	0.0616	0.3375	0.0482	0.1268
int_ban_2017	0.1931	0.0521	0.3245	0.485	0.0644
int_pri_2017	0.3446	0.1581	0.3980	0.0489	-0.0313
int_sel_2017	0.2433	-0.0845	0.4153	0.0161	0.2571

In the optimal case, all the rows should show the sign and scale of correlation with the principal component. For the first component, we observe that the loadings remain stable across countries, capturing both economic strength and the digital factors. On the other hand, for the second principal component. We notice that the loadings vary more than those for the first one, adding a potential issue in terms of interpretation. Unfortunately, this is something we cannot change.

B.2 Polychoric PCA: Green Preferences

A necessary input to build the principal components is the correlation matrix. For continuous variables, this is generally the Pearson correlation matrix. For ordinal variables, it is the polychoric correlation matrix.

The polychoric PCA is applied to the following nine questions that are listed below regarding the green preferences of the individuals. From the nine tables, we see that there is no need to normalise the variables since they are all based on a Likert scale from 1 to 5. This is crucial since the Principal Components capture the data that contains the most information, thus maximising the variance. Suppose that the variables had different scales, then probably the variables with higher values would have larger variances, severely biasing the Principal Components.

Table 21: To live in a community that enjoys high levels of air quality

Response	Freq.	Percent	Cum.
Not important at all	151	1.62	1.62
Not important	308	3.31	4.93
Moderate	1,457	15.63	20.56
Important	3,413	36.63	57.19
Very important	3,989	42.81	100.00
Total	9,319	100.00	

Table 22: To live in a community that supports the production and consumption of renewable energy

Response	Freq.	Percent	Cum.
Not important at all	357	3.83	3.83
Not important	723	7.77	11.60
Moderate	2,336	25.09	36.69
Important	3,339	35.86	72.55
Very important	2,556	27.45	100.00
Total	9,311	100.00	

Table 23: To live in a community where energy prices are affordable due to renewable sources.

Response	Freq.	Percent	Cum.
Not important at all	166	1.78	1.78
Not important	325	3.49	5.27
Moderate	1,436	15.42	20.70
Important	3,546	38.08	58.78
Very important	3,838	41.22	100.00
Total	9,311	100.00	

Table 24: To live in an area that has clean water production and provision.

Response	Freq.	Percent	Cum.
Not important at all	89	0.96	0.96
Not important	148	1.59	2.55
Moderate	866	9.31	11.87
Important	2,669	28.71	40.57
Very important	5,525	59.43	100.00
Total	9,297	100.00	

Table 25: To live in an area where I have access to green spaces

Response	Freq.	Percent	Cum.
Not important at all	129	1.38	1.39
Not important	257	2.76	4.14
Moderate	1,180	12.67	16.81
Important	3,075	33.01	49.83
Very important	4,673	50.17	100.00
Total	9,314	100.00	

Table 26: To live in an area where I have access to blue spaces

Response	Freq.	Percent	Cum.
Not important at all	211	2.27	2.27
Not important	601	6.46	8.72
Moderate	1,924	20.67	29.39
Important	3,125	33.57	62.97
Very important	3,447	37.03	100.00
Total	9,308	100.00	

Table 27: To live in an area where increased eco-friendly infrastructures

Response	Freq.	Percent	Cum.
Not important at all	334	3.59	3.59
Not important	690	7.42	11.01
Moderate	2,418	26.01	37.02
Important	3,285	35.33	72.35
Very important	2,571	27.65	100.00
Total	9,298	100.00	

Table 28: To live in an area where circular economy principles are used for waste management

Response	Freq.	Percent	Cum.
Not important at all	322	3.46	3.46
Not important	680	7.30	10.76
Moderate	2,311	24.81	35.57
Important	3,310	35.54	71.12
Very important	2,690	28.88	100.00
Total	9,313	100.00	

Table 29: To live in an area where the local community strongly supports green behaviour

Response	Freq.	Percent	Cum.
Not important at all	366	3.93	3.93
Not important	694	7.45	11.38
Moderate	2,232	23.96	35.34
Important	3,257	34.97	70.31
Very important	2,766	29.69	100.00
Total	9,315	100.00	

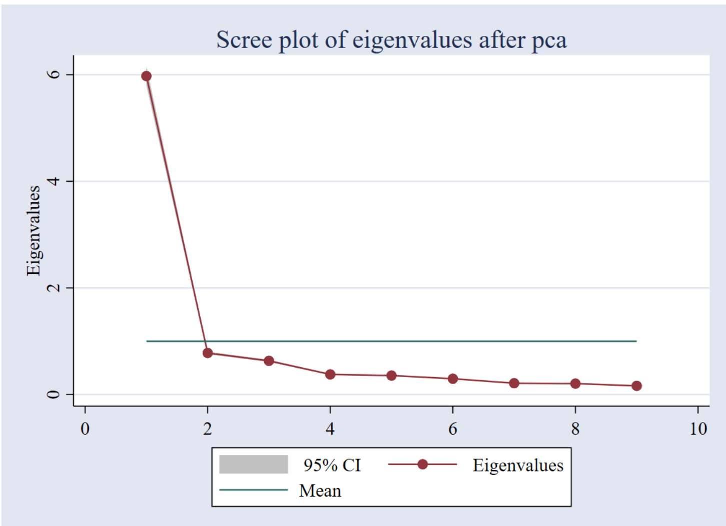


Figure 21: Eigenvalues. Proxy for relative importance of each PC

C Green Transition Indices by Country and Region

Table 30: GTOI and GTVI by Country of Interest

Country	GTOI 2017	GTOI 2022	GTVI 2017	GTVI 2022
EL	10.66	10.57	17.76	19.94
ES	26.29	27.10	19.34	19.34
FI	37.63	43.49	14.25	13.59
IT	29.05	28.78	17.31	17.01
NL	29.20	31.89	13.73	14.71

Table 31: Green Transition Indices by Region (2017 & 2022)

Region (NUTS2)	GTOI 2017	GTOI 2022	GTVI 2017	GTVI 2022
EL30	12.86	12.47	10.17	11.45
EL41	12.85	13.24	12.37	9.11
EL42	10.59	10.84	11.97	12.88
EL43	20.61	19.77	23.42	23.21
EL51	7.62	7.60	22.29	18.31
EL52	6.89	7.00	21.58	20.27
EL53	9.75	9.93	22.98	20.98
EL54	13.15	13.43	21.13	19.38
EL61	10.73	10.79	28.39	28.58
EL62	6.11	7.95	13.03	10.55
EL63	10.17	10.28	24.56	19.40
EL64	5.97	6.03	19.77	14.79
EL65	10.11	9.27	27.59	22.00
ES11	28.83	29.01	24.49	21.87
ES12	24.06	23.71	14.87	13.63
ES13	26.81	26.43	6.46	6.03
ES21	34.98	33.94	8.78	9.93
ES22	32.89	31.20	11.80	11.84
ES23	27.43	27.58	14.24	13.00
ES24	31.08	30.26	23.18	21.26
ES30	28.96	26.78	13.08	14.02
ES41	27.47	27.35	25.55	28.37
ES42	26.77	26.88	30.43	30.37
ES43	27.22	27.25	25.32	22.21
ES51	28.93	27.38	32.39	35.87
ES52	27.02	26.33	23.66	25.48
ES53	21.09	19.73	13.34	13.89
ES61	24.63	22.76	59.77	60.64
ES62	24.61	24.57	18.37	17.48
ES63	27.54	27.37	0.94	0.92
ES64	25.49	24.10	0.15	0.14
ES70	19.01	16.78	20.75	20.50
FI19	43.81	36.17	16.31	16.83
FI1B	54.40	45.75	7.16	7.28
FI1C	38.43	33.86	13.84	13.61
FI1D	47.55	43.85	25.38	27.49

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Table 31 – continued from previous page

Region (NUTS2)	GTOI 2017	GTOI 2022	GTVI 2017	GTVI 2022
FI20	33.26	28.51	5.27	6.03
ITC1	30.23	30.23	17.53	19.20
ITC2	30.48	31.42	3.54	3.44
ITC3	29.70	29.54	8.72	8.24
ITC4	27.68	27.17	34.02	36.76
ITF1	27.83	28.71	12.41	12.71
ITF2	27.92	28.53	12.80	14.09
ITF3	22.30	22.29	17.15	17.21
ITF4	27.72	28.50	23.53	22.96
ITF5	26.30	27.08	14.96	16.25
ITF6	23.70	24.04	18.39	17.60
ITG1	22.67	22.90	23.49	25.31
ITG2	27.71	28.66	18.76	17.94
ITH1	33.10	33.89	15.21	13.91
ITH2	34.98	36.39	11.09	11.65
ITH3	29.69	30.11	29.54	28.89
ITH4	32.80	30.73	9.31	8.92
ITH5	30.14	30.64	24.19	25.28
ITI1	30.91	30.14	21.59	21.29
ITI2	30.29	30.91	9.84	9.93
ITI3	29.18	28.95	8.22	8.63
ITI4	29.10	29.17	22.86	23.22
NL11	33.69	31.81	16.21	15.39
NL12	25.54	24.45	11.30	9.07
NL13	24.78	23.26	22.67	22.37
NL21	30.17	28.40	9.50	7.86
NL22	33.20	31.27	12.83	12.12
NL23	24.56	22.46	10.91	9.29
NL31	37.07	34.25	4.21	4.23
NL32	36.23	32.59	18.81	18.29
NL33	34.65	33.63	23.97	22.45
NL34	26.28	23.92	16.29	15.20
NL41	43.65	34.40	15.29	14.38
NL42	32.83	30.01	14.47	14.06

D Conditional Logit Full Tables

D.1 Realised Migration

Table 32: Conditional Logit Estimates Base ES3 - GTOI

Cluster	Variable	M1	M2	M3	M4
CLCODE	GTOI_2017	0.492***	0.785***	1.318***	1.157***
	PC1_2017		-1.072***		-0.202*

Continued on next page

Table 32 – continued from previous page

Cluster	Variable	M1	M2	M3	M4
	PC2_2017			14.044***	10.202***
CLU_EL1	Green_Preference	1.573	1.573	1.573	1.573
	Age	-0.065***	-0.065***	-0.065***	-0.065***
	highedudummy	0.994*	0.994*	0.994*	0.994*
	gender	0.439	0.439	0.439	0.439
	constant	3.329*	19.063	30.386***	26.073
CLU_EL2	Green_Preference	-0.616	-0.616	-0.616	-0.616
	Age	0.001	0.001	0.001	0.001
	highedudummy	0.231	0.231	0.231	0.231
	gender	0.381	0.381	0.381	0.381
	constant	6.786***	12.855***	24.364***	20.843***
CLU_ES1	Green_Preference	0.107	0.107	0.107	0.107
	Age	0.002	0.002	0.002	0.002
	highedudummy	1.310***	1.310***	1.310***	1.310***
	gender	0.540	0.540	0.540	0.540
	constant	-3.657***	1.193	-40.715***	-29.672
CLU_ES2	Green_Preference	-0.490	-0.490	-0.490	-0.490
	Age	0.018	0.018	0.018	0.018
	highedudummy	1.009	1.009	1.009	1.009
	gender	0.488	0.488	0.488	0.488
	constant	-5.789***	-2.926***	19.173***	12.847***
CLU_FI1	Green_Preference	-3.570***	-3.570***	-3.570***	-3.570***
	Age	0.003	0.003	0.003	0.003
	highedudummy	-0.597	-0.597	-0.597	-0.597
	gender	-1.086**	-1.086**	-1.086**	-1.086**
	constant	-14.018	-14.890	-56.126	-45.049
CLU_FI2	Green_Preference	-2.863***	-2.863***	-2.863***	-2.863***
	Age	-0.006	-0.006	-0.006	-0.006
	highedudummy	-0.873***	-0.873***	-0.873***	-0.873***
	gender	0.207	0.207	0.207	0.207
	constant	-5.736***	-9.059***	-6.314***	-6.931***
CLU_IT1	Green_Preference	0.101	0.101	0.101	0.101
	Age	-0.068***	-0.068***	-0.068***	-0.068***
	highedudummy	0.460	0.460	0.460	0.460
	gender	0.105	0.105	0.105	0.105
	constant	-5.017***	-1.154	20.917	14.485***
CLU_IT2	Green_Preference	-0.353	-0.353	-0.353	-0.353
	Age	0.038***	0.038***	0.038***	0.038***
	highedudummy	-0.719***	-0.719***	-0.719***	-0.719***
	gender	0.124	0.124	0.124	0.124
	constant	-3.486***	-0.647	-21.140***	-15.816***
CLU_IT3	Green_Preference	2.350	2.350	2.350	2.350
	Age	0.023	0.023	0.023	0.023
	highedudummy	0.021	0.021	0.021	0.021
	gender	-0.076	-0.076	-0.076	-0.076

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Table 32 – continued from previous page

Cluster	Variable	M1	M2	M3	M4
	constant	-5.992***	-7.369***	4.025**	1.020
CLU_NL1	Green_Preference	-3.673*	-3.673*	-3.673*	-3.673*
	Age	-0.006	-0.006	-0.006	-0.006
	highedudummy	-0.708	-0.708	-0.708	-0.708
	gender	-0.544	-0.544	-0.544	-0.544
	constant	-3.854**	0.040	0.608	0.014
CLU_NL2	Green_Preference	-3.462***	-3.462***	-3.462***	-3.462***
	Age	0.025***	0.025***	0.025***	0.025***
	highedudummy	-0.199	-0.199	-0.199	-0.199
	gender	-0.181	-0.181	-0.181	-0.181
	constant	-0.248	-0.346	-0.299	-0.358
χ^2		2784.80***	12748.43***	62187.10***	94264.84***
Cases		18612	18612	18612	18612

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

Table 33: Conditional Logit Estimates Base ES3 - GTVI

Cluster	Variable	M5	M6	M7	M8
CLCODE	GTOI_2017	0.492***	0.785***	1.318***	1.157***
	PC1_2017		-1.072***		-0.202*
	PC2_2017			14.044***	10.202***
CLU_EL1	Green_Preference	1.573	1.573	1.573	1.573
	Age	-0.065***	-0.065***	-0.065***	-0.065***
	highedudummy	0.994*	0.994*	0.994*	0.994*
	gender	0.439	0.439	0.439	0.439
	constant	3.329*	19.063	30.386***	26.073
CLU_EL2	Green_Preference	-0.616	-0.616	-0.616	-0.616
	Age	0.001	0.001	0.001	0.001
	highedudummy	0.231	0.231	0.231	0.231
	gender	0.381	0.381	0.381	0.381
	constant	6.786***	12.855***	24.364***	20.843***
CLU_ES1	Green_Preference	0.107	0.107	0.107	0.107
	Age	0.002	0.002	0.002	0.002
	highedudummy	1.310***	1.310***	1.310***	1.310***
	gender	0.540	0.540	0.540	0.540
	constant	-3.657***	1.193	-40.715***	-29.672
CLU_ES2	Green_Preference	-0.490	-0.490	-0.490	-0.490
	Age	0.018	0.018	0.018	0.018
	highedudummy	1.009	1.009	1.009	1.009
	gender	0.488	0.488	0.488	0.488
	constant	-5.789***	-2.926***	19.173***	12.847***
CLU_FI1	Green_Preference	-3.570***	-3.570***	-3.570***	-3.570***

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Table 33 – continued from previous page

Cluster	Variable	M5	M6	M7	M8
	Age	0.003	0.003	0.003	0.003
	highedudummy	-0.597	-0.597	-0.597	-0.597
	gender	-1.086**	-1.086**	-1.086**	-1.086**
	constant	-14.018	-14.890	-56.126	-45.049
CLU_FI2	Green_Preference	-2.863***	-2.863***	-2.863***	-2.863***
	Age	-0.006	-0.006	-0.006	-0.006
	highedudummy	-0.873***	-0.873***	-0.873***	-0.873***
	gender	0.207	0.207	0.207	0.207
	constant	-5.736***	-9.059***	-6.314***	-6.931***
CLU_IT1	Green_Preference	0.101	0.101	0.101	0.101
	Age	-0.068***	-0.068***	-0.068***	-0.068***
	highedudummy	0.460	0.460	0.460	0.460
	gender	0.105	0.105	0.105	0.105
	constant	-5.017***	-1.154	20.917	14.485***
CLU_IT2	Green_Preference	-0.353	-0.353	-0.353	-0.353
	Age	0.038***	0.038***	0.038***	0.038***
	highedudummy	-0.719***	-0.719***	-0.719***	-0.719***
	gender	0.124	0.124	0.124	0.124
	constant	-3.486***	-0.647	-21.140***	-15.816***
CLU_IT3	Green_Preference	2.350	2.350	2.350	2.350
	Age	0.023	0.023	0.023	0.023
	highedudummy	0.021	0.021	0.021	0.021
	gender	-0.076	-0.076	-0.076	-0.076
	constant	-5.992***	-7.369***	4.025**	1.020
CLU_NL1	Green_Preference	-3.673*	-3.673*	-3.673*	-3.673*
	Age	-0.006	-0.006	-0.006	-0.006
	highedudummy	-0.708	-0.708	-0.708	-0.708
	gender	-0.544	-0.544	-0.544	-0.544
	constant	-3.854**	0.040	0.608	0.014
CLU_NL2	Green_Preference	-3.462***	-3.462***	-3.462***	-3.462***
	Age	0.025***	0.025***	0.025***	0.025***
	highedudummy	-0.199	-0.199	-0.199	-0.199
	gender	-0.181	-0.181	-0.181	-0.181
	constant	-0.248	-0.346	-0.299	-0.358
χ^2		2784.80***	12748.43***	62187.10***	94264.84***
Cases		18612	18612	18612	18612

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

Table 34: Conditional Logit Estimates Base ES3 - Combined GTOI and GTVI

Cluster	Variable	M9	M10	M11	M12
CLCODE	GTVI_2017	-1.362***	2.391***	-0.383***	1.919***
	GTOI_2017	-1.400***	4.099***	0.413***	3.466***

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Table 34 – continued from previous page

Cluster	Variable	M9	M10	M11	M12
	PC1_2017		-3.148***		-2.593***
	PC2_2017			10.143***	1.763**
CLU_EL1	Green_Preference	1.047	1.044	1.043	1.043
	Age	-0.053***	-0.053***	-0.053***	-0.053***
	highedudummy	0.786	0.783	0.785	0.785
	gender	0.736*	0.737*	0.735*	0.735*
	constant	-36.758	113.045	9.903	95.267
CLU_EL2	Green_Preference	-1.063**	-1.068**	-1.070**	-1.071**
	Age	-0.003	-0.003	-0.003	-0.003
	highedudummy	0.001	-0.000	0.001	0.001
	gender	0.355**	0.356**	0.354**	0.354**
	constant	-23.005***	70.207***	9.471***	59.784***
CLU_ES1	Green_Preference	-0.521	-0.526	-0.528	-0.528
	Age	-0.022**	-0.022**	-0.022**	-0.022**
	highedudummy	0.721**	0.720**	0.720**	0.720**
	gender	0.835***	0.835***	0.834***	0.834***
	constant	-3.753***	16.253***	-29.014	8.372***
CLU_ES2	Green_Preference	-1.410**	-1.414**	-1.416**	-1.415**
	Age	0.014	0.014	0.014	0.014
	highedudummy	0.856*	0.854*	0.855*	0.855*
	gender	0.944**	0.945**	0.944**	0.944**
	constant	-6.272***	7.473***	13.128***	8.462***
CLU_FI1	Green_Preference	-4.018***	-4.022***	-4.024***	-4.025***
	Age	0.018	0.018	0.018	0.018
	highedudummy	-0.924*	-0.923*	-0.925*	-0.925*
	gender	-0.980*	-0.978*	-0.980*	-0.980*
	constant	20.030	-60.298	-30.872	-55.325
CLU_FI2	Green_Preference	-3.134***	-3.138***	-3.141***	-3.141***
	Age	0.019***	0.019***	0.019***	0.019***
	highedudummy	-1.009***	-1.009***	-1.009***	-1.009***
	gender	-0.044	-0.044	-0.045	-0.045
	constant	13.063***	-41.375***	0.885	-34.093***
CLU_IT1	Green_Preference	-0.497	-0.501	-0.503	-0.503
	Age	-0.061***	-0.061***	-0.061***	-0.061***
	highedudummy	0.221	0.220	0.220	0.220
	gender	-0.116	-0.115	-0.116	-0.116
	constant	-3.084*	8.729***	15.727***	9.938
CLU_IT2	Green_Preference	-0.302	-0.307	-0.309	-0.310
	Age	0.013**	0.013**	0.013**	0.013**
	highedudummy	-0.585***	-0.585***	-0.585***	-0.585***
	gender	0.256*	0.257*	0.256*	0.256*
	constant	0.307	3.587***	-13.787***	0.545
CLU_IT3	Green_Preference	2.783**	2.778**	2.768**	2.769**
	Age	-0.009	-0.009	-0.009	-0.009
	highedudummy	-0.455	-0.457	-0.456	-0.457

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Table 34 – continued from previous page

Cluster	Variable	M9	M10	M11	M12
	gender	0.459	0.459	0.458	0.458
	constant	-10.692***	0.812	0.609	0.837
CLU_NL1	Green_Preference	-2.170	-2.174	-2.176	-2.177
	Age	-0.017	-0.017	-0.017	-0.017
	highedudummy	-0.031	-0.031	-0.031	-0.031
	gender	0.059	0.060	0.058	0.058
	constant	0.110	-0.235	0.184	-0.195
CLU_NL2	Green_Preference	-3.747***	-3.751***	-3.753***	-3.754***
	Age	0.015**	0.015**	0.015**	0.015**
	highedudummy	-0.102	-0.103	-0.103	-0.103
	gender	-0.230	-0.230	-0.231	-0.231
	constant	0.100	0.177	0.123	0.183
Statistics	χ^2	37211.483	366193.94	65204.151	272076.43
	N	18780	18780	18780	18780

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

D.2 Intentions to Move

Table 35: Intention to Move Estimates Base ES3 - GTOI

Cluster	Variable	INT1	INT2	INT3	INT4
CLCODE	GTOI_2017	0.603***	1.040***	1.789***	1.182***
	PC1_2017		-1.591***		-1.259***
	PC2_2017			20.341***	3.863***
CLU_EL1	Green_Preference	1.260	1.280	1.282	1.279
	Age	0.007	0.007	0.007	0.007
	highedudummy	0.341	0.342	0.344	0.343
	gender	0.965*	0.966*	0.967*	0.964*
	constant	4.000**	27.358	43.041***	29.996
CLU_EL2	Green_Preference	-0.791	-0.767	-0.770	-0.767
	Age	-0.004	-0.004	-0.004	-0.004
	highedudummy	0.226	0.228	0.229	0.228
	gender	0.519*	0.521*	0.521*	0.519*
	constant	9.282***	18.305***	34.570***	21.335***
CLU_ES1	Green_Preference	1.764	1.787	1.787	1.788
	Age	-0.008	-0.008	-0.008	-0.008
	highedudummy	1.135**	1.136**	1.134**	1.137**
	gender	0.033	0.034	0.035	0.033
	constant	-3.899**	3.272**	-57.588***	-8.426
CLU_ES2	Green_Preference	0.788	0.811	0.808	0.810
	Age	0.028	0.028	0.028	0.028
	highedudummy	1.563**	1.565**	1.565**	1.566**
	gender	0.006	0.007	0.007	0.005

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Table 35 – continued from previous page

Cluster	Variable	INT1	INT2	INT3	INT4
	constant	-7.090***	-2.878	29.082***	3.087
CLU_FI1	Green_Preference	-1.382	-1.361	-1.362	-1.362
	Age	-0.001	-0.001	-0.001	-0.001
	highedudummy	-0.940*	-0.939*	-0.938*	-0.938*
	gender	0.660	0.661	0.661	0.659
	constant	-17.917	-19.315	-78.635	-30.764
CLU_FI2	Green_Preference	-2.178**	-2.155**	-2.159**	-2.156**
	Age	-0.006	-0.006	-0.006	-0.006
	highedudummy	-1.381***	-1.380***	-1.379***	-1.379***
	gender	0.306	0.308	0.308	0.306
	constant	-6.803***	-11.799***	-7.504***	-11.002***
CLU_IT1	Green_Preference	0.460	0.483	0.481	0.482
	Age	-0.026	-0.026	-0.026	-0.026
	highedudummy	-0.792	-0.791	-0.790	-0.790
	gender	-0.225	-0.224	-0.224	-0.226
	constant	-5.073***	0.616	32.538	6.524***
CLU_IT2	Green_Preference	0.789	0.811	0.809	0.811
	Age	0.006	0.006	0.006	0.006
	highedudummy	-0.764**	-0.762**	-0.761**	-0.762**
	gender	0.469	0.470	0.471	0.468
	constant	-3.088***	1.089	-28.637***	-4.665***
CLU_IT3	Green_Preference	-0.048	-0.023	-0.027	-0.023
	Age	-0.045***	-0.045***	-0.045***	-0.045***
	highedudummy	-1.022***	-1.020***	-1.020***	-1.019***
	gender	0.737**	0.739**	0.739**	0.737**
	constant	0.372	-1.696*	14.863***	1.483
CLU_NL1	Green_Preference	-2.113	-2.092	-2.095	-2.093
	Age	-0.021	-0.021	-0.021	-0.021
	highedudummy	-0.026	-0.025	-0.023	-0.024
	gender	1.080**	1.081**	1.082**	1.079**
	constant	-5.435***	0.288	1.121	0.260
CLU_NL2	Green_Preference	-3.129***	-3.107***	-3.109***	-3.107***
	Age	0.005	0.005	0.005	0.005
	highedudummy	-0.136	-0.135	-0.134	-0.134
	gender	-0.108	-0.106	-0.107	-0.109
	constant	0.189	0.006	0.152	-0.004
Statistics	χ^2	5888.803	40270.155	171696.73	66003.893
	N	13956	13956	13956	13956

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

Table 36: Intention to Move Estimates Base ES3 - GTVI

Cluster	Variable	INT5	INT6	INT7	INT8
CLCODE	GTVI_2017	-0.560***	-0.762***	-1.055***	-0.935***
	PC1_2017		-1.034***		-0.279
	PC2_2017			10.618***	7.129***
CLU_EL1	Green_Preference	1.287	1.252	1.262	1.282
	Age	0.007	0.007	0.007	0.007
	highedudummy	0.342	0.340	0.342	0.341
	gender	0.967*	0.965*	0.961*	0.966*
	constant	-10.374***	-1.156	-3.714**	-3.295
CLU_EL2	Green_Preference	-0.761	-0.798	-0.786	-0.765
	Age	-0.004	-0.004	-0.004	-0.004
	highedudummy	0.228	0.225	0.227	0.228
	gender	0.521*	0.519*	0.516*	0.521*
	constant	-0.665	0.674	2.518***	1.829**
CLU_ES1	Green_Preference	1.796	1.756	1.769	1.792
	Age	-0.008	-0.008	-0.008	-0.008
	highedudummy	1.137**	1.134**	1.135**	1.137**
	gender	0.035	0.033	0.030	0.035
	constant	-4.881***	-0.442	-33.619***	-22.970
CLU_ES2	Green_Preference	0.817	0.781	0.792	0.814
	Age	0.028	0.028	0.028	0.028
	highedudummy	1.565**	1.562**	1.564**	1.566**
	gender	0.007	0.005	0.002	0.007
	constant	-8.261***	-5.624***	9.984***	4.748**
CLU_FI1	Green_Preference	-1.356	-1.389	-1.380	-1.359
	Age	-0.001	-0.001	-0.001	-0.001
	highedudummy	-0.939*	-0.941*	-0.939*	-0.939*
	gender	0.661	0.660	0.656	0.661
	constant	-8.930	-4.597	-30.114	-21.827
CLU_FI2	Green_Preference	-2.150**	-2.185**	-2.174**	-2.154**
	Age	-0.006	-0.006	-0.006	-0.006
	highedudummy	-1.380***	-1.382***	-1.381***	-1.380***
	gender	0.308	0.306	0.303	0.308
	constant	-1.539*	-1.796	4.140***	2.267
CLU_IT1	Green_Preference	0.489	0.453	0.464	0.486
	Age	-0.026	-0.026	-0.026	-0.026
	highedudummy	-0.791	-0.793	-0.792	-0.791
	gender	-0.223	-0.225	-0.229	-0.224
	constant	-5.785***	-1.825*	13.875	8.561***
CLU_IT2	Green_Preference	0.818	0.781	0.793	0.815
	Age	0.006	0.006	0.006	0.006
	highedudummy	-0.762**	-0.764**	-0.763**	-0.762**
	gender	0.471	0.469	0.466	0.471
	constant	-2.750***	0.439	-15.349***	-10.325***
CLU_IT3	Green_Preference	-0.018	-0.056	-0.044	-0.020

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Table 36 – continued from previous page

Cluster	Variable	INT5	INT6	INT7	INT8
	Age	-0.045***	-0.045***	-0.045***	-0.045***
	highedudummy	-1.020***	-1.023***	-1.021***	-1.021***
	gender	0.739**	0.737**	0.733**	0.739**
	constant	-2.016**	-4.128***	3.540***	1.176
CLU_NL1	Green_Preference	-2.087	-2.120	-2.110	-2.090
	Age	-0.021	-0.021	-0.021	-0.021
	highedudummy	-0.025	-0.027	-0.025	-0.025
	gender	1.081**	1.079**	1.076**	1.081**
	constant	-4.713***	0.081	0.384	0.107
CLU_NL2	Green_Preference	-3.102***	-3.135***	-3.126***	-3.104***
	Age	0.005	0.005	0.005	0.005
	highedudummy	-0.135	-0.137	-0.136	-0.136
	gender	-0.106	-0.108	-0.111	-0.107
	constant	-0.392	-0.288	-0.382	-0.295
Statistics	χ^2	1329.137	387.373	26019.059	25287.818
	N	13956	13956	13956	13956

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

Table 37: Intention to Move Estimates Base ES3 - Combined GTOI and GTVI

Cluster	Variable	INT9	INT10	INT11	INT12
CLCODE	GTVI_2017	-2.087***	0.999***	-1.283***	0.807***
	GTOI_2017	-1.912***	2.599***	-0.424***	2.342***
	PC1_2017		-2.573***		-2.347***
	PC2_2017			8.295***	0.728
CLU_EL1	Green_Preference	1.264	1.273	1.282	1.272
	Age	0.007	0.007	0.007	0.007
	highedudummy	0.341	0.341	0.342	0.341
	gender	0.966*	0.966*	0.966*	0.966*
	constant	-52.810	70.056	-14.568	62.825
CLU_EL2	Green_Preference	-0.785	-0.774	-0.766	-0.776
	Age	-0.004	-0.004	-0.004	-0.004
	highedudummy	0.226	0.227	0.227	0.227
	gender	0.521*	0.520*	0.521*	0.520*
	constant	-31.678***	44.772***	-5.069***	40.536***
CLU_ES1	Green_Preference	1.771	1.782	1.791	1.780
	Age	-0.008	-0.008	-0.008	-0.008
	highedudummy	1.135**	1.136**	1.137**	1.135**
	gender	0.034	0.034	0.035	0.035
	constant	-7.176***	9.198***	-27.854	5.961***
CLU_ES2	Green_Preference	0.794	0.804	0.813	0.803
	Age	0.028	0.028	0.028	0.028
	highedudummy	1.563**	1.564**	1.565**	1.563**

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Table 37 – continued from previous page

Cluster	Variable	INT9	INT10	INT11	INT12
	gender	0.006	0.007	0.007	0.007
	constant	-10.316***	0.957	5.530**	1.376
CLU_FI1	Green_Preference	-1.378	-1.368	-1.360	-1.369
	Age	-0.001	-0.001	-0.001	-0.001
	highedudummy	-0.941*	-0.939*	-0.939*	-0.940*
	gender	0.660	0.661	0.661	0.661
	constant	23.435	-42.428	-18.288	-40.431
CLU_FI2	Green_Preference	-2.173**	-2.162**	-2.155**	-2.163**
	Age	-0.006	-0.006	-0.006	-0.006
	highedudummy	-1.382***	-1.381***	-1.380***	-1.381***
	gender	0.307	0.307	0.308	0.307
	constant	17.038***	-27.591***	7.012***	-24.624***
CLU_IT1	Green_Preference	0.466	0.476	0.485	0.474
	Age	-0.026	-0.026	-0.026	-0.026
	highedudummy	-0.792	-0.792	-0.791	-0.792
	gender	-0.225	-0.224	-0.224	-0.223
	constant	-5.788***	3.903***	9.572***	4.411
CLU_IT2	Green_Preference	0.795	0.805	0.814	0.803
	Age	0.006	0.006	0.006	0.006
	highedudummy	-0.763**	-0.763**	-0.762**	-0.763**
	gender	0.470	0.470	0.471	0.470
	constant	-0.563	2.108**	-12.118***	0.856
CLU_IT3	Green_Preference	-0.042	-0.031	-0.023	-0.033
	Age	-0.045***	-0.045***	-0.045***	-0.045***
	highedudummy	-1.021***	-1.021***	-1.021***	-1.021***
	gender	0.738**	0.738**	0.739**	0.738**
	constant	-8.305***	1.161	0.921	1.175
CLU_NL1	Green_Preference	-2.109	-2.099	-2.091	-2.100
	Age	-0.021	-0.021	-0.021	-0.021
	highedudummy	-0.027	-0.025	-0.025	-0.026
	gender	1.080**	1.081**	1.081**	1.080**
	constant	0.374	0.097	0.402	0.115
CLU_NL2	Green_Preference	-3.123***	-3.114***	-3.107***	-3.117***
	Age	0.005	0.005	0.005	0.005
	highedudummy	-0.136	-0.136	-0.135	-0.136
	gender	-0.107	-0.107	-0.107	-0.107
	constant	-0.382	-0.294	-0.384	-0.292
Statistics	χ^2	117644.550	242881.510	32305.619	200614.350
	N	13956	13956	13956	13956

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

E Nested Logit Full Table

F Second Cluster of Greece in the second Group of Clusters

Table 38: Nested Logit Estimates: GTOI

Cluster	Variable	NL21	NL22	NL23	NL24
CLCODE	GTOI_2017	0.657**	0.862***	1.094***	0.866***
	PC1_2017		-1.787		-0.454
	PC2_2017			9.930***	10.665***
CLU_EL1	Green_Preference	2.829	2.828	2.828	2.828
	q02_01	-0.190**	-0.190*	-0.190**	-0.190**
	highedudummy	2.021	2.020	2.020	2.021
	gender	1.763	1.762	1.762	1.762
	constant	3.255	25.963	20.560	23.722
CLU_EL2	Green_Preference	-3.276	-3.280*	-3.280***	-3.280***
	q02_01	-0.063**	-0.063**	-0.063***	-0.063***
	highedudummy	-0.281	-0.282	-0.282	-0.282
	gender	0.666*	0.665*	0.665**	0.665**
	constant	15.140**	21.043***	25.383***	22.976***
CLU_ES1	Green_Preference	0.892	0.890	0.890	0.891
	q02_01	-0.070**	-0.070**	-0.070**	-0.070**
	highedudummy	2.868	2.867	2.867	2.868
	gender	1.500*	1.500*	1.500*	1.500*
	constant	-5.401	2.979	-31.447	-30.923
CLU_ES2	Green_Preference	-3.265	-3.269*	-3.269***	-3.268**
	q02_01	-0.061***	-0.061***	-0.061***	-0.061***
	highedudummy	-0.163	-0.166	-0.166	-0.165
	gender	0.682	0.681	0.681**	0.681*
	constant	2.289	8.177*	20.526***	24.588***
CLU_FI1	Green_Preference	-6.127	-6.126	-6.126	-6.127
	q02_01	-0.051	-0.051	-0.051	-0.051
	highedudummy	-1.387	-1.387	-1.387	-1.387
	gender	-2.200	-2.199	-2.199	-2.200
	constant	-18.451	-11.669	-43.941	-35.001
CLU_FI2	Green_Preference	-3.617***	-3.617***	-3.617***	-3.617***
	q02_01	-0.064*	-0.064**	-0.064***	-0.064**
	highedudummy	-0.448	-0.447	-0.447	-0.447
	gender	0.640*	0.640**	0.640***	0.640***
	constant	-4.460	-5.617**	-2.590	2.094
CLU_IT1	Green_Preference	0.575	0.575	0.575	0.575
	q02_01	-0.198*	-0.198*	-0.198*	-0.198*
	highedudummy	0.744	0.744	0.744	0.745
	gender	1.360	1.360	1.360	1.360
	constant	-8.063	0.335	11.295	17.024
CLU_IT2	Green_Preference	13.446***	-3.241*	-3.241***	-3.240**
	q02_01	0.300**	-0.058***	-0.058***	-0.058***

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Table 38 – continued from previous page

Cluster	Variable	NL21	NL22	NL23	NL24
	highedudummy	-2.686	-0.425	-0.425	-0.426
	gender	0.150	0.628***	0.628***	0.628***
	constant	-38.963***	8.360**	-9.447*	-7.442
CLU_IT3	Green_Preference	0.469*	-18.719	-18.719	-18.719
	q02_01	0.007	-1.472***	-1.472***	-1.472***
	highedudummy	0.024	-0.630	-0.630	-0.630
	gender	-0.028	9.940**	9.940**	9.940**
	constant	-1.044	132.073**	141.385**	141.517**
CLU_NL1	Green_Preference	-14.712	-5.695	-5.695	-5.695
	q02_01	-0.082	-0.094*	-0.094**	-0.094*
	highedudummy	-6.095*	-2.219	-2.219	-2.219
	gender	-0.342	-0.009	-0.009	-0.009
	constant	8.952	7.106	2.230	8.606
CLU_NL2	Green_Preference	-11.653***	-3.714***	-3.714***	-3.714***
	q02_01	0.040	-0.059***	-0.059***	-0.059***
	highedudummy	-0.224	-0.344	-0.344	-0.344
	gender	-1.490	0.580*	0.580**	0.580**
	constant	4.378	3.548*	2.908**	5.098***
/typenew2	τ_1	2.740	2.739	2.739	2.740
	τ_2	0.151	0.149	0.149	0.150
	τ_3	-16.891	-16.892	-16.893	-16.893
Statistics	χ^2	800.742	2357.545	7473.131	12850.879
	N	18612	18612	18612	18612

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

Table 39: Nested Logit Estimates: GTVI

Cluster	Variable	NL25	NL26	NL27	NL28
CLCODE	GTVI_2017	-0.455	-3.505***	-0.709	-3.601***
	PC1_2017		-5.040***		-3.740**
	PC2_2017			3.774	12.452***
CLU_EL1	Green_Preference	2.828	2.828	2.828	2.828
	q02_01	-0.190*	-0.190*	-0.190*	-0.190**
	highedudummy	2.020	2.020	2.020	2.020
	gender	1.762	1.762	1.762	1.762
	constant	-10.483	9.006	-9.085**	8.046
CLU_EL2	Green_Preference	-3.280	-3.280	-3.280	-3.280*
	q02_01	-0.063	-0.063*	-0.063	-0.063**
	highedudummy	-0.282	-0.282	-0.282	-0.282
	gender	0.665	0.665	0.665	0.665*
	constant	4.594	7.515	5.586	9.960***
CLU_ES1	Green_Preference	0.890	0.891	0.890	0.890

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Table 39 – continued from previous page

Cluster	Variable	NL25	NL26	NL27	NL28
	q02_01	-0.070**	-0.070**	-0.070*	-0.070**
	highedudummy	2.867	2.867	2.867	2.867
	gender	1.500*	1.500*	1.500*	1.500*
	constant	-5.999	9.628	-16.445	-28.992
CLU_ES2	Green_Preference	-3.269	-3.269	-3.269	-3.269*
	q02_01	-0.061***	-0.061***	-0.061***	-0.061***
	highedudummy	-0.166	-0.166	-0.166	-0.166
	gender	0.681	0.681	0.681	0.681
	constant	2.024	1.793	8.010	21.323***
CLU_FI1	Green_Preference	-6.126	-6.126	-6.126	-6.126
	q02_01	-0.051	-0.051	-0.051	-0.051
	highedudummy	-1.387	-1.387	-1.387	-1.387
	gender	-2.199	-2.199	-2.199	-2.199
	constant	-6.266	-16.829	-15.002	-43.600
CLU_FI2	Green_Preference	-3.617***	-3.617***	-3.617***	-3.617***
	q02_01	-0.064	-0.064	-0.064	-0.064**
	highedudummy	-0.447	-0.447	-0.447	-0.447
	gender	0.640	0.640	0.640	0.640**
	constant	2.425	-13.908***	3.869	-5.251*
CLU_IT1	Green_Preference	0.575	0.575	0.575	0.575
	q02_01	-0.198*	-0.198*	-0.198*	-0.198*
	highedudummy	0.744	0.744	0.744	0.744
	gender	1.360	1.360	1.360	1.360
	constant	-7.463	-6.256	-1.164	13.826
CLU_IT2	Green_Preference	-3.241	-3.241	-3.241	-3.241
	q02_01	-0.058	-0.058*	-0.058	-0.058***
	highedudummy	-0.425	-0.425	-0.425	-0.425
	gender	0.628*	0.628**	0.628*	0.629***
	constant	3.419	10.422	-1.386	-7.418
CLU_IT3	Green_Preference	-18.719	-18.719	-18.719	-18.719
	q02_01	-1.472**	-1.472***	-1.472**	-1.472***
	highedudummy	-0.630	-0.630	-0.630	-0.630
	gender	9.940**	9.940**	9.941**	9.940**
	constant	132.392**	112.138*	133.987**	122.415*
CLU_NL1	Green_Preference	-5.695	-5.695	-5.695	-5.695
	q02_01	-0.094**	-0.094*	-0.094*	-0.094**
	highedudummy	-2.219	-2.219	-2.219	-2.219
	gender	-0.009	-0.009	-0.009	-0.009
	constant	-0.094	0.591	0.854	3.057
CLU_NL2	Green_Preference	-3.714	-3.714*	-3.714	-3.714***
	q02_01	-0.059**	-0.059***	-0.059***	-0.059***
	highedudummy	-0.344	-0.344	-0.344	-0.344
	gender	0.580	0.580	0.580	0.580*
	constant	2.604	-11.665**	2.044	-10.144***
/typenew2	τ_1	2.739	2.739	2.739	2.739

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Table 39 – continued from previous page

Cluster	Variable	NL25	NL26	NL27	NL28
	τ_2	0.149	0.149	0.149	0.149
	τ_3	-16.892	-16.892	-16.892	-16.892
Statistics	χ^2	238.321***	1285.974***	659.713***	9974.556***
	N	18612	18612	18612	18612

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

Table 40: Nested Logit Estimates: GTOI & GTVI

Cluster	Variable	NL29	NL30	NL31	NL32
CLCODE	GTVI_2017	0.401	-13.769	-0.545	-12.214
	GTOI_2017	-0.648	0.990	0.699*	2.014
	PC1_2017		-26.635		-26.769
	PC2_2017			8.759***	-0.511
CLU_EL1	Green_Preference	4.046	-0.647	2.828	0.383
	q02_01	-0.378**	-0.320**	-0.190**	-0.294**
	highedudummy	9.466	14.164	2.020	9.675
	gender	4.252	5.685	1.762	4.467
	constant	-26.253	104.902	7.578	149.716
CLU_EL2	Green_Preference	13.436	-1.715	-3.280**	-1.387
	q02_01	-0.260**	-0.078	-0.063**	-0.075
	highedudummy	6.451	0.174	-0.282	0.243
	gender	3.771*	0.953	0.665*	0.974
	constant	-35.740	36.806	18.149***	54.098*
CLU_ES1	Green_Preference	11.049	2.235	0.890	2.751
	q02_01	0.086	-0.040	-0.070**	-0.036
	highedudummy	5.029	16.081	2.867	11.663
	gender	1.531	1.676	1.500*	1.365
	constant	-25.464*	59.287	-29.555	71.299
CLU_ES2	Green_Preference	19.849	-1.574	-3.269**	-1.224
	q02_01	0.021	-0.063***	-0.061***	-0.058**
	highedudummy	16.609	0.919	-0.166	1.089
	gender	4.416	1.069	0.681	1.101
	constant	-68.620*	9.106	16.313***	13.311
CLU_FI1	Green_Preference	-15.351	-17.332	-6.126	-15.630
	q02_01	0.220	0.082	-0.051	0.060
	highedudummy	-1.684	-5.818	-1.387	-4.133
	gender	-14.370	-15.810	-2.199	-11.925
	constant	8.218	-67.060	-39.252	-65.084
CLU_FI2	Green_Preference	-7.336	-3.970**	-3.617***	-3.935**
	q02_01	-0.348*	-0.084	-0.064**	-0.082
	highedudummy	-6.872	-0.910	-0.447	-0.975
	gender	2.066	0.769	0.640**	0.763

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Table 40 – continued from previous page

Cluster	Variable	NL29	NL30	NL31	NL32
	constant	11.013	-79.588***	-1.429	-84.765***
CLU_IT1	Green_Preference	0.610	12.000	0.575	6.000
	q02_01	-0.407*	-0.219	-0.198*	-0.244
	highedudummy	4.855	9.133	0.744	6.440
	gender	3.775	-1.426	1.360	1.763
	constant	-15.067	-37.591	6.659	-12.295
CLU_IT2	Green_Preference	13.649**	-1.557	-3.241*	-1.222
	q02_01	0.300	-0.045	-0.058***	-0.038
	highedudummy	-2.660	-0.754	-0.425	-0.801
	gender	0.269	0.716	0.628***	0.711
	constant	-36.360**	44.373	-8.758*	46.579
CLU_IT3	Green_Preference	3.722	-18.153	-18.719	-15.703
	q02_01	0.037	-1.439**	-1.472***	-1.279**
	highedudummy	0.063	-0.689	-0.630	-0.642
	gender	-0.052	9.683*	9.940**	8.793*
	constant	-6.130	34.969	138.126**	23.334
CLU_NL1	Green_Preference	-10.445	-3.392	-5.695	-3.745
	q02_01	-0.091	-0.129**	-0.094*	-0.117**
	highedudummy	-6.653	-15.369	-2.219	-10.988
	gender	1.132	3.136	-0.009	2.211
	constant	14.289	14.578	-0.380	22.630
CLU_NL2	Green_Preference	-11.434***	-4.581	-3.714***	-4.616
	q02_01	0.042	-0.055*	-0.059***	-0.049*
	highedudummy	-0.218	-0.259	-0.344	-0.249
	gender	-1.549	0.391	0.580**	0.343
	constant	8.487	-58.557	0.898	-53.491
/typenew2	τ_1	10.785	15.855	2.739	11.709
	τ_2	11.487*	0.968	0.149	1.088
	τ_3	1.242	-16.470	-16.892	-13.764
Statistics	χ^2	586.481	5061.153	9563.132	25704.905
	N	18612	18612	18612	18612

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

G Second Cluster of Greece in the third Group of Clusters

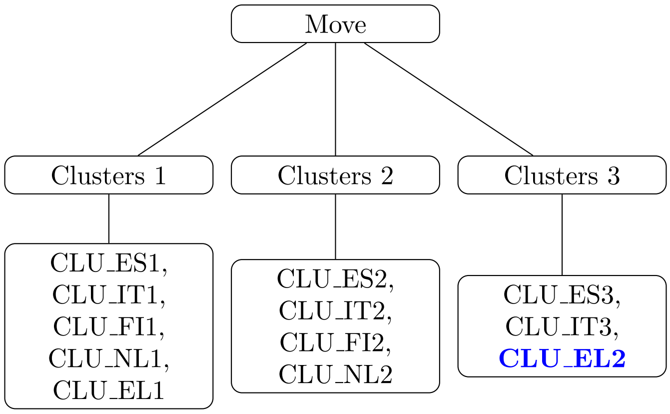

Figure 22: Alternative Nest Structure

Table 41: Nested Logit Estimates: GTOI

Cluster	Variable	NL21	NL22	NL23	NL24
CLCODE	GTOI_2017	0.256	5.400***	0.822***	1.384***
	PC1_2017		-5.731***		-2.222
	PC2_2017			1.411	4.245***
CLU_EL1	Green_Preference	4.570	3.928	3.967	4.159
	Age	-0.185	-0.256**	-0.241***	-0.282***
	highedudummy	3.775	3.098	3.119	7.934
	gender	2.283	-1.993	-2.232	-1.280
	constant	-10.890	113.939	-5.173	14.573
CLU_EL2	Green_Preference	-0.015	0.332	0.408	0.382
	Age	-0.000	-0.134	-0.130	-0.142
	highedudummy	0.006	-1.473	-1.255	-1.524
	gender	0.011	-12.578	-12.760	-12.853
	constant	3.808	120.641***	44.020	57.299**
CLU_ES1	Green_Preference	3.459	2.008	1.950	2.352
	Age	0.026	-0.111	-0.113	-0.105
	highedudummy	5.013	4.626	4.001	9.750
	gender	0.762	-2.677	-2.706	-2.625
	constant	-14.346	5.916	-19.718	-26.615
CLU_ES2	Green_Preference	-0.184	-7.450	-7.468	-7.392
	Age	0.015	-0.095	-0.094	-0.097
	highedudummy	1.058	-3.495	-3.419	-3.501
	gender	0.420	-4.629	-4.694	-4.722
	constant	-5.773	11.648	10.516	22.884
CLU_FI1	Green_Preference	-8.873	-7.225	-6.399	-10.414*
	Age	0.091	-0.068	-0.077	-0.010
	highedudummy	-1.669	-2.354	-2.036	-4.001
	gender	-6.742	-8.760	-7.906	-14.951
	constant	-14.620	-126.110	-35.114	-47.694
CLU_FI2	Green_Preference	-2.824***	-2.863	-2.838	-2.837

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Table 41 – continued from previous page

Cluster	Variable	NL21	NL22	NL23	NL24
	Age	-0.010	-0.046	-0.045	-0.049
	highedudummy	-0.998***	0.398	0.489	0.360
	gender	0.100	-4.276	-4.354	-4.340
	constant	-2.458	-77.197***	-12.070	-15.113***
CLU_IT1	Green_Preference	1.861	4.773	3.231	5.642
	Age	-0.198	-0.239	-0.246**	-0.286**
	highedudummy	1.513	2.134	1.425	5.232
	gender	1.907	-2.440	-3.032	-2.641
	constant	-15.012	-27.534	-19.898	-25.633
CLU_IT2	Green_Preference	-0.096	-7.936	-7.929	-7.916
	Age	0.039***	-0.124	-0.123	-0.126
	highedudummy	-0.814***	0.000	0.086	-0.014
	gender	0.006	-3.978	-4.046	-4.069
	constant	-3.146*	4.192	0.306	4.200
CLU_IT3	Green_Preference	0.054	-21.855	-21.986	-22.146
	Age	0.001	-2.362**	-2.408*	-2.378**
	highedudummy	0.002	5.601	5.950	5.689
	gender	-0.006	14.635	15.004	14.760
	constant	-0.290	195.386*	210.083	205.641*
CLU_NL1	Green_Preference	-4.367	-4.836	-4.891	-4.212
	Age	-0.030	-0.151	-0.147*	-0.170**
	highedudummy	-4.584	-4.525	-3.780	-9.642
	gender	0.039	-3.598	-3.884	-2.274
	constant	-2.831	-26.237**	-11.490*	-2.750
CLU_NL2	Green_Preference	-3.479***	-1.484	-1.445	-1.477
	Age	0.025***	-0.107	-0.107	-0.109
	highedudummy	-0.270	-1.178	-1.097	-1.194
	gender	-0.329	-3.324	-3.385	-3.426
	constant	0.750	-23.770***	-6.257	-4.593
/typenew2	τ_1	5.361	4.717	4.002	9.704
	τ_2	1.087*	-2.007	-2.017	-1.999
	τ_3	0.026	-26.146	-27.046	-26.066
Statistics	χ^2	716.796	43200.310	816.751	1331.994
	N	18612	18612	18612	18612

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

Table 42: Nested Logit Estimates: GTVI

Cluster	Variable	NL25	NL26	NL27	NL28
CLCODE	GTVI_2017	-0.057	-2.941**	-0.493	-2.665***
	PC1_2017		-8.618**		-2.714*
	PC2_2017			3.382**	9.926***

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Table 42 – continued from previous page

Cluster	Variable	NL25	NL26	NL27	NL28
CLU_EL1	Green_Preference	4.669	4.465	4.646	3.407
	Age	-0.170	-0.304**	-0.279***	-0.222**
	highedudummy	3.030	13.758	6.821	1.858
	gender	2.040	-1.184	-1.629	-2.457
	constant	-12.683	11.093	-31.557***	-2.597
CLU_EL2	Green_Preference	-0.025	0.390	0.452	0.056
	Age	-0.000	-0.146	-0.140	-0.129
	highedudummy	0.011	-1.566	-1.500	-1.529
	gender	0.019	-12.897	-12.821	-12.160
	constant	-0.116	40.636	31.980	33.945
CLU_ES1	Green_Preference	3.292	2.225	2.425	1.270
	Age	0.022	-0.104	-0.106	-0.116
	highedudummy	4.134	15.621	8.549*	2.653
	gender	0.824	-2.238	-2.646	-2.587
	constant	-12.491	-1.567	-33.227	-31.707
CLU_ES2	Green_Preference	0.188	-7.436	-7.350	-7.637
	Age	0.013	-0.099	-0.097	-0.092
	highedudummy	1.323	-3.528	-3.466	-3.564
	gender	0.530	-4.740	-4.701	-4.511
	constant	-6.227	25.415*	14.894	25.180*
CLU_FI1	Green_Preference	-7.497	-12.416*	-9.933*	-5.167
	Age	0.080	0.023	-0.024	-0.100
	highedudummy	-1.425	-6.516	-3.558	-1.849
	gender	-5.604	-20.405*	-13.479*	-6.055
	constant	-7.128	-9.785	-27.577	-40.452
CLU_FI2	Green_Preference	-2.880***	-2.840	-2.822	-2.932
	Age	-0.017	-0.050	-0.049	-0.042
	highedudummy	-1.078**	0.354	0.366	0.400
	gender	0.147	-4.345	-4.329	-4.158
	constant	1.044	-11.344	-0.708	-7.414
CLU_IT1	Green_Preference	2.129	7.423	4.368	1.265
	Age	-0.180	-0.274	-0.278**	-0.230**
	highedudummy	1.155	9.565	3.916	0.542
	gender	1.642	-3.669	-2.268	-2.859
	constant	-11.528	-38.592	-29.473	3.047
CLU_IT2	Green_Preference	0.290	-7.969	-7.864	-8.056
	Age	0.042	-0.128	-0.126	-0.121
	highedudummy	-0.866**	-0.016	-0.005	-0.031
	gender	0.029	-4.078	-4.054	-3.842
	constant	-2.968**	27.245**	0.340	-4.216
CLU_IT3	Green_Preference	0.091	-22.363	-22.123	-21.370
	Age	0.002	-2.365**	-2.377**	-2.326**
	highedudummy	0.002	5.747	5.767	5.334
	gender	-0.012	14.664	14.743	14.489
	constant	-0.559	181.271	206.373*	191.885*

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Table 42 – continued from previous page

Cluster	Variable	NL25	NL26	NL27	NL28
CLU_NL1	Green_Preference	-4.901	-3.728	-4.262	-4.870
	Age	-0.028	-0.181**	-0.166**	-0.137
	highedudummy	-3.727	-15.334	-8.314*	-2.621
	gender	-0.282	-0.963	-2.558	-4.026
	constant	0.366	16.360	-7.766	-3.443
CLU_NL2	Green_Preference	-3.632***	-1.481	-1.471	-1.531
	Age	0.024***	-0.111	-0.109	-0.105
	highedudummy	-0.240	-1.205	-1.178	-1.203
	gender	-0.348	-3.436	-3.415	-3.175
	constant	1.827	-9.660	-3.957	-13.008***
/typenew2	τ_1	4.482	15.357**	8.498***	2.677
	τ_2	1.275	-2.012	-1.985	-2.030
	τ_3	0.046	-26.166	-26.363	-25.367
Statistics	χ^2	562.034	230.689	654.439	2898.917
	N	18612	18612	18612	18612

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

Table 43: Nested Logit Estimates: GTOI + GTVI (NL29–NL32)

Cluster	Variable	NL29	NL30	NL31	NL32
CLCODE	GTVI_2017	8.382	0.561	0.374	1.865
	GTOI_2017	3.723	3.739***	0.978	3.815
	PC1_2017		-8.515		-3.415
	PC2_2017			7.230	0.514
CLU_EL1	Green_Preference	11.891	0.612	3.587	3.917
	Age	-1.377*	-0.314	-0.170	-0.127
	highedudummy	129.422	12.979*	2.492	1.726
	gender	-2.048	4.541	1.943	1.265
	constant	-163.380	114.051	15.818	102.367
CLU_EL2	Green_Preference	-81.114**	-0.211	-0.236	-0.236
	Age	0.274	-0.001	-0.000	-0.000
	highedudummy	35.118**	0.083	0.096	0.095
	gender	-14.291	0.146	0.167	0.167
	constant	52.312	70.015	17.705	65.371***
CLU_ES1	Green_Preference	-9.969	5.141	3.133	2.044
	Age	0.444**	0.065	0.021	0.010
	highedudummy	150.604	14.172	4.009	2.629
	gender	-4.686	0.153	0.835	0.813
	constant	-178.017	6.909	-30.199	8.586
CLU_ES2	Green_Preference	21.300	4.889	-0.668	-0.126
	Age	-0.644	-0.043	0.018	0.015
	highedudummy	59.258	4.587	0.789	1.160
	gender	-2.855	2.113	0.349	0.499

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Table 43 – continued from previous page

Cluster	Variable	NL29	NL30	NL31	NL32
	constant	-80.425	2.913	9.690	5.611
CLU_FI1	Green_Preference	-171.408*	-18.901	-7.330	-4.878
	Age	0.245	0.153	0.067	0.033
	highedudummy	-27.598	-4.798	-1.516	-1.265
	gender	-46.391	-14.084	-4.979	-2.779
	constant	-57.366	-57.599	-37.073	-61.541
CLU_FI2	Green_Preference	-3.159	-3.187	-2.807***	-2.867
	Age	-0.934***	-0.106	-0.002	-0.011
	highedudummy	-2.360	-1.773	-0.873	-0.986
	gender	4.594	0.780	0.097	0.159
	constant	5.795	-43.018***	-4.414	-39.625
CLU_IT1	Green_Preference	-103.248	-5.865	2.149	1.524
	Age	-1.777	-0.342	-0.171	-0.134
	highedudummy	-47.404	5.320	1.038	0.554
	gender	76.550	7.701	1.525	0.846
	constant	-151.417	-9.429	2.789	4.212
CLU_IT2	Green_Preference	52.309**	3.802	-0.581	-0.024
	Age	0.497***	0.090	0.036*	0.040
	highedudummy	0.249	-1.390	-0.724*	-0.802
	gender	-1.839	0.095	0.028	0.063
	constant	-58.791	7.994	-11.066	1.429
CLU_IT3	Green_Preference	296.354***	0.799	0.986	0.912
	Age	0.497	0.012	0.013	0.013
	highedudummy	4.409	0.013	0.024	0.015
	gender	0.950	-0.065	-0.064	-0.068
	constant	-456.097***	-11.173	4.062	0.945
CLU_NL1	Green_Preference	32.029	-1.415	-4.641	-4.775
	Age	0.258	-0.044	-0.021	-0.011
	highedudummy	-111.223	-13.668	-3.384	-1.992
	gender	-2.890	1.668	-0.313	-0.741
	constant	-24.635	14.197	0.953	2.065
CLU_NL2	Green_Preference	-51.228**	-5.147	-3.346***	-3.543
	Age	0.212	0.024	0.025***	0.025
	highedudummy	16.533**	0.052	-0.276	-0.231
	gender	-7.849	-0.523	-0.251	-0.279
	constant	83.071	-2.407	1.824	-0.866
/typenew2	τ_1	125.068	14.493	4.119	2.540
	τ_2	36.099	3.441	0.878	1.136
	τ_3	81.929	0.358	0.413	0.413
Statistics	χ^2	252.611		7325.714	
	N	18612	18612	18612	18612

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

H Mechanisms

Table 44: Nested Logit Estimates Realised Move: Green Preference Interaction

Cluster	Variable	NL33	NL34	NL35	NL36
CLCODE	GTOI_GP_2017	-0.607***			
	GTVI_GP_2017		0.380***		
	Δ GTOI_GP_2017			2.001***	
	Δ GTVI_GP_2017				1.527***
	PC1_2017	-12.582	-2.078***	-21.428	-2.268***
	PC2_2017	-13.582	-14.711***	-17.037	-14.843***
CLU_EL1	q02_01	-0.452	-0.114	-0.447	-0.197***
	highedudummy	15.876	2.071	74.065	1.165
	gender	12.930	0.944	9.089	1.466*
	constant	20.009	4.645	4.151	6.918
CLU_EL2	q02_01	-0.338**	0.012*	-0.074	-0.163***
	highedudummy	10.244	0.033	1.779	1.647*
	gender	5.636*	0.244	1.429	1.566**
	constant	-25.339	-1.690	21.204	-1.566
CLU_ES1	q02_01	0.176	0.018	0.141	-0.133***
	highedudummy	49.108	3.141	77.596	1.512
	gender	-0.340	0.650	-0.713	1.694***
	constant	3.803	42.657	14.410	46.365
CLU_ES2	q02_01	-0.043	0.024***	0.002	-0.117**
	highedudummy	24.952	0.471	4.782	3.890
	gender	5.138	0.188	1.605	2.106
	constant	-70.122	-21.664***	27.701	-32.688***
CLU_FI1	q02_01	0.782	0.040	0.501	-0.134***
	highedudummy	-30.378	-1.408	-55.536	-0.657
	gender	-59.714	-3.162	-86.763	0.046
	constant	-31.046	31.434***	4.168	35.278***
CLU_FI2	q02_01	-0.564***	0.010	-0.104	-0.194***
	highedudummy	-11.108*	-0.544	-2.276*	-1.913**
	gender	3.367	0.104	0.591	1.719***
	constant	-4.391	-7.958***	13.737	-11.067***
CLU_IT1	q02_01	-1.557	-0.129	-0.380	-0.199***
	highedudummy	20.658	0.666	29.495	0.628
	gender	-4.258	0.793	12.582	1.066
	constant	-92.051	-23.889***	-155.347	-20.024***
CLU_IT2	q02_01	0.437**	0.033***	0.106*	-0.063
	highedudummy	-6.496*	-0.466	-1.673**	-1.329*
	gender	-0.326	0.055	0.094	1.306**
	constant	16.831	23.637***	89.219	19.180***
CLU_IT3	q02_01	0.049***	0.070	0.024	-2.453***
	highedudummy	-0.016	1.019	0.036	2.368
	gender	-0.337	-0.301	-0.085	17.756***
	constant	-30.165	-34.945	-43.290	247.660

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Table 44 – continued from previous page

Cluster	Variable	NL33	NL34	NL35	NL36
CLU_NL1	q02_01	-0.043	-0.010	-0.086	-0.143***
	highedudummy	-59.803	-2.332	-92.975	-0.761
	gender	6.362	-0.603	11.213	0.609
	constant	35.582	1.003	83.430	2.503***
CLU_NL2	q02_01	0.052	0.026***	0.032*	-0.108***
	highedudummy	0.968	-0.198	-0.060	0.036
	gender	-1.787	-0.078	-0.504	0.745*
	constant	4.829	0.776	26.281	0.920
/typenew2	τ_1	57.016	2.742	81.849	1.095
	τ_2	19.124	0.531	3.822	3.013
	τ_3	1.338	7.268	0.927	-51.754
Statistics	χ^2	89.944	6684.229	89.621	59894.291
	N	18612	18612	18612	18612

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

Table 45: Nested Logit Estimates Realised Move: Change in GTOI and GTVI

Cluster	Variable	NL37	NL38
CLCODE	Δ GTOI	-2.003***	
	Δ GTVI		-1.771
	PC1_2017	-0.582	0.501
	PC2_2017	2.927	4.064*
CLU_EL1	Green_Pref	2.828	2.828
	q02_01	-0.190*	-0.190**
	highedudummy	2.020	2.020
	gender	1.762	1.762
	constant	5.947	-3.084
CLU_EL2	Green_Pref	-3.280	-3.280
	q02_01	-0.063*	-0.063*
	highedudummy	-0.282	-0.282
	gender	0.665	0.665
	constant	9.198**	2.070
CLU_ES1	Green_Pref	0.890	0.890
	q02_01	-0.070**	-0.070**
	highedudummy	2.867	2.867
	gender	1.500*	1.500*
	constant	-11.292	-14.300
CLU_ES2	Green_Pref	-3.269	-3.269
	q02_01	-0.061***	-0.061***
	highedudummy	-0.166	-0.166
	gender	0.681	0.681
	constant	13.467	10.754

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Table 45 – continued from previous page

Cluster	Variable	NL37	NL38
CLU_FI1	Green_Pref	-6.126	-6.126
	q02_01	-0.051	-0.051
	highedudummy	-1.387	-1.387
	gender	-2.199	-2.199
	constant	-14.683	-7.546
CLU_FI2	Green_Pref	-3.617***	-3.617***
	q02_01	-0.064	-0.064
	highedudummy	-0.447	-0.447
	gender	0.640*	0.640*
	constant	0.131	10.446***
CLU_IT1	Green_Pref	0.575	0.575
	q02_01	-0.198*	-0.198*
	highedudummy	0.744	0.744
	gender	1.360	1.360
	constant	8.446	2.594
CLU_IT2	Green_Pref	-3.241	-3.241
	q02_01	-0.058*	-0.058*
	highedudummy	-0.425	-0.425
	gender	0.628**	0.628**
	constant	6.009	0.875
CLU_IT3	Green_Pref	-18.719	-18.719
	q02_01	-1.472***	-1.472***
	highedudummy	-0.630	-0.630
	gender	9.940**	9.940**
	constant	138.752**	139.073**
CLU_NL1	Green_Pref	-5.695	-5.695
	q02_01	-0.094*	-0.094*
	highedudummy	-2.219	-2.219
	gender	-0.009	-0.009
	constant	6.771	5.417
CLU_NL2	Green_Pref	-3.714**	-3.714*
	q02_01	-0.059***	-0.059***
	highedudummy	-0.344	-0.344
	gender	0.580	0.580
	constant	4.038***	4.804
/typenew2	τ_1	2.739	2.739
	τ_2	0.149	0.149
	τ_3	-16.893	-16.893
Statistics	χ^2	1704.625	2100.253
	N	18612	18612

*Note:** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust SE used. Survey weights applied.

I Summary Statistics: I.1 to I.3: Full Dataset, I.4 Only five Countries

I.1 Summary Statistics: Both movers and non-movers

Table 46: Education Level

Education Level	Freq.	Percent	Cum.
Less than a High School Diploma	338	3.62	3.62
High School Diploma	3,146	33.72	37.34
Bachelor's Degree or equivalent	3,378	36.20	73.54
Master's Degree or equivalent	2,226	23.86	97.40
PhD or equivalent	243	2.60	100.00
Total	9,331	100.00	

Table 47: Main Activity Status

Activity	Freq.	Percent	Cum.
Employed	5,579	59.79	59.79
Student	1,844	19.76	79.55
Unemployed	837	8.97	88.52
Retired	607	6.51	97.73
Household activity/homemaker	252	2.70	91.22
Other	212	2.27	100.00
Total	9,331	100.00	

Table 48: Main Occupation Status

Occupation	Freq.	Percent	Cum.
Professional	2,002	27.04	27.04
Technicians and Associate Professionals	1,363	18.41	45.45
Clerical Support Worker	1,081	14.60	60.05
Service and Sales Worker	838	11.32	91.28
Elementary Occupation	746	10.08	70.13
Manager	728	9.83	79.96
Craft and Related Trades Worker	272	3.67	94.95
Plant and Machine Operators and Assemblers	185	2.50	97.45
Skilled Agricultural, Forestry and Fish	141	1.90	99.35
Armed Forces Occupation	47	0.63	100.00
Total	7,403	100.00	

Table 49: Marital Status

Status	Freq.	Percent	Cum.
Single (never married)	5,061	54.24	54.24
Married/domestic partnership	3,792	40.64	94.88
Divorced	326	3.49	99.25
Widowed	82	0.88	95.76
Separated	70	0.75	100.00
Total	9,331	100.00	

Table 50: Children Below Age 18 in Household

Children Status	Freq.	Percent	Cum.
No	7,274	77.96	77.96
Yes, one child	1,160	12.43	90.39
Yes, two or more children	897	9.61	100.00
Total	9,331	100.00	

Table 51: Gross Annual Household Income

Income Bracket	Freq.	Percent	Cum.
5,000 or less	927	9.93	9.93
5,001 – 15,000	1,577	16.90	26.84
15,001 – 25,000	1,838	19.70	46.53
25,001 – 35,000	1,568	16.80	63.34
35,001 – 45,000	1,175	12.59	75.93
45,001 – 55,000	750	8.04	83.97
55,001 – 65,000	506	5.42	89.39
65,001 – 75,000	397	4.25	93.64
75,001 or more	593	6.36	100.00
Total	9,331	100.00	

Table 52: Working Arrangement in the Last 12 Months

Working Arrangement	Freq.	Percent	Cum.
Fixed scheduled working only at the employer/client premises	3,419	36.64	36.64
Flexible working arrangements including both on site and remote working, but at least 3 days per week on site	1,414	15.15	51.80
Mostly (at least 3 days per week) or fully remote working	1,017	10.90	62.69
Flexible working arrangements as freelancer: flexible work from home, office, coworking spaces, third places, or other space	813	8.71	71.41
Seasonal working: 3 to 6 months in one or several workplaces at a time	378	4.05	75.46
I haven't worked the last 12 months due to retirement	532	5.70	81.16
I haven't worked the last 12 months due to other reasons	1,758	18.84	100.00
Total	9,331	100.00	

Table 53: Preferred Destination for High/Very High Probability of Movement

Destination	Freq.	Percent	Cum.
A capital metropolitan region	1,656	24.59	24.59
A larger city (>50,000 inhabitants)	2,579	38.30	62.89
A smaller town (>5,000 inhabitants)	1,545	22.94	85.83
A rural village (<5,000 inhabitants)	954	14.17	100.00
Total	6,734	100.00	

Table 54: Current Country of Residence

Country	Freq.	Percent	Cum.
Austria	48	0.51	0.51
Belgium	41	0.44	0.95
Czech Republic	42	0.45	1.40
Denmark	12	0.13	1.53
Estonia	32	0.34	1.88
Finland	985	10.56	12.43
France	189	2.03	14.46
Germany	374	4.01	18.47
Greece	1,282	13.74	32.21
Hungary	124	1.33	33.54
Ireland	79	0.85	34.38
Italy	1,985	21.28	55.66
Latvia	23	0.25	55.91
Luxembourg	3	0.03	55.94
Netherlands	1,249	13.39	69.32
Poland	597	6.40	75.72
Portugal	632	6.77	82.50
Slovakia	1	0.01	82.51
Slovenia	30	0.32	82.83
South Africa	1	0.01	82.84
Spain	1,549	16.60	99.44
Sweden	52	0.56	100.00
Total	9,330	100.00	

I.2 Summary Statistics: Movers

Table 55: Education Level (Movers Only)

Education Level	Freq.	Percent	Cum.
Less than a High School Diploma	133	4.93	4.93
High School Diploma	959	35.54	40.47
Bachelor's Degree or equivalent	941	34.88	75.35
Master's Degree or equivalent	596	22.09	97.44
PhD or equivalent	69	2.56	100.00
Total	2,698	100.00	

Table 56: Main Activity Status (Movers Only)

Activity	Freq.	Percent	Cum.
Employed	1,701	63.05	63.05
Student	424	15.72	78.76
Unemployed	226	8.38	87.14
Retired	185	6.86	97.44
Household activity/homemaker	93	3.45	90.59
Other	69	2.56	100.00
Total	2,698	100.00	

Table 57: Main Occupation Status (Movers Only)

Occupation	Freq.	Percent	Cum.
Professional	548	22.64	22.64
Technicians and Associate Professionals	422	17.44	40.08
Clerical Support Worker	385	15.91	55.99
Elementary Occupation	311	12.85	68.84
Service and Sales Worker	272	11.24	89.71
Manager	233	9.63	78.47
Craft and Related Trades Worker	94	3.88	93.59
Plant and Machine Operators and Assemblers	77	3.18	96.77
Skilled Agricultural, Forestry and Fish	60	2.48	99.26
Armed Forces Occupation	18	0.74	100.00
Total	2,420	100.00	

Table 58: Marital Status (Movers Only)

Marital Status	Freq.	Percent	Cum.
Single (never married)	1,214	45.00	45.00
Married/domestic partnership	1,306	48.41	93.40
Divorced	127	4.71	99.07
Widowed	26	0.96	94.37
Separated	25	0.93	100.00
Total	2,698	100.00	

Table 59: Children Under 18 in Household (Movers Only)

Children	Freq.	Percent	Cum.
No	1,942	71.98	71.98
Yes, one child	431	15.97	87.95
Yes, two or more children	325	12.05	100.00
Total	2,698	100.00	

Table 60: Gross Annual Household Income (Movers Only)

Income Bracket	Freq.	Percent	Cum.
5,000 or less	268	9.93	9.93
5,001 – 15,000	452	16.75	26.69
15,001 – 25,000	514	19.05	45.74
25,001 – 35,000	439	16.27	62.01
35,001 – 45,000	335	12.42	74.43
45,001 – 55,000	235	8.71	83.14
55,001 – 65,000	165	6.12	89.25
65,001 – 75,000	116	4.30	93.55
75,001 or more	174	6.45	100.00
Total	2,698	100.00	

Table 61: Working Arrangement in the Last 12 Months (Movers Only)

Working Arrangement	Freq.	Percent	Cum.
Fixed scheduled working only at the employer/client premises	1,107	41.03	41.03
Flexible working arrangements including both on site and remote working, but at least 3 days per week on site	422	15.64	56.67
Mostly (at least 3 days per week) or fully remote working	277	10.27	66.94
Flexible working arrangements as freelancer: flexible work from home, office, coworking spaces, third places, or other space	217	8.04	74.98
Seasonal working: 3 to 6 months in one or several workplaces at a time	100	3.71	78.69
I haven't worked the last 12 months due to retirement	165	6.12	84.80
I haven't worked the last 12 months due to other reasons	410	15.20	100.00
Total	2,698	100.00	

Table 62: Preferred Destination for High/Very High Probability of Movement

Destination	Freq.	Percent	Cum.
A capital metropolitan region	545	23.34	23.34
A larger city (> 50,000 inhabitants)	832	35.63	58.97
A smaller town (> 5,000 inhabitants)	537	23.00	81.97
A rural village (< 5,000 inhabitants)	421	18.03	100.00
Total	2,335	100.00	

Table 63: Current Country of Residence (Movers Only)

Country	Freq.	Percent	Cum.
Austria	16	0.59	0.59
Belgium	13	0.48	1.07
Czech Republic	7	0.26	1.33
Denmark	1	0.04	1.37
Estonia	15	0.56	1.93
Finland	310	11.49	13.42
France	51	1.89	15.31
Germany	85	3.15	18.46
Greece	337	12.49	30.95
Hungary	14	0.52	31.47
Ireland	15	0.56	32.02
Italy	429	15.90	47.92
Latvia	5	0.19	48.11
Netherlands	503	18.64	66.75
Poland	104	3.85	70.61
Portugal	78	2.89	73.50
Slovenia	4	0.15	73.65
South Africa	1	0.04	73.68
Spain	700	25.95	99.63
Sweden	10	0.37	100.00
Total	2,698	100.00	

I.3 Summary Statistics: Non-Movers

Table 64: Education Level (Non-Movers Only)

Education Level	Freq.	Percent	Cum.
Less than a High School Diploma	205	3.09	3.09
High School Diploma	2,187	32.97	36.06
Bachelor's Degree or equivalent	2,437	36.74	72.80
Master's Degree or equivalent	1,630	24.57	97.38
PhD or equivalent	174	2.62	100.00
Total	6,633	100.00	

Table 65: Main Activity Status (Non-Movers Only)

Activity	Freq.	Percent	Cum.
Employed	3,878	58.47	58.47
Student	1,420	21.41	79.87
Unemployed	611	9.21	89.08
Household activity/homemaker	159	2.40	91.48
Retired	422	6.36	97.84
Other	143	2.16	100.00
Total	6,633	100.00	

Table 66: Main Occupation Status (Non-Movers Only)

Occupation	Freq.	Percent	Cum.
Manager	495	9.93	9.93
Professional	1,454	29.18	39.11
Technicians and Associate Professionals	941	18.88	58.00
Clerical Support Worker	696	13.97	71.96
Service and Sales Worker	566	11.36	83.32
Skilled Agricultural, Forestry and Fish	81	1.63	84.95
Craft and Related Trades Worker	178	3.57	88.52
Plant and Machine Operators and Assemblers	108	2.17	90.69
Elementary Occupation	435	8.73	99.42
Armed Forces Occupation	29	0.58	100.00
Total	4,983	100.00	

Table 67: Marital Status (Non-Movers Only)

Marital Status	Freq.	Percent	Cum.
Single (never married)	3,847	58.00	58.00
Married/domestic partnership	2,486	37.48	95.48
Widowed	56	0.84	96.32
Divorced	199	3.00	99.32
Separated	45	0.68	100.00
Total	6,633	100.00	

Table 68: Children Under 18 in Household (Non-Movers Only)

Children	Freq.	Percent	Cum.
No	5,332	80.39	80.39
Yes, one child	729	10.99	91.38
Yes, two or more children	572	8.62	100.00
Total	6,633	100.00	

Table 69: Gross Annual Household Income (Non-Movers Only)

Income Bracket	Freq.	Percent	Cum.
5,000 or less	659	9.94	9.94
5,001 – 15,000	1,125	16.96	26.90
15,001 – 25,000	1,324	19.96	46.86
25,001 – 35,000	1,129	17.02	63.88
35,001 – 45,000	840	12.66	76.54
45,001 – 55,000	515	7.76	84.31
55,001 – 65,000	341	5.14	89.45
65,001 – 75,000	281	4.24	93.68
75,001 or more	419	6.32	100.00
Total	6,633	100.00	

Table 70: Working Arrangement in the Last 12 Months (Non-Movers Only)

Working Arrangement	Freq.	Percent	Cum.
Fixed scheduled working only at the employer/client premises	2,312	34.86	34.86
Flexible working arrangements including both on site and remote working, but at least 3 days per week on site	992	14.96	49.81
Mostly (at least 3 days per week) or fully remote working	740	11.16	60.97
Flexible working arrangements as freelancer	596	8.99	69.95
Seasonal working: 3 to 6 months in one or several workplaces	278	4.19	74.14
I haven't worked due to retirement	367	5.53	79.68
I haven't worked due to other reasons	1,348	20.32	100.00
Total	6,633	100.00	

Table 71: Preferred Destination for High/Very High Probability of Movement (Non-Movers Only)

Destination	Freq.	Percent	Cum.
A capital metropolitan region	1,111	25.26	25.26
A larger city (> 50,000 inhabitants)	1,747	39.71	64.97
A smaller town (> 5,000 inhabitants)	1,008	22.91	87.88
A rural village (< 5,000 inhabitants)	533	12.12	100.00
Total	4,399	100.00	

Table 72: Current Country of Residence (Non-Movers Only)

Country	Freq.	Percent	Cum.
Austria	32	0.48	0.48
Belgium	28	0.42	0.90
Czech Republic	35	0.53	1.43
Denmark	11	0.17	1.60
Estonia	17	0.26	1.85
Finland	675	10.18	12.03
France	138	2.08	14.11
Germany	289	4.36	18.47
Greece	945	14.25	32.72
Hungary	110	1.66	34.38
Ireland	64	0.97	35.34
Italy	1,556	23.46	58.81
Latvia	18	0.27	59.08
Luxembourg	3	0.05	59.12
Netherlands	746	11.25	70.37
Poland	493	7.43	77.80
Portugal	554	8.35	86.16
Slovakia	1	0.02	86.17
Slovenia	26	0.39	86.57
Spain	849	12.80	99.37
Sweden	42	0.63	100.00
Total	6,632	100.00	

I.4 Summary Statistics: Movers within the five pilot countries for which we know the country vs the region of origin

To run the models where we include the information of the origin characteristics, we must ensure that we do not have selection bias due to missing data. The survey results do not always report the region of origin but the country of origin. To ensure that the sample is not statistically different by excluding those for who we only know the country of origin we will test for it. In every table, we report the Pearson Design-Based F statistics to test the difference between the final observations and the left-out observations. The test statistic is adjusted for the survey design by using pweights.

Table 73: Distribution of Education Levels: Country vs Region

Education Level	Freq. (Country)	Percent (Country)	Freq. (Region)	Percent (Region)
Less than HS	104	6.52 %	65	6.49 %
HS Diploma	656	41.15 %	430	42.96 %
Bachelor's	506	31.74 %	289	28.87 %
Master's	293	18.38 %	194	19.38 %
PhD	35	2.20 %	23	2.30 %
Total	1594	100.00 %	1001	100.00 %

Pearson F(3.94, 6222.32)= 1.3934 & p = 0.2340

Table 74: Main Activity Status: Country vs Region

Activity Status	Freq. (Country)	Percent (Country)	Freq. (Region)	Percent (Region)
Employed	1070	67.13 %	651	65.03 %
Student	157	9.85 %	100	9.99 %
Unemployed	134	8.41 %	81	8.09 %
Homemaker	55	3.45 %	42	4.20 %
Retired	140	8.78 %	100	9.99 %
Other	38	2.38 %	27	2.70 %
Total	1594	100.00 %	1001	100.00 %

Pearson F(4.26, 6724.62)= 0.4675 & p = 0.7713

Table 75: Main Occupation Status: Country vs Region

Occupation	Freq. (Country)	Percent (Country)	Freq. (Region)	Percent (Region)
Manager	126	8.40 %	74	7.99 %
Professional	237	15.80 %	142	15.33 %
Technicians	273	18.20 %	158	17.06 %
Clerical Support	294	19.60 %	183	19.76 %
Service	145	9.67 %	94	10.15 %
Agricultural	45	3.00 %	34	3.67 %
Craft	73	4.87 %	39	4.21 %
Machine Operators	64	4.27 %	44	4.75 %
Elementary	234	15.60 %	154	16.63 %
Armed Forces	9	0.60 %	4	0.43 %
Total	1500	100.00 %	926	100.00 %

Pearson F(8.07, 12030.24)= 2.0506 & p = 0.0365

Table 76: Marital Status: Country vs Region

Marital Status	Freq. (Country)	Percent (Country)	Freq. (Region)	Percent (Region)
Single	615	38.58 %	384	38.36 %
Married/Partnership	848	53.20 %	535	53.45 %
Widowed	20	1.25 %	10	1.00 %
Divorced	93	5.83 %	61	6.09 %
Separated	18	1.13 %	11	1.10 %
Total	1594	100.00 %	1001	100.00 %

Pearson F(3.45, 5447.44)= 1.0326 & p = 0.3829

Table 77: Children Below 18: Country vs Region

Children	Freq. (Country)	Percent (Country)	Freq. (Region)	Percent (Region)
No	1068	67.00 %	679	67.83 %
One Child	299	18.76 %	188	18.78 %
Two or More	227	14.24 %	134	13.39 %
Total	1594	100.00 %	1001	100.00 %

Pearson F(1.97, 3103.87)= 2.6892 & p = 0.0691

Table 78: Gross Annual Household Income: Country vs Region

Income Range	Freq. (Country)	Percent (Country)	Freq. (Region)	Percent (Region)
5,000 or less	134	8.41 %	87	8.69 %
5,001 – 15,000	247	15.50 %	171	17.08 %
15,001 – 25,000	317	19.89 %	186	18.58 %
25,001 – 35,000	277	17.38 %	177	17.68 %
35,001 – 45,000	219	13.74 %	138	13.79 %
45,001 – 55,000	149	9.35 %	91	9.09 %
55,001 – 65,000	94	5.90 %	64	6.39 %
65,001 – 75,000	73	4.58 %	43	4.30 %
75,001 or more	84	5.27 %	44	4.40 %
Total	1594	100.00 %	1001	100.00 %

Pearson $F(7.65, 12079.77) = 0.7351$ & $p = 0.6544$