Model Uncertainty and Measures of Inequality of Opportunity: Online Appendix

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Abstract

We argue that normative disagreements about which factors constitute circumstances in the equality of opportunity literature lead to substantial model uncertainty in empirical analyses. To systematically address this issue, we employ linear Bayesian Model Averaging (BMA) methods. Using data from the 2011 and 2019 waves of the European Union Statistics on Income and Living Conditions covering 31 EU countries, we estimate measures of absolute and relative inequality of opportunity. We compare our linear BMA findings to those using popular regression tree-based machine learning models including Bayesian Additive Regression Trees, Random Forest, and Extreme Gradient Boosting. Our findings show that ignoring model uncertainty and nonlinearity can substantially overstate IOp estimates across countries. Notably, linear BMA and Random Forest yield more conservative and robust estimates compared to traditional linear approaches, with Random Forest also emerging as the most reliable tree-based method.

Keywords: Equality of opportunity, Great Gatsby Curve, model uncertainty, Bayesian model averaging, Bayesian additive regression trees

JEL Classification Codes: C3, C14, C24, C51, D85

Outline

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A.1 Linear BMA

This appendix outlines the methodology for implementing Linear Bayesian Model Averaging (BMA) using the `BMS` package Feldkircher and Zeugner (2015), which provides a flexible framework for Bayesian model averaging. The analysis incorporates robustness checks for prior specifications to ensure that results are reliable and interpretable, even under varying assumptions.

The `BMS` package facilitates the efficient implementation of BMA by offering pre-defined priors for regression coefficients and model spaces, as well as advanced Markov Chain Monte Carlo (MCMC) algorithms for exploring the model space. The use of `BMS` enables robust posterior inference and detailed diagnostics, making it well-suited for the analysis of inequality of opportunity.

A.1.1 Tuning Parameters

The implementation of BMA involves several key parameters that influence the performance of the algorithm and the robustness of the results:

- **Burn-in Period (`burn`):** Specifies the number of initial iterations discarded to allow the Markov Chain Monte Carlo (MCMC) algorithm to converge. A burn-in of 1,000,000 iterations ensures that the chain stabilizes before samples are collected.
- **Number of Iterations (`iter`):** Defines the total number of iterations after the burn-in period. We use 2,000,000 iterations to achieve sufficient exploration of the model space.
- ***g*-Prior Specification (`g`):** Controls the prior variance of regression coefficients. We compare results using the Unit Information Prior (UIP) and the Benchmark Risk Information Criterion (BRIC).
- **Model Priors (`mprior`):** Determines the prior distribution over the model space. Uniform priors assume equal probability for all models, while hierarchical priors account for variable groupings based on theoretical considerations.

- **Model Memory Limit (`nmodel`):** Sets the maximum number of models retained in memory, ensuring computational feasibility. We limit this to 10,000 models.
- **Hierarchical Priors (`mprior.size`):** Specifies the prior probabilities for groups of variables, enabling hierarchical modeling of theoretical groupings.
- **Sampling Algorithm (`mcmc`):** Defines the MCMC approach used to explore the model space, such as birth-death (bd) sampling or tessellation-based (tess) sampling.
- **Intercept Inclusion (`user.int`):** Determines whether an intercept is explicitly included in the model.

These parameters allow flexibility in the implementation of BMA, enabling robustness checks across alternative prior specifications and computational strategies.

A.1.2 Hierarchical Priors

To reflect theoretical groupings of variables, we implement hierarchical priors that organize predictors into predefined groups based on conceptual relevance. For example, we classify circumstances into four categories: (i) Father characteristics; (ii) Mother characteristics; (iii) Individual characteristics; (iv) Household characteristics.

Each group (or "theory") is assigned a prior inclusion probability of 0.5, assuming independence between groups. Within a group, all variables share equal prior weights, conditional on the inclusion of the group in the model. This hierarchical structure ensures that prior probabilities reflect theoretical divisions rather than arbitrary variable selection, accommodating interdependencies among variables within a group.

Mathematically, the prior probability of a model M_m is given by:

$$\pi(M_m) = \prod_{g \in G} \pi_g \prod_{j \in V_g} \pi_j, \tag{A.1}$$

where G denotes the set of groups, V_g represents the variables within group g, π_g is the prior probability of inclusion for group g, and π_j is the weight assigned to each variable within V_g.

A.1.3 Tessellation-Defined Dilution Priors

To address potential biases caused by the independence of irrelevant alternatives (IIA), we implement tessellation-defined dilution priors. These priors allocate probabilities across clusters of similar models rather than individual models, ensuring that structurally similar models do not dominate the posterior distribution.

The model space is partitioned into clusters represented by Voronoi tessellations on a high-dimensional sphere, as described by Moser and Hofmarcher (2014). Each cluster is assigned a uniform prior probability, distributing weights evenly among groups of related models. This approach prevents models with overlapping variables from collectively receiving excessive prior probability, mitigating overrepresentation of particular variable combinations.

A.1.4 Robustness Checks

The robustness of the BMA framework is evaluated by comparing posterior inclusion probabilities (PIPs), coefficient estimates, and posterior model probabilities (PMPs) across different prior specifications and sampling algorithms. Specifically, we compare results using hierarchical priors versus tessellation-defined dilution priors, evaluate alternative g-prior specifications (UIP vs. BRIC) to assess the influence of prior variance assumptions on regression coefficients, analyze the sensitivity of posterior estimates to MCMC sampling approaches (e.g., birth and death MCMC vs. tessellation method. Figures A.1, A.2, and A.3 present estimates of absolute IoP from linear BMA using the Gini coefficient, MLD, and Theil index as inequality measures. These figures highlight the sensitivity of IoP estimates to prior choices while demonstrating minimal variation among IoP indices, underscoring the robustness of results across specifications.

A.2 BART-BMA

Following Chipman et al. (2010) and Hernández et al. (2018) this appendix outlines the estimation procedure of BART-BMA, which is implemented using the R package `bartBMA`.

A.2.1 BART-BMA Likelihood

The likelihood for the BART-BMA model (9) is expressed as:

$$p(Y|\mathcal{M}_\ell^T, \sigma^2) = \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(Y_i - \sum_{t=1}^{T_\ell} g_t(C_i; \mathcal{T}_{t,\ell}, \Theta_{t,\ell}))^2}{2\sigma^2}\right). \tag{A.2}$$

The posterior probability of model $\mathcal{M}_\ell^T$ is proportional to its likelihood and prior:

$$p(\mathcal{M}_\ell^T|Y) \propto p(Y|\mathcal{M}_\ell^T, \sigma^2) \cdot p(\mathcal{M}_\ell^T). \tag{A.3}$$

Final predictions are obtained by averaging over models weighted by their posterior probabilities:

$$\hat{Y}_i = \sum_{\ell=1}^{L} w^\ell \sum_{t=1}^{T_\ell} g_t(C_i; \mathcal{T}_{t,\ell}, \Theta_{t,\ell}), \tag{A.4}$$

where w^ℓ represents the posterior probability of model ℓ, L is the number of retained models, and T_ℓ is the number of trees in model ℓ.

A.2.2 BART-BMA Fitting

The fitting process in BART-BMA uses an MCMC sampler to approximate the posterior distribution of the model parameters, including the set of trees, terminal node parameters, and residual standard deviation. The Gibbs sampler iteratively proposes modifications to the tree structures:

- **GROW**: Select a terminal node and split it into two daughter nodes.
- **PRUNE**: Choose an internal node with two terminal daughter nodes and collapse it.
- **CHANGE**: Select a random internal node and modify the splitting rule.
- **SWAP**: Swap the roles of parent and child internal nodes to adjust tree structure.

For each proposed tree T_j in the sum-of-trees model, the Bayesian Information Criterion (BIC) is used to approximate the posterior probability:

$$\text{BIC} = \log p(Y|\mathcal{M}_\ell^T, \sigma^2) - \frac{\dim(\mathcal{M}_\ell^T)}{2} \log N, \tag{A.5}$$

where $\dim(\mathcal{M}_\ell^T)$ represents the number of parameters in the model.

Using Occam's Window, models with BIC values significantly worse than the best model are discarded. This step ensures computational efficiency by focusing on models with high posterior support. The final predictions are obtained by averaging over the remaining models, weighted by their posterior probabilities.

A.2.3 Greedily Growing Trees

The Pruned Exact Linear Time (PELT) algorithm is utilized in BART-BMA to efficiently identify predictive split points in regression trees (Yao, 1984). It detects changes in the mean of the outcome variable when ordered by a predictor variable C_p. PELT treats the ordered outcome variable as a univariate stochastic process, searching for change points that optimize the separation of the outcome variable into distinct regions, akin to identifying distributional changes.

In BART-BMA, PELT is applied at each node to propose potential split points for tree growth. Each identified change point is evaluated based on its contribution to reducing residual variance. Splits proposed by PELT are assessed using the Bayesian Information Criterion (BIC), ensuring that only those that enhance the overall model fit are retained. For further details, see (Hernández et al., 2018).

A.2.4 Tuning Parameters

Key tuning parameters in BART-BMA include:

- **Tree Depth** (κ, λ): The probability of splitting decreases with depth d, controlled by $\kappa(1 + d)^{-\lambda}$, where $\kappa = 0.95$ and $\lambda = 2$ are typical values.
- **Shrinkage** (υ): Terminal node parameters follow a normal prior $N(0, \sigma^2/\upsilon)$, with υ

controlling regularization strength.

- **Model Selection Threshold**: Occam's Window retains models with BIC values close to the best model, ensuring computational efficiency.
- **Maximum number of models to keep in Occam's window**: We allow here for a maximum of 100,000 models.
- **Maximum number of splits in a tree**: We allow here for a maximum of 30 splits per tree.

A.2.5 Variable Importance

For a given model $\mathcal{M}_\ell^T$, let $\kappa_{p\ell}$ denote the number of splits involving C_p. The variable importance score (VIS) is defined as:

$$\widehat{VI}_k^{BART-BMA} = \frac{\sum_{\ell=1}^{L} w^\ell \kappa_{p\ell}}{\sum_{p=1}^{P} \sum_{\ell=1}^{L} w^\ell \kappa_{p\ell}}, \tag{A.6}$$

where P is the total number of predictors, and L is the number of retained models.

A.3 Conditional Inference Forest Algorithm

Following Brunori et al. (2023) this appendix outlines the construction of a CIF, adapting the general structure of random forest algorithms (Hastie et al., 2009) while incorporating the principles of Conditional Inference Trees for splitting. CIF is implemented using the R package `partykit`.

A.3.1 Algorithm for Conditional Inference Forests

To construct a Conditional Inference Forest:

1. For $b = 1$ to T^* (number of trees):

(a) Draw a bootstrap sample $\mathcal{Z}_b^* = \{Z_{b1}^*, Z_{b2}^*, \ldots, Z_{bn}^*\}$ of size n, sampled with replacement from the original data $\mathcal{Z} = \{Z_1, Z_2, \ldots, Z_N\}$, where $Z_i = (Y_i, C_i')'$.

(b) Grow a Conditional Inference Tree $\mathcal{G}_b^*$ on $\mathcal{Z}_b^*$ by recursively applying the following steps at each node:

i. Perform a global test of independence between the response variable Y and each predictor C_k using a linear test statistic.

ii. Compute the conditional distribution of the test statistic under the null hypothesis $H_0 : f(Y|C_k) = f(Y)$, using a permutation-based approach to calculate p-values.

iii. Select the predictor C_k with the smallest adjusted p-value. If the p-value is below the significance threshold α^*, proceed to the next step; otherwise, stop splitting.

iv. Identify the optimal split point for the selected predictor C_k to maximize the association with Y.

v. Partition the data at the split point into two daughter nodes and repeat the process for each node until the stopping criteria are met (e.g., reaching a minimum node size).

(c) Output the resulting tree $\mathcal{G}_b^*$.

2. Aggregate the predictions from all T^* trees in the forest.

A.3.2 Prediction

To predict at a new observation C_i:

- For regression, the prediction is the average prediction across all trees:

$$\widehat{m}^{CRF}(C_i) = \frac{1}{T^*} \sum_{b=1}^{T^*} \mathcal{G}_b^*(C_i; \xi_b^*, \mathcal{Z}_b^*), \tag{A.7}$$

where $\mathcal{G}_b^*(C_i; \xi_b^*, \mathcal{Z}_b^*)$ is the prediction of the b-th tree.

A.3.3 Tuning Parameters

Key parameters for the CIF algorithm include:

- **Significance Level (α^*):** The threshold for p-values in the independence tests. Lower values result in stricter splits and shallower trees. We set α^* to 0.01.
- **Number of Variables ($\bar{K}^*$):** The subset of predictors considered at each split. This ensures balanced evaluation of predictors. We set $\bar{K}^*$ to the square root of the number of input variables.
- **Number of Trees (T^*):** The size of the forest. A larger T^* reduces variance but increases computational cost. We set T^* to 200.

A.3.4 Variable Importance

To evaluate variable importance, CRFs use a permutation-based approach that compares the prediction accuracy before and after permuting C_k, averaged over all trees using the out-of-bag (OOB) sample (Breiman, 2001). For each tree b and circumstance C_k, permutation importance is computed as follows:

$$VI_k^b = \frac{1}{\bar{B}} \sum_{c_i \in \overline{\mathcal{Z}}_b^*} \mathbb{I}\left(y_i = \tilde{\mathcal{G}}_b^*(c_i; \xi_b^*, \mathcal{Z}_b^*)\right) - \frac{1}{\bar{B}} \sum_{c_i \in \overline{\mathcal{Z}}_b^*} \mathbb{I}\left(y_i = \tilde{\mathcal{G}}_b^{*k}(c_i; \xi_b^*, \mathcal{Z}_b^*)\right), \tag{A.8}$$

where $\bar{B}$ is the size of the OOB sample, $\tilde{\mathcal{G}}_b^*(c_i; \xi_b^*, \mathcal{Z}_b^*)$ is the predicted value from the b-th tree based on the OOB sample, and $\tilde{\mathcal{G}}_b^{*k}(c_i; \xi_b^*, \mathcal{Z}_b^*)$ is the predicted value from the same tree when the values of the circumstance C_k are randomly permuted across all OOB observations of that tree. The first term computes the percentage of observations classified correctly before permutation, while the second term computes the percentage of observations classified correctly after permutation. The overall variable importance for C_k is obtained by averaging over all B trees:

$$\widehat{VI}_k^{C-Forest} = \frac{1}{B} \sum_{b=1}^{B} VI^b(C_k). \tag{A.9}$$

Higher $VI(C_k)$ values indicate greater predictive importance of the variable C_k in modeling the response.

A.4 XGBOOST

A.4.1 Algorithmic Implementation

The XGBoost algorithm is implemented using the `xgboost` library in R, following the framework outlined by Chen and Guestrin (2016). The algorithm proceeds as described below.

1. Initialization: Set the initial prediction to a constant value, typically the mean of the target variable:

$$\hat{\mathcal{G}}_0(C_i) = \bar{Y} = \frac{1}{N}\sum_{i=1}^{N} Y_i. \tag{A.10}$$

2. For each iteration $t = 1, \ldots, R$:

   (a) **Compute the gradients and Hessians**: For each observation i, calculate the gradient and Hessian of the loss function with respect to the current prediction:

$$g_i^{(t)} = \frac{\partial \ell(Y_i, \hat{\mathcal{G}}_i^{(t-1)})}{\partial \hat{\mathcal{G}}_i^{(t-1)}}, \quad h_i^{(t)} = \frac{\partial^2 \ell(Y_i, \hat{\mathcal{G}}_i^{(t-1)})}{\partial (\hat{\mathcal{G}}_i^{(t-1)})^2}. \tag{A.11}$$

   For the squared error loss $\ell(Y_i, \hat{Y}_i) = (Y_i - \hat{Y}_i)^2$, these become:

$$g_i^{(t)} = -2(Y_i - \hat{\mathcal{G}}_i^{(t-1)}), \quad h_i^{(t)} = 2. \tag{A.12}$$

   (b) Fit a regression tree: Construct a regression tree $\widehat{\mathcal{G}}_t(C_i)$ to predict the negative gradients $-g_i^{(t)}$ using the training data $\{C_i, -g_i^{(t)}\}$.

   (c) Optimize leaf weights: For each leaf j in the tree $\widehat{\mathcal{G}}_t$, compute the optimal weight ω_j that minimizes the regularized objective function. The optimal weight is given by:

$$\omega_j = -\frac{\sum_{i \in I_j} g_i^{(t)}}{\sum_{i \in I_j} h_i^{(t)} + \lambda}, \tag{A.13}$$

where I_j is the set of indices of observations in leaf j, and λ is the regularization parameter controlling the ℓ_2-norm of the leaf weights.

(d) Update the model: Add the new tree's predictions to the ensemble:

$$\hat{\mathcal{G}}_i^{(t)} = \hat{\mathcal{G}}_i^{(t-1)} + \eta \widehat{\mathcal{G}}_t(C_i), \tag{A.14}$$

where $\eta \in (0, 1]$ is the learning rate (shrinkage parameter) that scales the contribution of each tree.

3. The final model after R iterations is:

$$\hat{Y}_i = \hat{\mathcal{G}}_i^{(R)} = \sum_{r=0}^{R} \widehat{\mathcal{G}}_r(C_i). \tag{A.15}$$

A.4.2 Regularization and Objective Function

The objective function at each iteration t is approximated using a second-order Taylor expansion

$$\mathcal{L}^{(t)} \approx \sum_{i=1}^{N} \left[g_i^{(t)} \widehat{\mathcal{G}}_t(C_i) + \frac{1}{2} h_i^{(t)} \widehat{\mathcal{G}}_t^2(C_i) \right] + \Omega(\widehat{\mathcal{G}}_t), \tag{A.16}$$

where the regularization term $\Omega(\widehat{\mathcal{G}}_t)$ is as previously defined

$$\Omega(\widehat{\mathcal{G}}_t) = \gamma L_t + \frac{1}{2} \lambda \sum_{j=1}^{L_t} \omega_j^2, \tag{A.17}$$

with L_t being the number of leaves in tree t, ω_j the weight of leaf j, γ the regularization parameter controlling the number of leaves, and λ controlling the ℓ_2-norm of the leaf weights.

The goal is to minimize $\mathcal{L}^{(t)}$ with respect to the structure of $\widehat{\mathcal{G}}_t$ and the leaf weights ω_j.

The optimal split is chosen to maximize the gain, which is computed as

$$\text{Gain} = \frac{1}{2}\left(\frac{\left(\sum_{i\in I_L} g_i^{(t)}\right)^2}{\sum_{i\in I_L} h_i^{(t)} + \lambda} + \frac{\left(\sum_{i\in I_R} g_i^{(t)}\right)^2}{\sum_{i\in I_R} h_i^{(t)} + \lambda} - \frac{\left(\sum_{i\in I_P} g_i^{(t)}\right)^2}{\sum_{i\in I_P} h_i^{(t)} + \lambda}\right) - \gamma, \tag{A.18}$$

where I_P, I_L, and I_R are the sets of observations in the parent node, left child, and right child, respectively.

A.4.3 Tuning Parameters

Several hyperparameters need to be tuned for optimal performance:

- Learning rate (η): Controls the contribution of each tree. Smaller values require more trees but can improve generalization. We use as grid for tuning this parameter the values $(0.01, 0.05, 0.1, 0.2, 0.3)$. The default is 0.3.
- Maximum depth (`max_depth`): Limits the depth of each tree to prevent overfitting. We use as grid for tuning this parameter the values $(4, 6, 8, 10, 12, 14)$. The default is 6.
- Subsample ratio (`subsample`): Fraction of the training data used to build each tree, introducing randomness. We use as grid for tuning this parameter the values $(0.7, 0.8, 0.9, 1)$. The default is 1.
- Subsample ratio of columns when constructing each tree (`colsample_bytree`) : We use as grid for tuning this parameter the values $(0.7, 0.8, 0.9, 1)$. The default is 1.
- Regularization parameters (λ, γ): Control the complexity of the model by penalizing large leaf weights and deep trees. We use the default values, $\lambda = 1$ and $\gamma = 0$.
- Minimum child weight (`min_child_weight`): Minimum sum of instance weights (Hessian) needed in a child node to allow a split. We use as grid for tuning this parameter the values $(1, 2, 3, 4, 5, 6)$. The default is 1.

These hyperparameters can be tuned using cross-validation or grid search to find the combination that minimizes validation error. We used K=5 fold cross validation for minimizing the root mean squared error. We stop training the validation set if the performance has not improved for 10 rounds.

A.4.4 Variable Importance

In XGBoost, variable importance is evaluated using the Gain metric, which quantifies the contribution of each feature to the model's predictive performance. Gain measures the improvement in the objective function resulting from splits that involve a particular feature.

For a given feature C_p, the Gain from a split at node j in tree $\widehat{\mathcal{G}}_r$ is defined as the reduction in the objective function achieved by partitioning the data based on C_p. Formally, it is expressed as

$$\text{Gain}_{j,r}(C_p) = \mathcal{L}(\text{parent}) - \left[\mathcal{L}(\text{left child}) + \mathcal{L}(\text{right child})\right], \tag{A.19}$$

where $\mathcal{L}(\cdot)$ denotes the regularized mean squared error; $\mathcal{L}(\text{parent})$ is the objective function value before the split; $\mathcal{L}(\text{left child})$ and $\mathcal{L}(\text{right child})$ are the objective function values after the split for the left and right child nodes, respectively. The objective function in XGBoost incorporates both the loss function and a regularization term to control model complexity. For a split involving feature C_p, the Gain can be derived from the second-order Taylor expansion of the objective function. Specifically, the Gain for a split at node j is given by

$$\text{Gain}_{j,r}(C_p) = \frac{1}{2}\left(\frac{\left(\sum_{i\in I_L} g_i^{(t)}\right)^2}{\sum_{i\in I_L} h_i^{(t)} + \lambda} + \frac{\left(\sum_{i\in I_R} g_i^{(t)}\right)^2}{\sum_{i\in I_R} h_i^{(t)} + \lambda} - \frac{\left(\sum_{i\in I_P} g_i^{(t)}\right)^2}{\sum_{i\in I_P} h_i^{(t)} + \lambda}\right) - \gamma, \tag{A.20}$$

where I_P, I_L, and I_R are the sets of observations in the parent node, left child node, and right child node, respectively. $g_i^{(t)}$ and $h_i^{(t)}$ are the first and second derivatives (gradients and Hessians) of the loss function with respect to the prediction for observation i at iteration t, as defined in Equation (A.11). λ is the regularization parameter controlling the ℓ_2-norm of the leaf γ is the regularization parameter controlling the number of leaves in the tree.

The overall importance of a feature C_p in the ensemble of trees is aggregated as follows. For each tree $\widehat{\mathcal{G}}_r$ in the ensemble, compute the total Gain contributed by feature C_p

$$TG_r(C_p) = \sum_{j\in\mathcal{J}_r(C_p)} \text{Gain}_{j,r}(C_p), \tag{A.21}$$

where $\mathcal{J}_r(C_p)$ is the set of all nodes in tree $\widehat{\mathcal{G}}_r$ where C_p is used as the splitting feature. Then we aggregate the total Gain across all trees in the ensemble to obtain the overall importance of C_p:

$$\widehat{VI}_k^{XGBoost} = \sum_{r=1}^{R} TG_r(C_p). \tag{A.22}$$

Circumstances with higher cumulative Gain are considered more important, as they contribute more significantly to reducing the loss function and enhancing the model's predictive accuracy.

A.5 Inequality Measures

The Gini index is defined as

$$Gini = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|Y_i - Y_j|}{2n^2\bar{Y}}, \tag{A.23}$$

where Y_i and Y_j are individual incomes, $\bar{Y}$ is the mean income, and n is the number of observations. As alternative measurements, we consider Generalized Entropy (GE) indices. Generalized Entropy indices depend on the parameter α, which determines sensitivity to inequality at different parts of the income distribution:

The Generalized Entropy (GE) index is defined as

$$GE_\alpha = \begin{cases} \frac{1}{\alpha(\alpha-1)}\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{Y_i}{\bar{Y}}\right)^\alpha - 1\right], & \text{if } \alpha \neq 0 \text{ and } \alpha \neq 1, \\ \frac{-1}{n}\sum_{i=1}^{n}\ln\left(\frac{Y_i}{\bar{Y}}\right), & \text{if } \alpha = 0, \\ \frac{1}{n}\sum_{i=1}^{n}\frac{Y_i}{\bar{Y}}\ln\left(\frac{Y_i}{\bar{Y}}\right), & \text{if } \alpha = 1. \end{cases} \tag{A.24}$$

We consider three types of GE_α, the Mean Log Deviation (MLD) with $\alpha = 0$, the Theil Index with $\alpha = 1$ and GE_α with $\alpha = 2$, which refers to half the squared coefficient of variation.

A.6 Variable Definitions and Transformations

To address the role of individual characteristics and avoid issues associated with non-ordered categorical structures, variables with multiple non-ordinal categories — such as employment status or tenancy status — were transformed into binary (dummy) variables. Specifically, categories converted into binary dummy variables include the respondent's citizenship; the country of birth and citizenship of both parents; the occupational activity status of both parents; the father's type of occupation; and family type.

In contrast, ordinal variables, such as education level or the household's financial situation, were retained in their original format. These ordinal variables include the education levels of both parents, the household's financial situation, the household's ability to meet end-of-month needs, the number of adults, the number of children, and the number of employed individuals in the household when the respondent was approximately 14 years old. Gender is captured through a dummy variable equal to 1 if the respondent is female. For tenancy status, we only consider ownership, represented by a dummy variable equal to 1 if the household owns the residence.

A specific adjustment was made for parental education levels to account for missing information, particularly when the respondent did not know their mother or father. As detailed in Table Table 1, including a "missing" category in an ordinal variable-ranging from 1 (lowest education level) to 4 (highest education level) would compromise the variable's ordinal nature. To address this, missing parental education levels were replaced with the median level of education for the respective country, preserving the variable's ordinal structure.

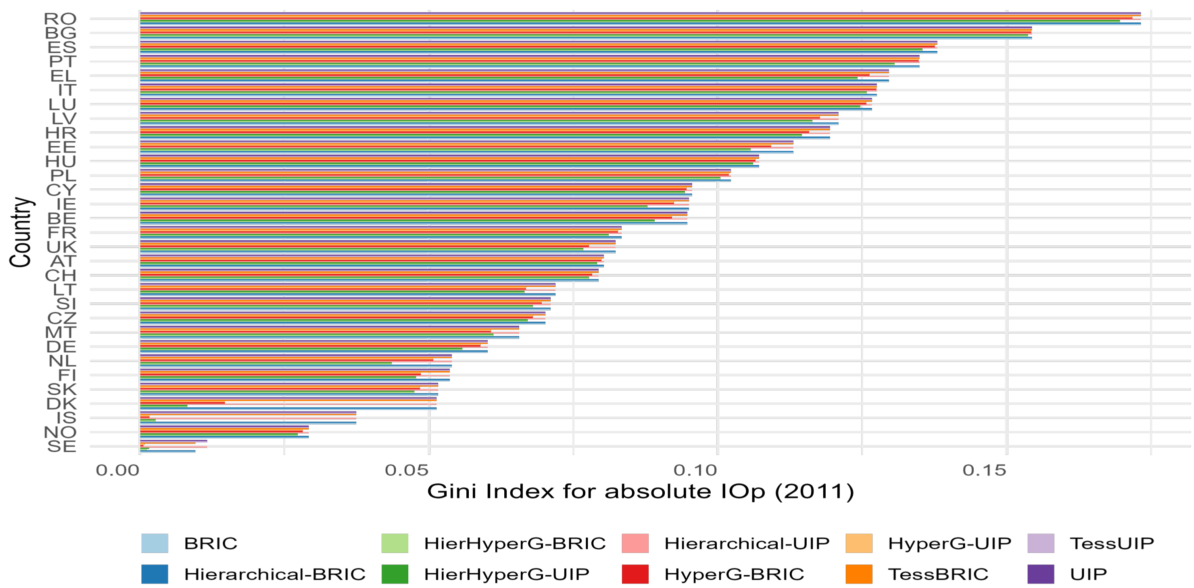
Variables related to the mother's managerial position and occupation type were excluded from the analysis due to the high proportion of missing values across several countries. Following Brunori et al. (2023), the father's employment type was classified into three broad categories: (i) high-skilled non-manual (managers, professionals, technicians, and associate professionals); (ii) low-skilled non-manual (clerical support workers, service and sales workers, armed forces occupations); and (iii) skilled manual and elementary occupations (skilled agricultural, forestry, and fishery workers; craft and related trades workers; plant and machine operators; assemblers; and elementary occupations). Fathers categorized as unemployed, unknown, or deceased were grouped separately.

Figures

Figure A.1: Robustness of Absolute IoP Estimates Across Priors (Gini-Based)

This figure presents absolute inequality of opportunity (IoP) estimates using the Gini coefficient as the inequality measure, derived from Linear-BMA under various prior specifications. The priors include BRIC, Hierarchical-BRIC, HyperG-BRIC, UIP, and their hierarchical and tessellation variants, with each prior represented by a distinct color. The graphs illustrate the sensitivity of IoP estimates to prior choices, emphasizing the robustness of the results across different specifications.

(a) Wave 2011



(b) Wave 2019

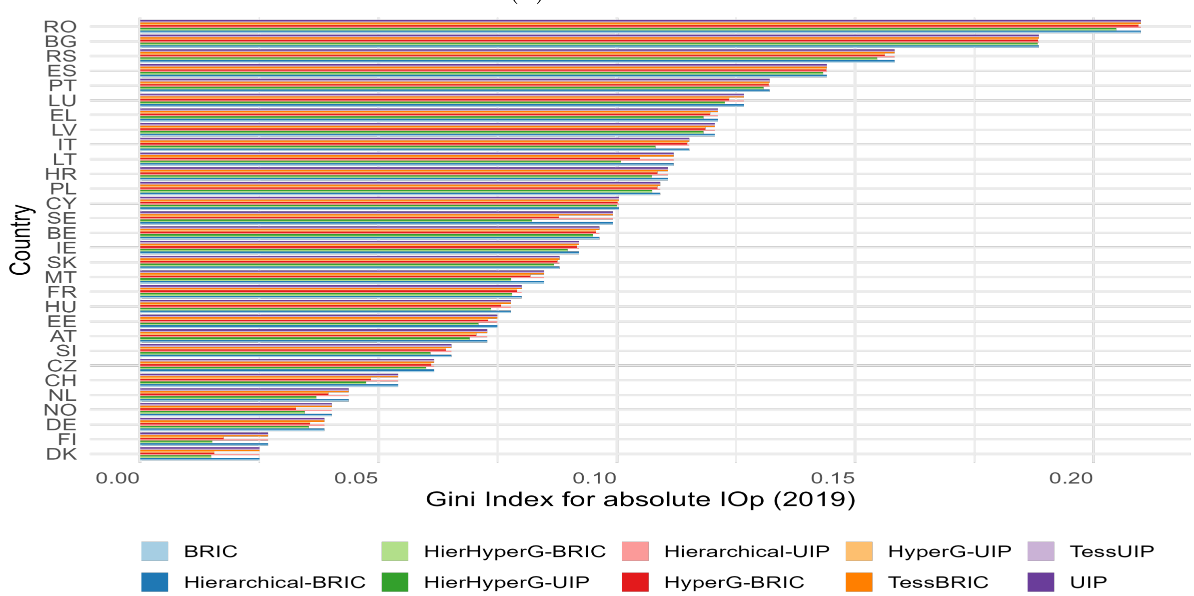
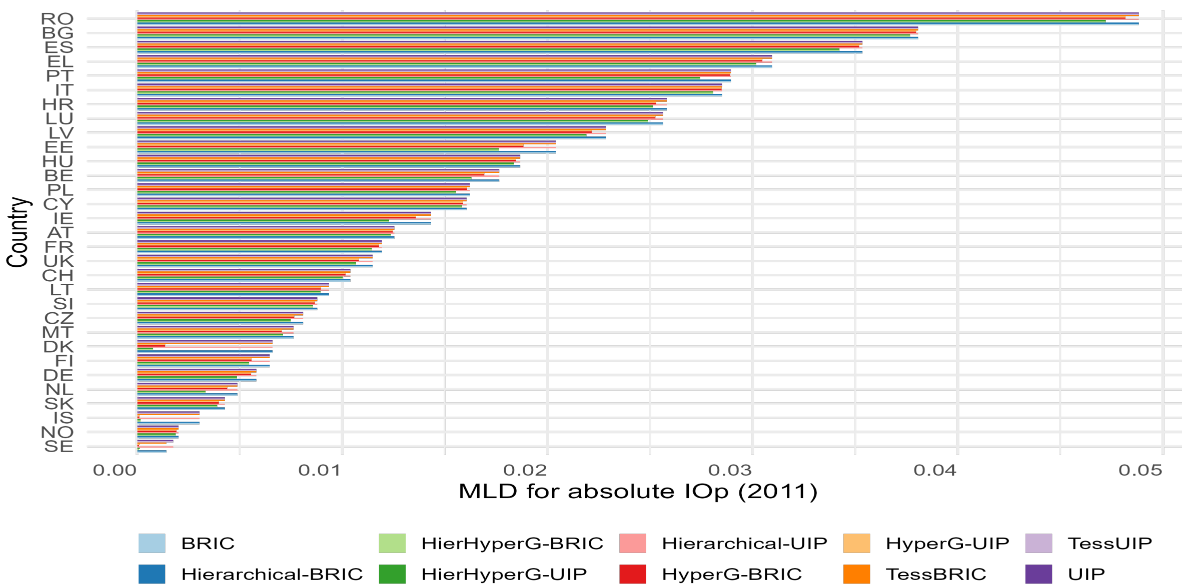


Figure A.2: Robustness of Absolute IoP Estimates Across Priors (MLD-Based)
This figure presents absolute inequality of opportunity estimates using the MLD as the inequality measure, derived from Linear-BMA under various prior specifications. The priors include BRIC, Hierarchical-BRIC, HyperG-BRIC, UIP, and their hierarchical and tessellation variants, with each prior represented by a distinct color. The graphs illustrate the sensitivity of IOp estimates to prior choices, emphasizing the robustness of the results across different specifications.

(a) Wave 2011



(b) Wave 2019

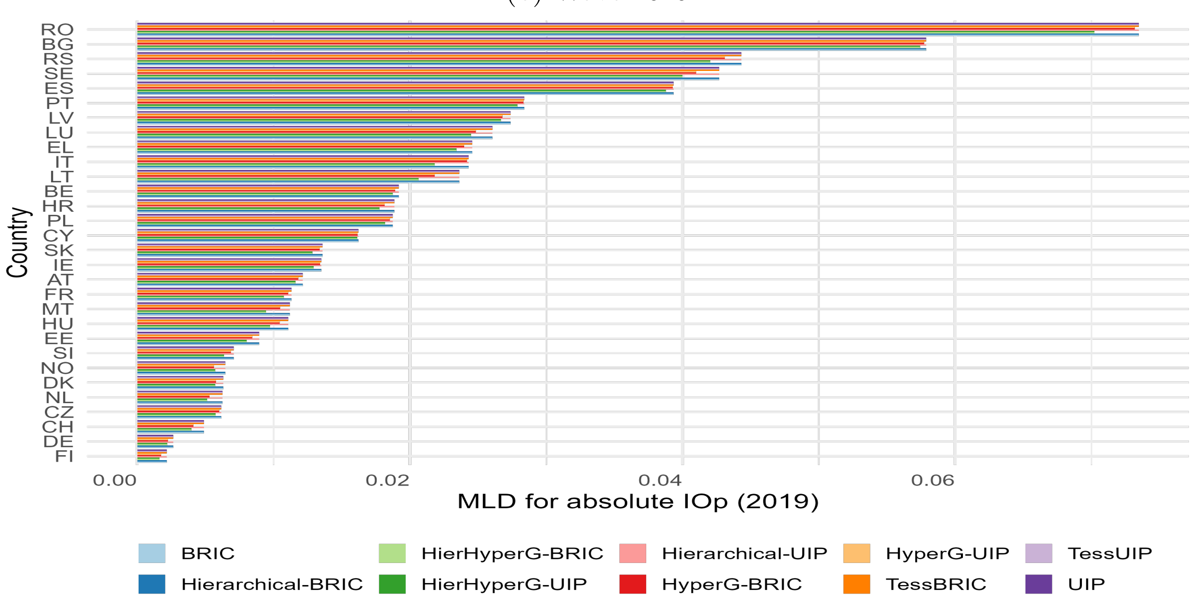
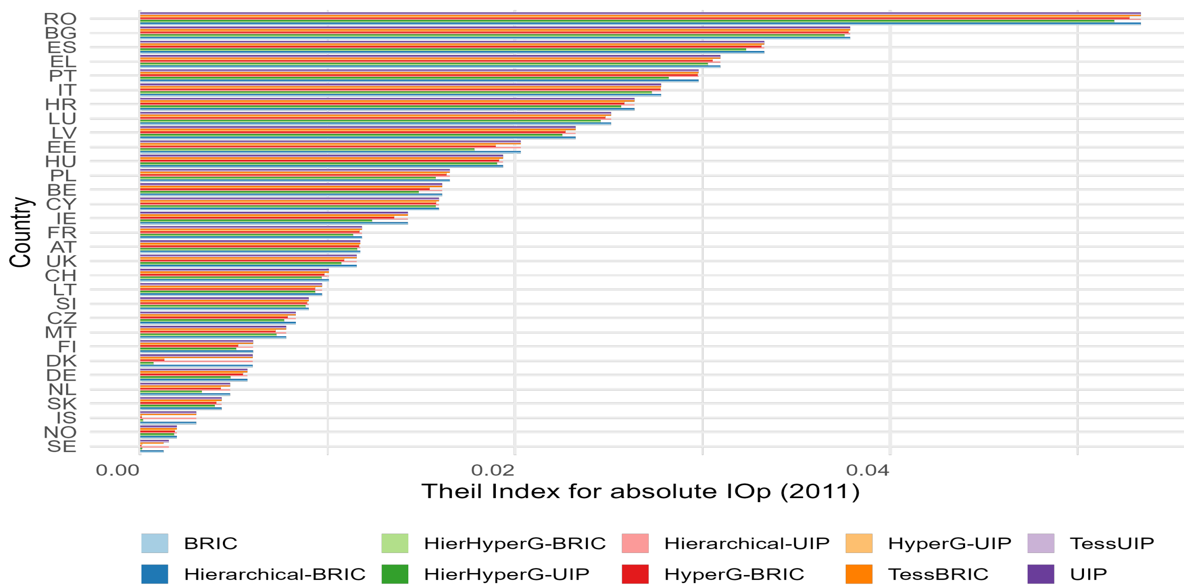


Figure A.3: Robustness of Absolute IoP Estimates Across Priors (Theil Index-Based)

This figure presents absolute inequality of opportunity estimates using the Theil Index as the inequality measure, derived from Linear-BMA under various prior specifications. The priors include BRIC, Hierarchical-BRIC, HyperG-BRIC, UIP, and their hierarchical and tessellation variants, with each prior represented by a distinct color. The graphs illustrate the sensitivity of IoP estimates to prior choices, emphasizing the robustness of the results across different specifications.

(a) Wave 2011



(b) Wave 2019

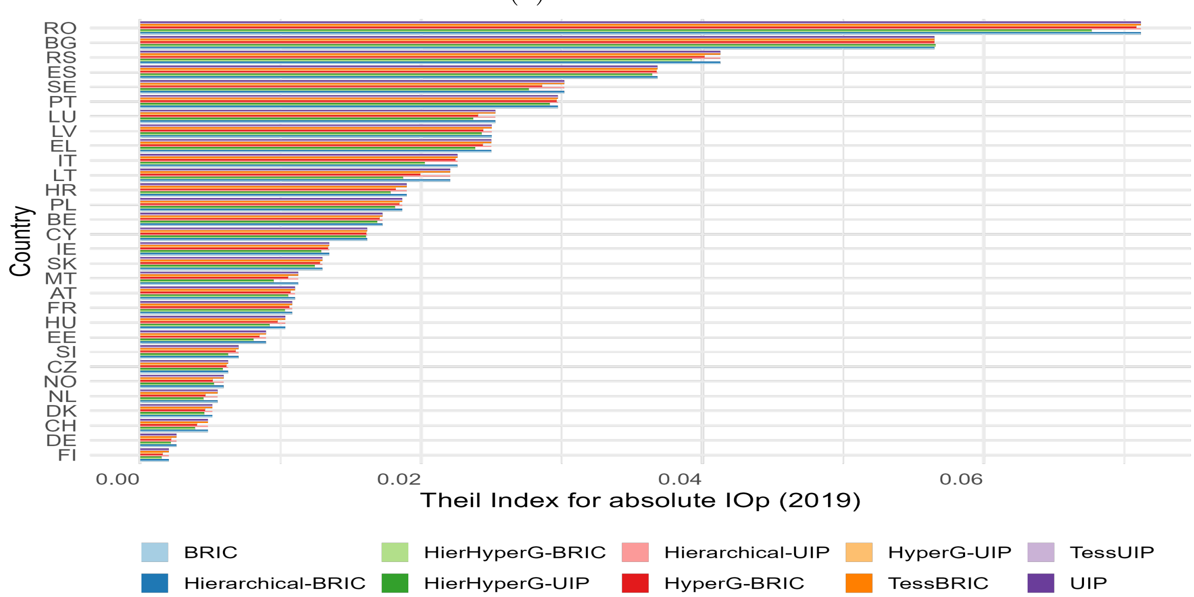
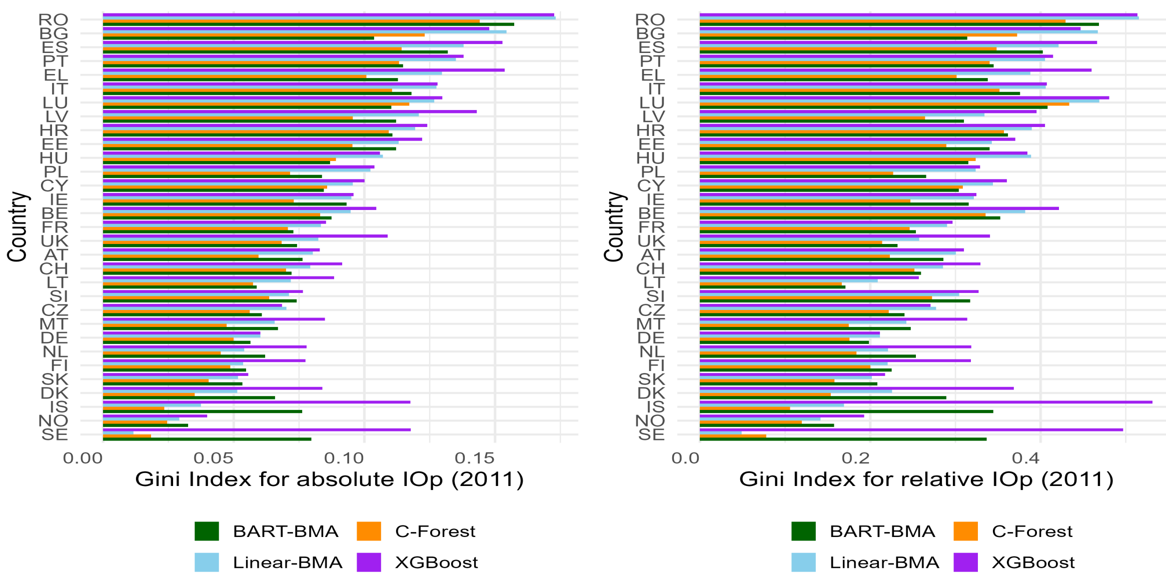


Figure A.4: IoP Estimates - Linear-BMA and Tree-based Methods

This set of figures presents Inequality of Opportunity estimates derived from the Linear-BMA, BART-BMA, C-Forest, and XGBoost approaches. Panel (A) refers to Wave 2011, while panel (B) corresponds to Wave 2019. The figures on the left show IoP in absolute terms, while the figures on the right display IoP in relative terms. All estimates are based on the Gini coefficient as the measure of inequality.

(A) Wave 2011



(B) Wave 2019

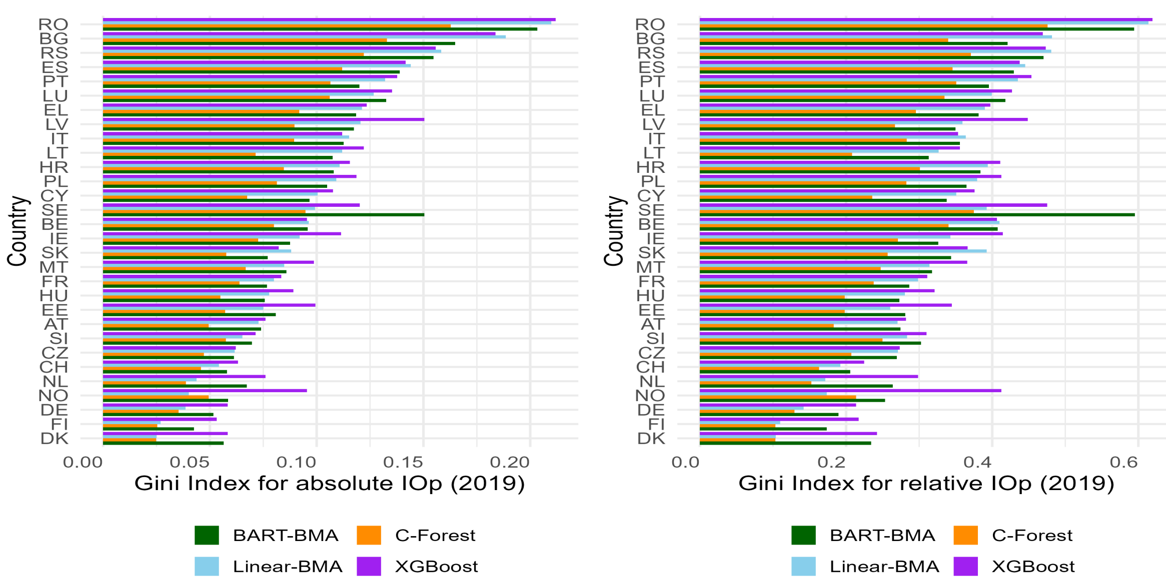


Figure A.5: Change in IoP Between Waves 2011 and 2019Tree-based models

This panel of figures illustrates the changes in IoP estimates Tree-based models based on the Gini coefficient.

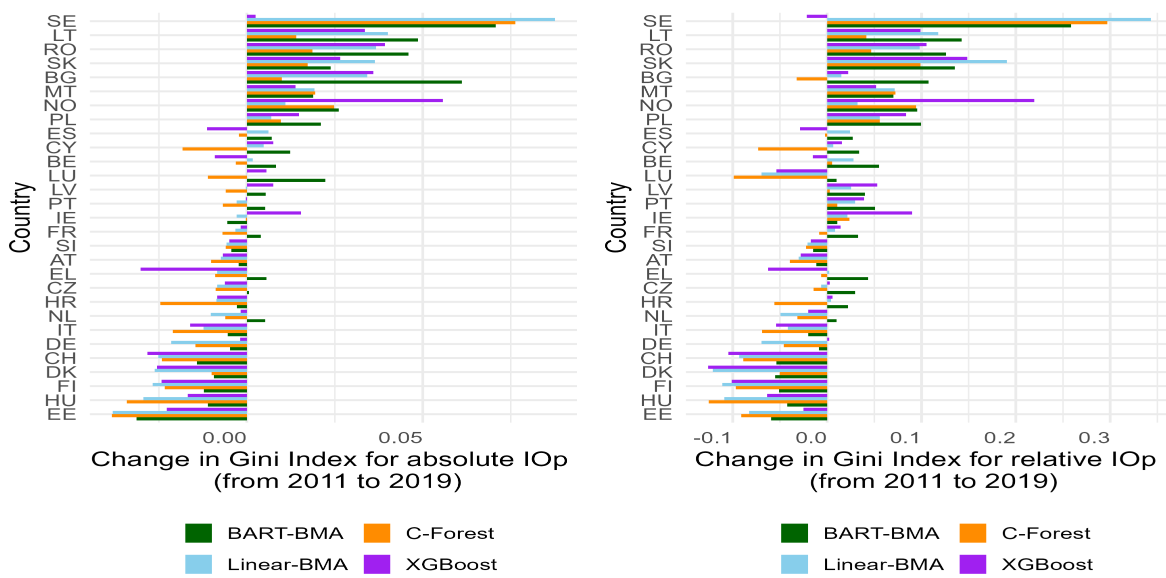
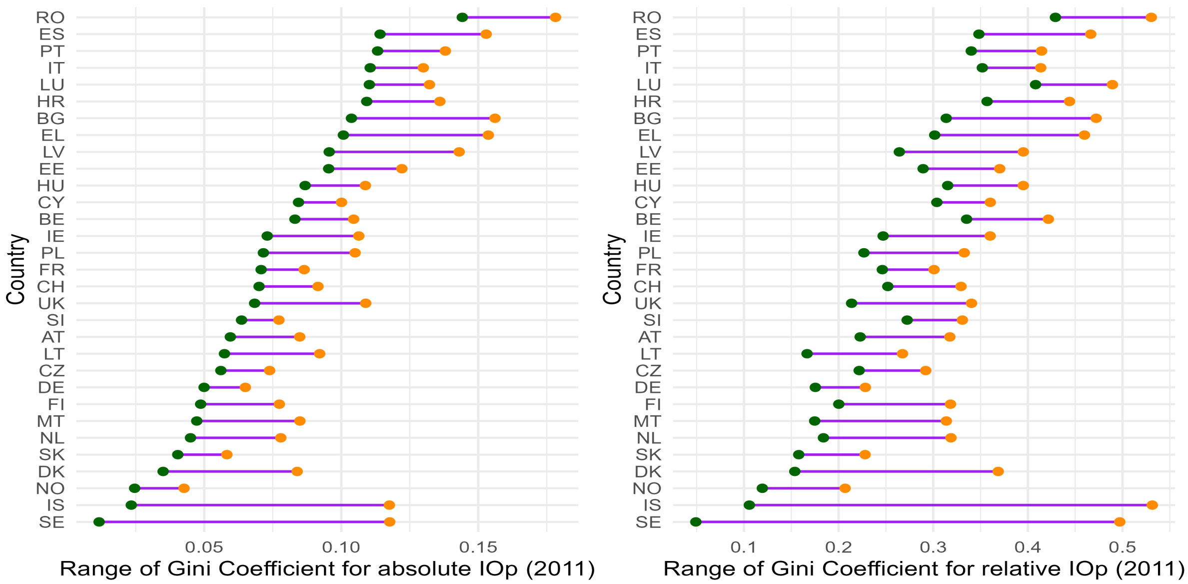


Figure A.6: Bounds of IoP Estimates Based on Various Methods

This panel of figures present the bounds of various measures of Inequality of Opportunity using the Gini index, derived from multiple methods: Linear-KS, Posterior Mode, Linear-BMA, BART-BMA, C-Forest, and XGBoost. The figures on the left show IoP estimates for 2011, while those on the right display estimates for 2019. All indicators are presented in relative terms.

(a) Wave 2011



(b) Wave 2019

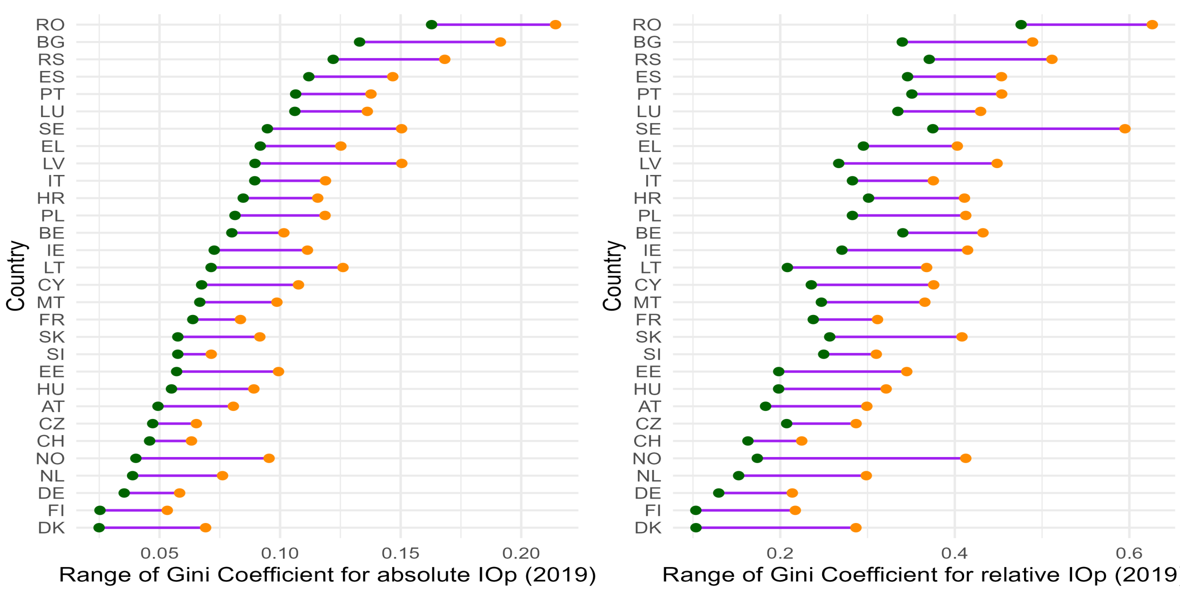
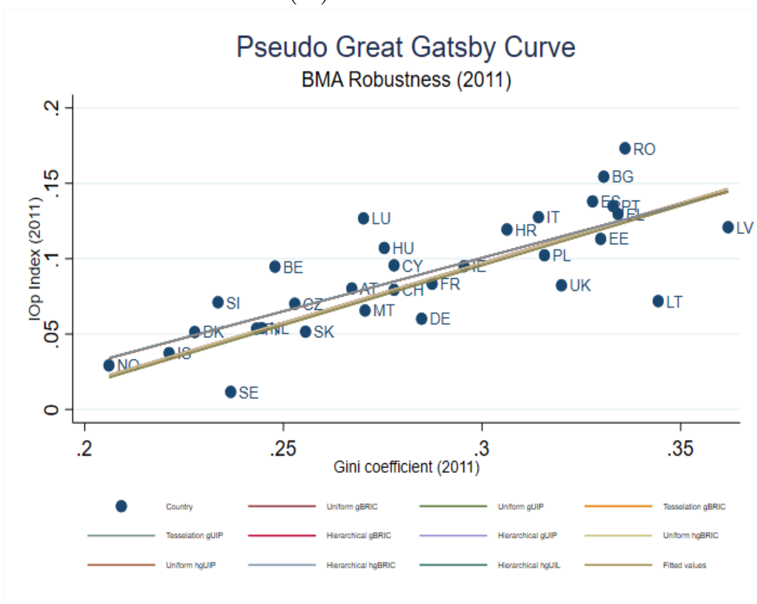


Figure A.7: Robustness for the Pseudo Great Gatsby Curves
This figure provides the relationship between Inequality of Opportunity and Income Inequality.IoP estimates derived from different Linear BMA priors specifications. Panel (A) refers to Wave 2011, while panel (B) corresponds to Wave 2019.

(A) Wave 2011



(B) Wave 2019

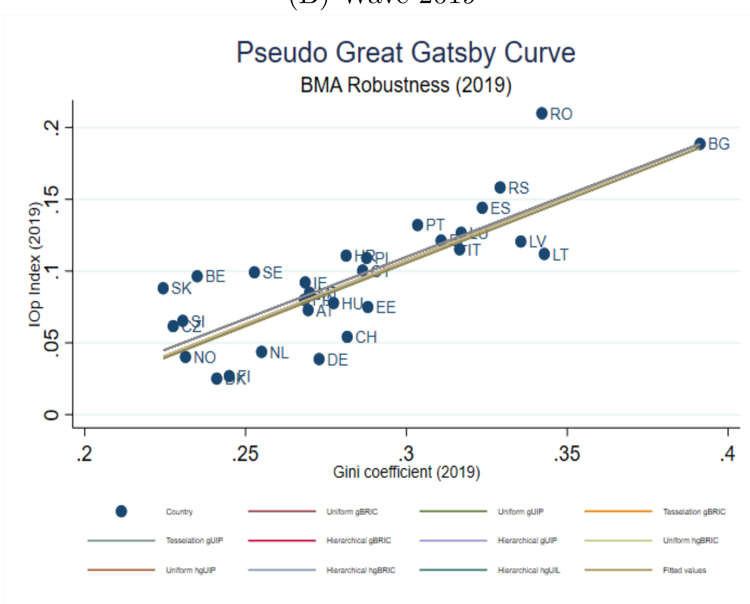
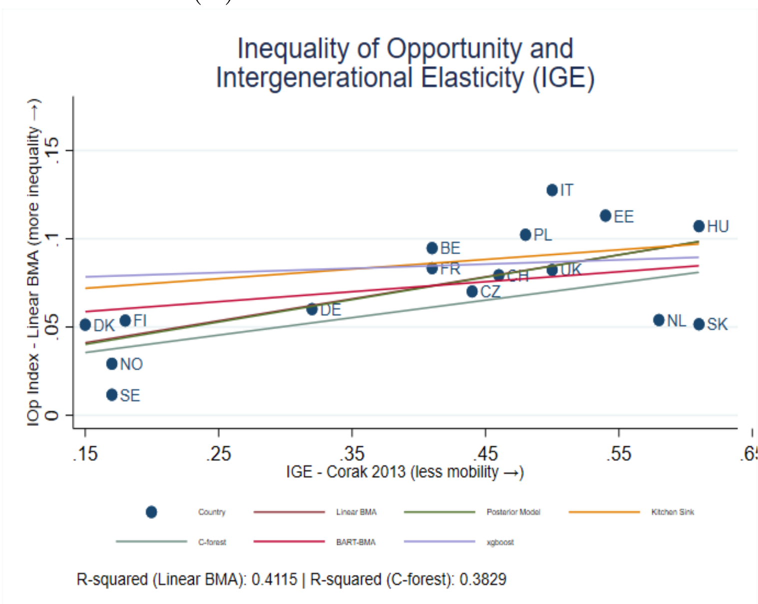


Figure A.8: Inequality of Opportunity and Intergenerational Elasticity of Earning
These figures provide evidence on the relationship between Inequality of Opportunity (y-axis) and IGE (x-axis)

(A) Wave 2011 - All Methods



(B) Wave 2011 - Linear BMA and C-Forest

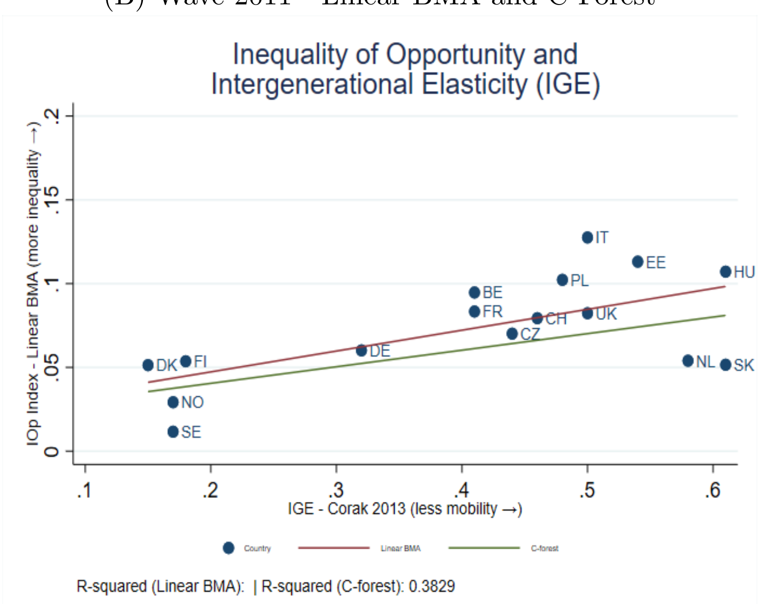


Figure A.9: Number of people aged between 36 and 40.
This figure shows the sample size by country, focusing on individuals aged between 36 and 40.

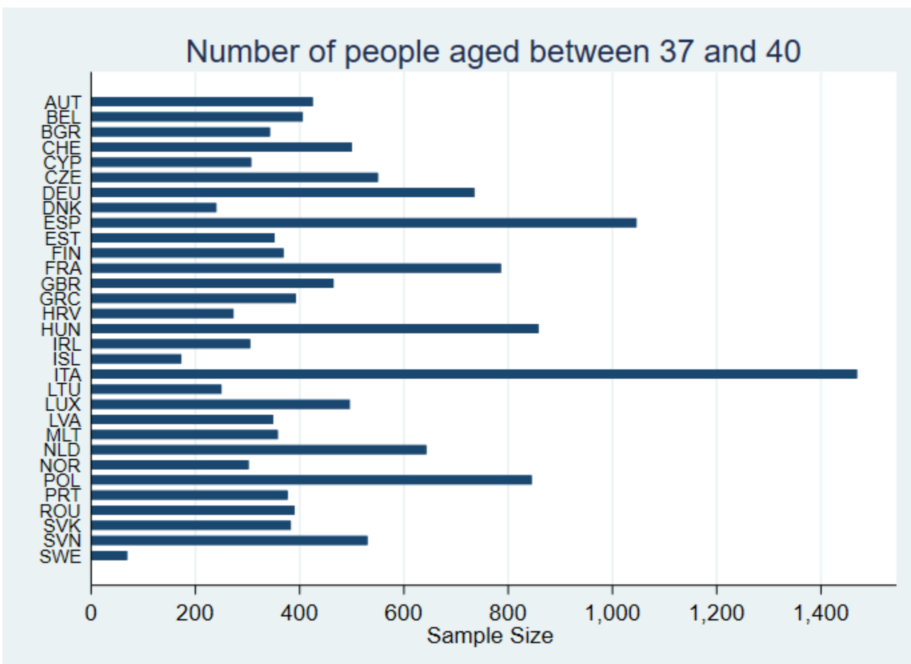
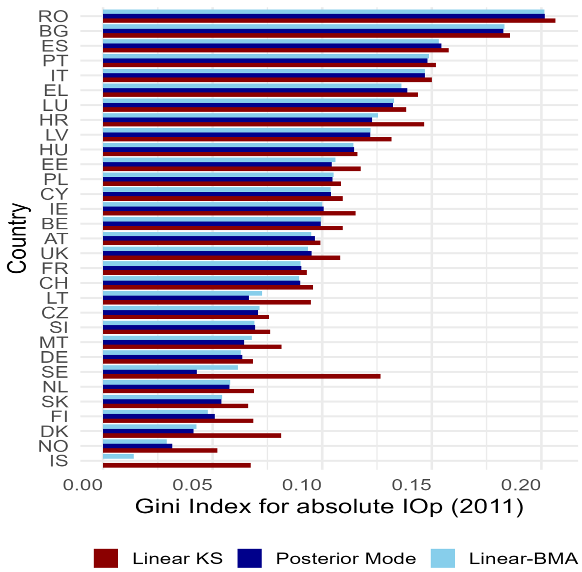
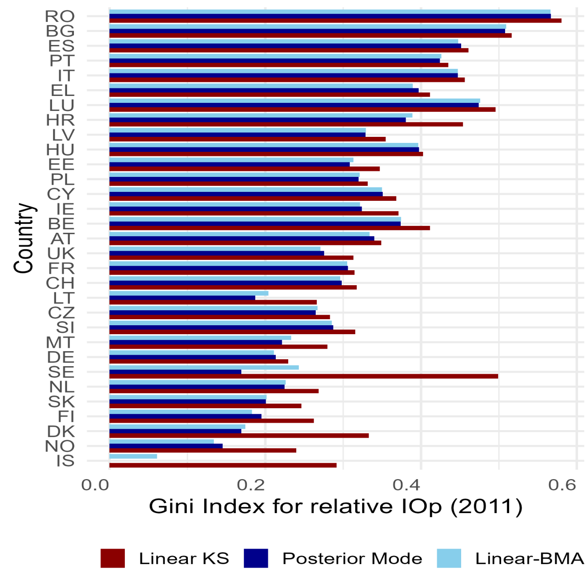


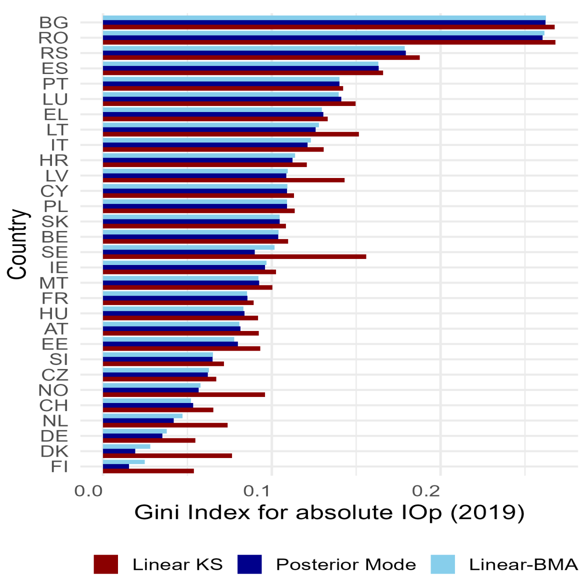
Figure A.10: IOp Estimates - Linear Models - Age-adjusted Income Distributions
This set of figures presents Inequality of Opportunity estimates derived from the Linear-KS, Posterior Mode, and Linear-BMA approaches for Waves 2011 and 2019. For each country, we adjust income for age and age squared, then add back the country-specific mean income. Panel (A) refers to Wave 2011, while panel (B) corresponds to Wave 2019. The figures on the left show IOp in absolute terms, and the figures on the right display IOp in relative terms. All estimates are based on the Gini coefficient as the measure of inequality.

(A) Wave 2011





(B) Wave 2019



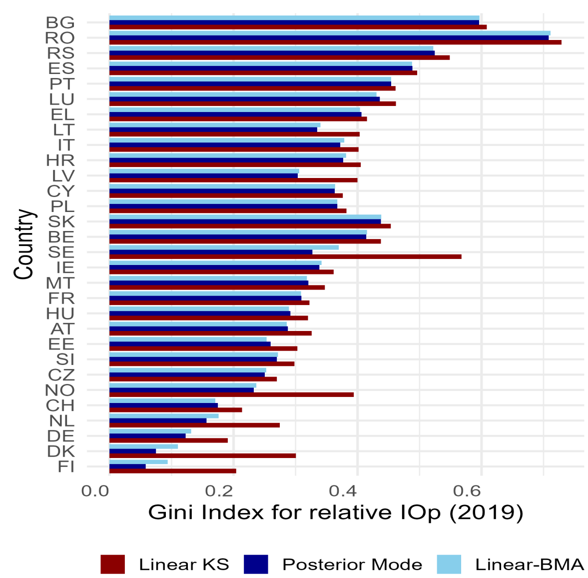
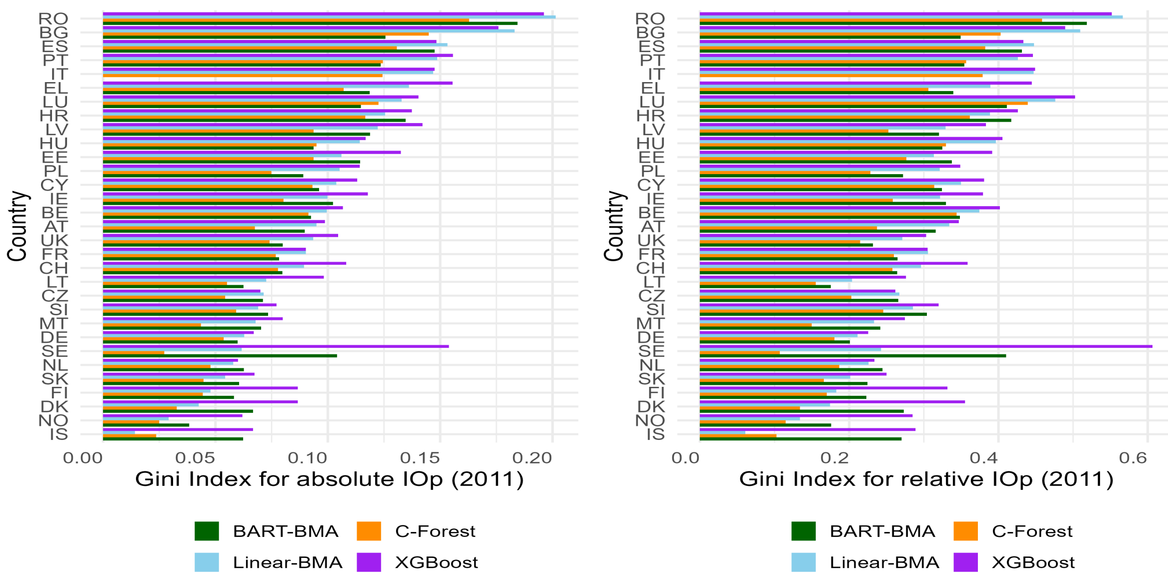


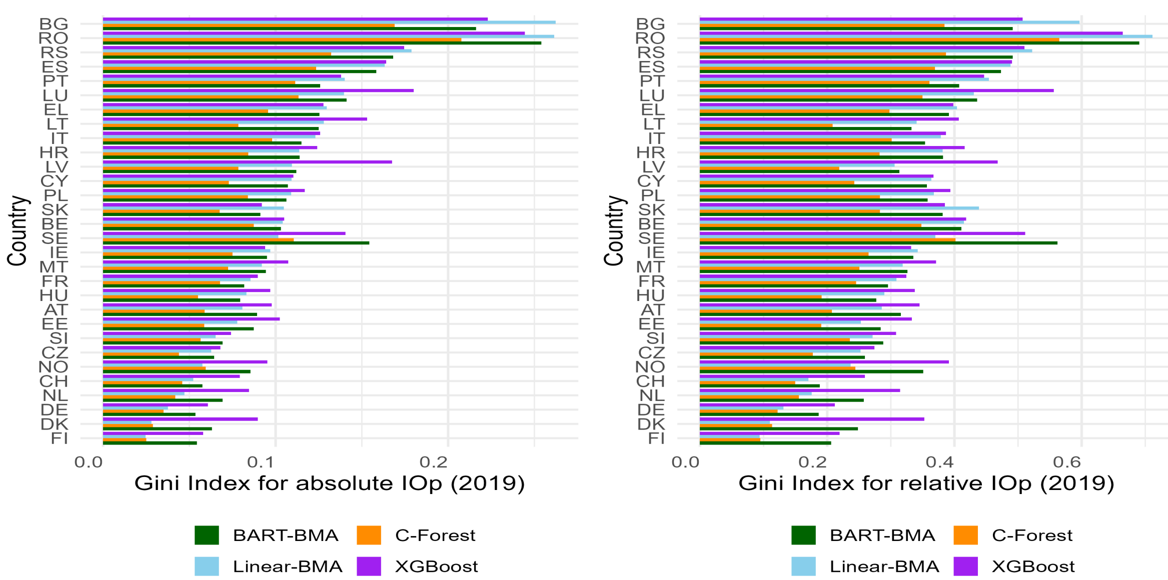
Figure A.11: IoP Estimates - Linear-BMA and Tree-based Methods - Age-adjusted Income Distributions

This set of figures presents Inequality of Opportunity estimates derived from the Linear-BMA, BART-BMA, C-Forest, and XGBoost approaches. For each country, we adjust income for age and age squared, then add back the country-specific mean income. Panel (A) refers to Wave 2011, while panel (B) corresponds to Wave 2019. The figures on the left show IoP in absolute terms, while the figures on the right display IoP in relative terms. All estimates are based on the Gini coefficient as the measure of inequality.

(A) Wave 2011



(B) Wave 2019



Tables

Table A.1: Summary statistics for Income

This table provides summary statistics by country in 2011 and 2019. The column provides the total number of observations and the remaining five columns summarize the distribution of equivalized disposable household income PPP adjusted: mean, standard deviation and Gini index, respectively.

	2011				2019			
Country	**N**	**Mean**	**SD**	**Gini**	**N**	**Mean**	**SD**	**Gini**
AT	6220	25822.59	13559.18	0.267	5398	25772.31	13329.88	0.269
BE	6011	21.989	10.210	0.248	6212	23174.09	10385.38	0.235
BG	7146	8044.97	5379.53	0.331	6715	11702.34	10339.4	0.391
CH	7583	26536.39	14853.23	0.278	7096	31667.28	17161.06	0.282
CY	4589	22296.34	12.128	0.278	4362	22586.62	14208.04	0.286
CZ	8711	13701.82	6695.02	0.253	7283	16688.85	7077.73	0.228
DE	12683	24018.78	12735.05	0.285	9732	26010.14	13949.47	0.273
DK	5795	25743.47	10.301	0.228	4367	28372.49	11811.74	0.241
EE	5338	10355.61	6288.5	0.330	6022	15632.68	8002.69	0.288
EL	6184	12864.69	8905.98	0.334	14733	11107.59	6858.92	0.311
ES	15481	18084.27	11094.19	0.328	17229	18368.74	11090.94	0.324
FI	9743	24533.47	11940.67	0.243	9454	26122.18	12763.45	0.245
FR	11078	23251.59	13.798	0.287	10255	23601.26	12914.76	0.268
HR	6945	9.828	5.764	0.306	7515	12268.35	6634.01	0.281
HU	13330	9988.97	5456.16	0.275	5574	9593.48	4893.29	0.277
IE	4318	20704.1	11.970	0.295	4238	22999.76	12703.41	0.269
IS	3682	22628.31	9242.7	0.221	N/A	N/A	N/A	N/A
IT	21070	20.420	12.263	0.314	17613	20470.65	11663.72	0.317
LT	5403	8786.89	5604.43	0.344	4801	15070.94	10041.63	0.343
LU	6765	28.799	15.451	0.270	4719	28842.45	18281.41	0.317
LV	6423	8188.93	5.747	0.362	4509	12976.28	8622.96	0.336
MT	4431	17155.64	8950.54	0.271	3538	20727.47	10759.52	0.270
NL	11411	24354.62	10672.32	0.245	11362	24563.26	11999.04	0.255
NO	5026	28171.47	10.868	0.206	6207	28909.88	12922.14	0.231
PL	15545	11235.09	7.128	0.316	19743	13957.88	7991.95	0.288
PT	5899	12.731	8.849	0.333	13767	13198.72	8683.95	0.303
RO	7820	5636.55	3.530	0.336	7217	9284.36	5653.28	0.342
RS	N/A	N/A	N/A	N/A	6492	6741.84	4308.51	0.329
SE	6599	20500.91	8.342	0.237	5206	22387.92	9585.13	0.253
SI	13183	10796.54	4.630	0.234	10756	12060.45	5175.58	0.230
SK	6779	12256.34	5624.33	0.256	6073	11156.28	4500.36	0.224
UK	7391	21572.09	14182.21	0.320	N/A	N/A	N/A	N/A

Table A.2: Summary Statistics - Set of Circumstances

These tables summarize the statistics for the circumstances analyzed in 2011 and 2019. For Father Circumstances, the variables Citizenship/Country of Birth (categorized as EU, Non-EU, or Non-European countries) and Occupational Activity Status (classified as Dead/Unknown, House Worker, Other Inactive, or Part-time Employed) have been omitted. Similarly, for Mother Circumstances, the variables Citizenship/Country of Birth (categorized as EU, Non-EU, or Non-European countries) and Occupational Activity Status (classified as Dead/Unknown, Other Inactive, or Part-time Employed) have also been omitted. For Household Circumstances, the variables Tenancy Status of the House (Don't know, Tenant, Public House) and Family Type (e.g., lived with only father or mother, lived in a private household without any parent, or in a collective household/institution) have been omitted as well. Additionally, information regarding parental citizenship or supervisory status is unavailable for Slovenia.

Panel A: Fathers

	2011											2019										
Country	N	Citiz. Resid	Birth Area Native	Empl.	Self-Empl	Unempl	Retired	Manual and elementary occupations	Low-Skill non-man	High-Skill non-man	Average Education	N	Citiz. Resid	Birth Area Native	Empl.	Self-Empl	Unempl	Retired	Manual and elementary occupations	Low-Skill non-manual	High-Skill non-manual	Average Education
AT	6074	0.79	0.83	0.71	0.22	0.00	0.01	0.57	0.21	0.15	2.74	4767	0.75	0.72	0.72	0.19	0.00	0.01	0.48	0.22	0.20	2.14
BE	4573	0.74	0.76	0.74	0.13	0.01	0.01	0.42	0.14	0.31	2.56	5771	0.68	0.66	0.71	0.16	0.01	0.01	0.37	0.22	0.29	1.88
BG	5946	0.93	0.93	0.90	0.03	0.00	0.00	0.71	0.09	0.13	2.48	5807	0.94	0.95	0.91	0.02	0.01	0.00	0.64	0.11	0.19	1.81
CH	6487	0.68	0.70	0.66	0.29	0.00	0.00	0.44	0.12	0.38	2.89	4679	0.65	0.61	0.70	0.20	0.00	0.00	0.00	0.13	0.78	2.28
CY	4508	0.82	0.83	0.55	0.40	0.00	0.01	0.67	0.14	0.14	2.27	4216	0.76	0.76	0.60	0.31	0.01	0.00	0.56	0.18	0.18	1.7
CZ	6341	0.88	0.91	0.89	0.02	0.00	0.01	0.60	0.09	0.22	2.37	6804	0.86	0.84	0.85	0.03	0.00	0.00	0.58	0.07	0.24	1.76
DE	10524	0.88	0.94	0.82	0.13	0.01	0.01	0.49	0.12	0.33	3.15	5987	0.81	0.77	0.76	0.09	0.01	0.01	0.39	0.10	0.37	2.46
DK	2054	0.93	0.97	0.69	0.29	0.00	0.01	0.52	0.16	0.31	2.87	2071	0.87	0.86	0.65	0.24	0.00	0.02	0.43	0.09	0.38	2.13
EE	4935	0.67	0.71	0.81	0.01	0.00	0.01	0.60	0.03	0.18	2.58	5406	0.65	0.65	0.75	0.02	0.01	0.00	0.53	0.03	0.21	2.31
EL	5750	0.90	0.93	0.39	0.58	0.00	0.00	0.72	0.12	0.12	2.18	13588	0.91	0.91	0.41	0.54	0.00	0.00	0.65	0.21	0.08	1.42
ES	14699	0.90	0.91	0.68	0.24	0.00	0.02	0.60	0.15	0.17	2.17	16154	0.80	0.80	0.67	0.22	0.01	0.01	0.58	0.17	0.15	1.54
FI	2996	0.80	0.80	0.56	0.22	0.02	0.01	0.51	0.07	0.21	2.44	4411	0.88	0.88	0.58	0.26	0.02	0.03	0.46	0.10	0.29	1.99
FR	10157	0.80	0.87	0.75	0.18	0.00	0.01	0.54	0.12	0.27	2.23	8100	0.78	0.73	0.73	0.14	0.01	0.01	0.40	0.12	0.21	1.63
HR	5950	0.82	0.83	0.74	0.12	0.04	0.02	0.61	0.11	0.14	2.40	6854	0.86	0.79	0.76	0.13	0.02	0.02	0.61	0.12	0.16	1.67
HU	12186	0.96	0.97	0.90	0.04	0.00	0.01	0.71	0.08	0.15	2.40	4288	0.89	0.89	0.85	0.04	0.01	0.01	0.69	0.07	0.12	1.81
IE	3091	0.80	0.78	0.66	0.23	0.05	0.01	0.51	0.12	0.24	2.49	3373	0.75	0.74	0.63	0.20	0.03	0.01	0.26	0.36	0.23	1.87
IS	1444	0.93	0.93	0.64	0.33	0.00	0.00	0.53	0.12	0.32	2.81	.	.	.	.	.	.	.	.	.	.	.
IT	20740	0.85	0.85	0.60	0.26	0.01	0.02	0.55	0.14	0.17	2.19	16267	0.81	0.80	0.64	0.22	0.00	0.01	0.53	0.15	0.19	1.65
LT	4550	0.90	0.92	0.92	0.01	0.00	0.00	0.72	0.05	0.16	2.35	3582	0.81	0.79	0.78	0.02	0.01	0.01	0.58	0.03	0.19	2.1
LU	6594	0.40	0.41	0.76	0.17	0.00	0.01	0.57	0.09	0.27	2.50	3208	0.28	0.27	0.76	0.11	0.00	0.01	0.50	0.15	0.22	1.91
LV	6080	0.58	0.65	0.77	0.00	0.00	0.01	0.58	0.05	0.15	2.46	3246	0.61	0.61	0.75	0.01	0.01	0.01	0.53	0.04	0.19	2.29
MT	4035	0.96	0.96	0.72	0.21	0.01	0.01	0.51	0.22	0.20	2.11	3165	0.89	0.89	0.75	0.18	0.00	0.01	0.47	0.20	0.25	1.78
NL	5456	0.90	0.93	0.73	0.18	0.01	0.00	0.39	0.14	0.39	2.70	4725	0.90	0.87	0.72	0.18	0.00	0.00	0.36	0.14	0.40	1.83
NO	2245	0.91	0.93	0.72	0.25	0.00	0.01	0.46	0.10	0.41	2.97	2078	0.75	0.73	0.68	0.22	0.00	0.00	0.24	0.07	0.38	2.27
PL	12703	0.95	0.98	0.67	0.28	0.00	0.00	0.75	0.07	0.12	2.52	13790	0.92	0.91	0.64	0.26	0.00	0.00	0.69	0.05	0.15	1.87
PT	5735	0.95	0.96	0.64	0.26	0.00	0.01	0.66	0.12	0.12	1.84	12993	0.88	0.87	0.66	0.22	0.01	0.01	0.59	0.14	0.16	1.38
RO	5705	0.94	0.94	0.59	0.28	0.00	0.02	0.76	0.05	0.07	2.12	6620	0.93	0.93	0.76	0.14	0.00	0.00	0.76	0.04	0.08	1.88
RS	.	.	.	.	.	.	.	.	.	.	.	5019	0.87	0.81	0.84	0.00	0.05	0.01	0.57	0.17	0.11	1.9
SE	467	0.83	0.87	0.75	0.19	0.01	0.03	0.52	0.16	0.27	2.55	1883	0.77	0.74	0.72	0.22	0.01	0.01	0.40	0.11	0.42	2.01
SI	4694	0.79	.	0.77	0.10	0.01	0.02	0.60	0.10	0.18	2.34	4162	0.78	0.72	0.78	0.11	0.01	0.02	0.56	0.09	0.24	1.97
SK	6159	0.94	0.95	0.92	0.01	0.00	0.01	0.66	0.08	0.19	2.70	5376	0.90	0.89	0.87	0.01	0.01	0.00	0.61	0.09	0.19	1.69
UK	5802	0.83	0.89	0.80	0.14	0.02	0.01	0.49	0.13	0.32	2.52	.	.	.	.	.	.	.	.	.	.	.

Note: The table is continued on the next page ...

Table A.2 continued: Panel B: Mother

	2011									2019								
Country	N	Citiz. Resid	Birth Area Native	Empl.	Self-Empl	Unempl	Retired	House worker	Average Education	N	Citiz. Resid	Birth Area Native	Empl.	Self-Empl	Unempl	Retired	House worker	Average Education
AT	6082	0.84	0.79	0.37	0.17	0	0	0.43	2.41	4750	0.8	0.76	0.51	0	0.15	0	0.01	1.71
BE	4507	0.78	0.75	0.35	0	0.01	0	0.59	2.42	5771	0.72	0.69	0.33	0.08	0.1	0.01	0	1.68
BG	5872	0.98	0.93	0.89	0.03	0.01	0	0.05	2.52	5807	0.97	0.97	0.88	0.02	0.01	0.01	0	1.76
CH	6493	0.69	0.65	0.37	0.15	0	0	0.44	2.55	4680	0.7	0.63	0.15	0.32	0.09	0	0	1.87
CY	4504	0.83	0.82	0.29	0.19	0	0	0.51	2.12	4216	0.79	0.78	0.38	0.01	0.14	0	0	1.49
CZ	6420	0.95	0.88	0.89	0.01	0	0	0.07	2.32	6803	0.92	0.9	0.87	0.01	0.02	0	0	1.57
DE	10550	0.94	0.88	0.46	0.05	0.01	0	0.46	2.8	5989	0.88	0.84	0.34	0.27	0.06	0.01	0	2.15
DK	2054	0.93	0.92	0.58	0.07	0	0.01	0.33	2.63	2059	0.92	0.91	0.55	0.18	0.07	0.01	0.02	1.87
EE	4909	0.8	0.68	0.89	0	0	0	0.06	2.7	5396	0.79	0.77	0.85	0.01	0.01	0.01	0	2.1
EL	5751	0.93	0.9	0.15	0.34	0	0	0.49	2.07	13588	0.93	0.92	0.17	0.01	0.27	0	0	1.28
ES	14721	0.91	0.9	0.16	0.07	0	0	0.74	2.04	16084	0.84	0.83	0.21	0.04	0.09	0	0	1.31
FI	2948	0.91	0.8	0.63	0.22	0.02	0	0.06	2.52	4411	0.93	0.93	0.61	0.04	0.17	0.02	0.03	1.85
FR	10155	0.89	0.82	0.43	0.09	0	0	0.44	2.16	7998	0.82	0.77	0.41	0.09	0.08	0	0	1.45
HR	5952	0.84	0.83	0.3	0.07	0.03	0.01	0.58	2.2	6854	0.9	0.83	0.43	0	0.07	0.02	0.01	1.42
HU	12171	0.98	0.97	0.72	0.02	0	0.01	0.23	2.32	4295	0.95	0.94	0.75	0.01	0.02	0	0	1.55
IE	3091	0.78	0.8	0.24	0.05	0.01	0	0.68	2.52	3369	0.8	0.79	0.21	0.11	0.05	0	0	1.72
IS	1445	0.93	0.91	0.59	0.1	0	0	0.29	2.42	.								
IT	20514	0.89	0.85	0.23	0.1	0	0.01	0.62	2.13	16265	0.83	0.82	0.26	0.02	0.08	0	0	1.49
LT	4555	0.96	0.9	0.84	0.02	0	0	0.11	2.44	3582	0.94	0.91	0.85	0.01	0.01	0	0.01	1.84
LU	6574	0.41	0.39	0.3	0.12	0	0	0.53	2.3	3205	0.29	0.28	0.32	0.09	0.05	0	0	1.6
LV	6048	0.8	0.59	0.89	0	0	0.01	0.06	2.6	3243	0.76	0.75	0.87	0	0.01	0.01	0.01	1.95
MT	4028	0.96	0.96	0.06	0.01	0	0	0.91	2	3160	0.92	0.91	0.1	0.02	0.02	0	0	1.61
NL	5451	0.95	0.9	0.28	0.06	0	0	0.63	2.48	4725	0.93	0.89	0.07	0.29	0.08	0	0	1.5
NO	2328	0.92	0.9	0.63	0.1	0.01	0.01	0.24	2.83	2078	0.79	0.76	0.53	0.2	0.08	0	0	2.07
PL	12689	0.99	0.95	0.47	0.31	0.01	0	0.18	2.46	13790	0.97	0.96	0.52	0.01	0.27	0.01	0	1.71
PT	5733	0.96	0.95	0.33	0.2	0	0.01	0.41	1.75	12993	0.94	0.92	0.38	0.03	0.11	0.01	0	1.2
RO	5590	0.96	0.94	0.33	0.27	0.01	0.01	0.32	2.12	6620	0.98	0.98	0.46	0.02	0.18	0.01	0	1.65
RS	.	.	.	.	.	.	.	.	.	5019	0.89	0.83	0.49	0	0	0.06	0.01	1.62
SE	467	0.87	0.82	0.65	0.06	0	0.02	0.24	2.63	1768	0.8	0.76	0.73	0	0.06	0.01	0.02	1.97
SI	4693	.	0.81	0.58	0.07	0	0.01	0.3	2.26	4162	0.86	0.8	0.66	0.01	0.06	0.02	0.01	1.7
SK	6136	0.98	0.93	0.85	0.01	0	0	0.11	2.57	5376	0.97	0.96	0.86	0.01	0.01	0.01	0	1.52
UK	5801	0.9	0.83	0.58	0.05	0.08	0	0.27	2.32	.	.	.	.	.	.	.	.	.

Note: The table is continued on the next page ...

Table A.2 continued: Panel C: Household and Individual

	2011										2019								
		Households Circ.							Individual Circ.									Individual Circ.	
Country	N	Ability to ends meet	Financial situation of the household	Both parents in HH	Howner	# Adults	# Childs	# Earners	Birth Area Native	Famale	N	Financial situation of the household	Both parents in HH	Howner	# Adults	# Childs	# Earners	Birth Area Native	Famale
AT	6082	3.31	3.64	0.87	0.6	2.71	2.55	1.77	0.84	0.52	4750	3.92	0.86	0.7	2.41	2.79	1.82	0.81	0.53
BE	4507	3.94	4.16	0.87	0.75	2.36	2.79	1.51	0.82	0.51	5771	4.21	0.85	0.77	2.27	2.7	1.6	0.77	0.51
BG	5872	3.88	4.16	0.93	0.91	2.45	2.02	2.03	0.99	0.5	5807	4.3	0.95	0.9	2.4	1.94	2.01	1	0.5
CH	6493	3.77	4.28	0.86	0.54	2.52	2.49	1.87	0.77	0.54	4680	4.33	0.85	0.57	2.37	2.35	1.83	0.75	0.52
CY	4504	3.2	3.55	0.92	0.79	2.68	2.79	1.68	0.8	0.55	4216	4.09	0.9	0.8	2.43	2.71	1.57	0.77	0.54
CZ	6420	3.46	3.94	0.86	0.61	2.11	2.25	1.94	0.97	0.58	6803	4.12	0.86	0.71	4.26	2.17	1.93	0.96	0.52
DE	10550	4.08	4.02	0.87	0.53	2.27	2.27	1.68	0.94	0.53	5989	4.33	0.86	0.56	2.53	1.86	1.78	0.92	0.54
DK	2054	3.99	4.4	1	0.8	2.38	2.31	2.42	0.93	0.52	2059	4.44	0.81	0.79	2.1	2.04	1.92	0.93	0.51
EE	4909	3.57	3.89	0.77	0.83	2.15	2.22	1.81	0.88	0.52	5396	3.42	0.75	0.75	2.07	2.12	1.78	0.92	0.53
EL	5751	3.11	3.62	0.94	0.86	2.35	2.39	1.62	0.9	0.51	13588	4.05	0.95	0.87	2.28	2.43	1.58	0.92	0.52
ES	14721	3.55	3.81	0.9	0.81	2.91	2.44	2.11	0.9	0.52	16084	3.97	0.91	0.83	2.65	2.55	1.53	0.85	0.51
FI	2948	3.9	3.99	0.81	0.77	2.35	2.22	1.83	0.95	0.47	4411	4.19	0.82	0.81	2.23	2.28	1.84	0.94	0.49
FR	10155	3.63	3.88	0.86	0.64	2.48	1.77	1.67	0.9	0.52	7998	3.94	0.85	0.65	2.46	2.33	1.68	0.88	0.53
HR	5952	3.01	3.52	0.9	0.91	2.6	2.37	1.33	0.88	0.52	6854	3.85	0.9	0.93	2.56	2.22	1.51	0.88	0.51
HU	12171	3.15	3.72	0.88	0.84	2.18	2.28	1.77	0.99	0.54	4295	3.84	0.87	0.91	2.14	2.33	1.82	0.98	0.58
IE	3091	3.36	3.93	0.91	0.74	3.19	3.21	3.23	0.79	0.57	3369	4.06	0.88	0.82	2.61	3.1	1.69	0.79	0.54
IS	1445	3.71	4.03	0.92	0.9	2.43	2.65	1.91	0.91	0.49	.	.	.	.	.	.	.	.	.
IT	20514	3.37	3.74	0.9	0.67	2.59	2.36	1.61	0.91	0.52	16265	4.09	0.93	0.76	2.31	1.95	1.4	0.86	0.51
LT	4555	3.39	3.9	0.89	0.7	2.34	2.6	2.05	0.93	0.54	3582	3.97	0.82	0.79	2.18	2.45	1.87	0.95	0.57
LU	6574	3.68	3.96	0.88	0.73	2.56	2.72	1.65	0.48	0.52	3205	4.13	0.86	0.79	2.47	2.67	1.54	0.37	0.53
LV	6048	3.62	3.94	0.76	0.45	1.97	2.29	1.76	0.87	0.55	3243	3.9	0.77	0.53	2.14	2.18	1.78	0.92	0.54
MT	4028	3.41	3.85	0.94	0.56	3.09	2.76	1.9	0.95	0.52	3160	4.2	0.94	0.69	2.57	2.26	1.52	0.89	0.49
NL	5451	4.24	4.43	0.91	0.6	2.08	3.09	1.51	0.94	0.53	4725	4.45	0.9	0.31	2.32	2.5	1.65	0.93	0.53
NO	2328	3.98	4.36	0.94	0.92	2.04	1.85	1.78	0.92	0.46	2078	4.29	0.81	0.92	2.07	2.66	1.76	0.79	0.48
PL	12689	3.28	3.91	0.92	0.67	2.79	2.49	2.01	1	0.53	13790	4.02	0.91	0.77	2.67	2.48	2.05	1	0.55
PT	5733	2.7	3.16	0.87	0.56	2.73	2.73	2.24	0.92	0.53	12993	3.62	0.87	0.66	2.64	1.99	1.88	0.9	0.53
RO	5590	2.95	3.46	0.92	0.86	2.76	2.34	1.9	1	0.5	6620	3.89	0.93	0.95	2.46	2.24	1.7	1	0.5
RS	.	.	.	.	.	.	.	.	.	.	5019	3.78	0.91	0.92	2.39	2.06	1.47	0.91	0.49
SE	467	3.87	4.31	0.84	0.77	2.09	2.38	1.76	0.88	0.51	1768	4.32	0.91	0.8	2.2	2.38	1.82	0.8	0.49
SI	4693	3.07	3.31	0.86	0.75	2.54	2.19	1.79	0.88	0.53	4162	3.77	0.88	0.85	2.53	2.11	1.74	0.9	0.53
SK	6136	3.29	3.93	0.93	0.7	2.52	2.35	2.08	0.99	0.54	5376	4.22	0.89	0.86	2.37	2.4	2.02	0.99	0.53
UK	5801	3.61	4.01	0.87	0.65	2.36	2.41	2.28	0.88	0.55	.	.	.	.	.	.	.	.	.

Table A.3: Correlation Matrix

This table reports the correlation matrix between the Inequality of Opportunity based on different specifications of priors for Waves 2011 and 2019. The first six specifications correspond to fixed prior structures, while the remaining are based on hierarchical prior structures. * denotes significance at 1%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Panel A: Wave 2011					
(1) BRIC	1.000*									
(2) UIP	0.999*	1.000*								
(3) TessBRIC	1.000*	0.999*	1.000*							
(4) TessUIP	0.999*	1.000*	0.999*	1.000*						
(5) HypergBRIC	0.983*	0.983*	0.983*	0.983*	1.000*					
(6) HypergUIP	0.983*	0.983*	0.983*	0.983*	1.000*	1.000*				
(7) HierBRIC	1.000*	0.999*	1.000*	0.999*	0.983*	0.983*	1.000*			
(8) HierUIP	0.999*	1.000*	0.999*	1.000*	0.983*	0.983*	0.999*	1.000*		
(9) HierHypergBRIC	0.980*	0.980*	0.980*	0.980*	0.999*	0.999*	0.980*	0.980*	1.000*	
(10) HierHypergUIP	0.980*	0.980*	0.980*	0.980*	0.999*	0.999*	0.980*	0.980*	0.999*	1.000*
					Panel B: Wave 2019					
(1) BRIC	1.000*									
(2) UIP	1.000*	1.000*								
(3) TessBRIC	1.000*	1.000*	1.000*							
(4) TessUIP	1.000*	1.000*	1.000*	1.000*						
(5) HypergBRIC	0.998*	0.998*	0.998*	0.998*	1.000*					
(6) HypergUIP	0.998*	0.998*	0.998*	0.998*	1.000*	1.000*				
(7) HierBRIC	1.000*	1.000*	1.000*	1.000*	0.998*	0.998*	1.000*			
(8) HierUIP	1.000*	1.000*	1.000*	1.000*	0.998*	0.998*	1.000*	1.000*		
(9) HierHypergBRIC	0.997*	0.997*	0.997*	0.997*	0.999*	0.999*	0.997*	0.997*	1.000*	
(10) HierHypergUIP	0.997*	0.997*	0.997*	0.997*	0.999*	0.999*	0.997*	0.997*	1.000*	1.000*

Table A.4: Out-of-Sample Mean Squared Error - 2011

This table reports the out-of-sample Mean Squared Error (MSE) for predicting the logarithm of income across various countries using the best Linear model prior specification for each country in comparison with UIP prior, BART-BMA, C-Forest, and XGBoost methods. Results are shown for the 2011. The values represent the average MSE computed through 10-fold cross-validation. Lower values indicate better predictive performance, with the best-performing model for each country and wave highlighted in green.

	Linear Models			Non-linear Models		
Country	Best Lin. BMA	BMA Type	MSE rel. to UIP	BART-BMA	C-Forest	XGBoost
AT	0.25	tessbric	≥ 0.9999	0.253	0.249	0.249
BE	0.3	bric	≥ 0.9999	0.305	0.297	0.302
BG	0.347	tessuip	≥ 0.9999	0.365	0.334	0.33
CH	0.347	tessbric	≥ 0.9999	0.352	0.346	0.352
CY	0.219	uip	1	0.225	0.219	0.219
CZ	0.198	bric	≥ 0.9999	0.202	0.201	0.202
DE	0.484	uip	1	0.486	0.481	0.489
DK	0.792	hierhyperguip	≥ 0.999	0.748	0.747	0.792
EE	0.586	bric	≥ 0.9999	0.591	0.583	0.587
EL	1.371	tessbric	≥ 0.9999	1.388	1.366	1.383
ES	1.08	bric	≥ 0.9999	1.087	1.08	1.088
FI	0.371	tessuip	≥ 0.9999	0.376	0.367	0.385
FR	0.311	uip	1	0.316	0.309	0.31
HR	0.924	hierhyperguip	≥ 0.999	0.929	0.916	0.933
HU	0.238	bric	≥ 0.9999	0.248	0.237	0.236
IE	0.475	uip	1	0.444	0.439	0.44
IS	0.442	hierhyperguip	≥ 0.99	0.462	0.442	0.48
IT	1.056	uip	1	1.066	1.05	1.052
LT	0.885	hierhyperguip	≥ 0.99	0.914	0.9	0.911
LU	0.51	bric	≥ 0.9999	0.522	0.507	0.517
LV	0.973	hierhyperguip	≥ 0.99	0.996	0.967	0.973
MT	0.344	tessuip	≥ 0.9999	0.351	0.344	0.348
NL	0.357	bric	≥ 0.9999	0.382	0.378	0.388
NO	0.231	hierbric	≥ 0.9999	0.246	0.242	0.254
PL	0.383	bric	≥ 0.9999	0.391	0.381	0.382
PT	0.329	tessbric	≥ 0.9999	0.341	0.329	0.328
RO	0.467	uip	1	0.48	0.462	0.463
SE	0.61	tessuip	≥ 0.9999	0.579	0.552	0.581
SI	0.181	bric	≥ 0.9999	0.181	0.18	0.18
SK	0.217	uip	1	0.219	0.217	0.219
UK	0.987	tessbric	≥ 0.9999	0.991	0.984	0.999

Table A.5: Out-of-Sample Mean Squared Error - 2019

This table reports the out-of-sample Mean Squared Error (MSE) for predicting the logarithm of income across various countries using the best Linear model prior specification for each country in comparison with UIP prior, BART-BMA, C-Forest, and XGBoost methods. Results are shown for the 2019. The values represent the average MSE computed through 10-fold cross-validation. Lower values indicate better predictive performance, with the best-performing model for each country and wave highlighted in green.

	Linear Models			Non-linear Models		
Country	Best Lin. BMA	BMA Type	MSE rel. to UIP	BART-BMA	C-Forest	XGBoost
AT	0.315	hyperguip	≥ 0.999	0.303	0.299	0.307
BE	0.286	bric	≥ 0.95	0.3	0.294	0.303
BG	0.37	uip	1	0.386	0.372	0.365
CH	0.285	bric	≥ 0.9999	0.288	0.282	0.284
CY	0.247	uip	1	0.251	0.248	0.249
CZ	0.151	uip	1	0.151	0.15	0.15
DE	0.538	tessbric	≥ 0.9999	0.539	0.537	0.545
DK	0.656	hypergbric	≥ 0.999	0.665	0.649	0.687
EE	0.722	hierbric	≥ 0.9999	0.728	0.721	0.739
EL	0.867	bric	≥ 0.9999	0.806	0.792	0.805
ES	0.734	tessbric	≥ 0.9999	0.741	0.733	0.734
FI	0.289	tessbric	≥ 0.9999	0.301	0.3	0.305
FR	0.262	uip	1	0.263	0.261	0.261
HR	0.464	hypergbric	≥ 0.9999	0.463	0.459	0.46
HU	0.407	uip	1	0.402	0.391	0.397
IE	0.206	tessbric	≥ 0.9999	0.206	0.204	0.203
IT	0.951	uip	1	0.955	0.949	0.958
LT	0.677	tessbric	≥ 0.9999	0.683	0.671	0.682
LU	0.472	bric	≥ 0.9999	0.475	0.465	0.469
LV	0.896	tessuip	≥ 0.9999	0.907	0.879	0.897
MT	0.289	tessbric	≥ 0.9999	0.302	0.298	0.302
NL	0.559	hierbric	≥ 0.85	0.563	0.546	0.585
NO	0.367	tessuip	≥ 0.9999	0.37	0.363	0.383
PL	0.58	uip	1	0.583	0.58	0.581
PT	0.329	tessuip	≥ 0.9999	0.338	0.328	0.326
RO	0.846	bric	≥ 0.9999	0.927	0.913	0.919
RS	0.967	hyperguip	≥ 0.999	0.988	0.961	0.966
SE	0.921	hierhypergbric	≥ 0.99	0.796	0.747	0.842
SI	0.171	tessuip	≥ 0.9999	0.172	0.17	0.171
SK	0.256	uip	1	0.238	0.231	0.231

Table A.6: Top 15 Circumstances - Bart-BMA

This table presents the top 15 variables with the highest Posterior Inclusion Probabilities (PIPs) from BART-BMA for Waves 2011 and 2019. Panel A corresponds to Wave 2011, while Panel B corresponds to Wave 2019. Variables are sorted by their average PIP values, and a heatmap is used to visually represent the magnitude of the PIPs, with darker shades indicating higher probabilities. (F) denotes Father, (M) denotes Mother, (H) represents Household characteristics, and (I) represents Individual characteristics.

	Panel A: Wave 2011																														
	AT	BE	BG	CH	CY	CZ	DE	DK	EE	EL	ES	FI	FR	HR	HU	IE	IS	IT	LT	LU	LV	MT	NL	NO	PL	PT	RO	SE	SI	SK	UK
No. of adults (H)	0.16	1.00	0.41	0.02	0.39	0.03	0.10	0.00	1.00	1.00	1.00	0.21	0.02	1.00	0.00	1.00	0.21	1.00	0.09	0.00	0.13	1.00	0.33	0.06	1.00	1.00	1.00	0.03	0.22	1.00	1.00
No. of children (H)	0.18	0.25	1.00	0.10	1.00	1.00	0.00	0.18	0.35	0.15	0.15	0.00	0.84	0.00	0.05	0.00	1.00	0.09	0.33	0.04	0.94	0.12	0.38	0.10	0.11	0.22	0.28	0.42	0.40	0.00	0.00
No. of workers (H)	1.00	0.00	0.39	1.00	0.12	0.27	1.00	1.00	0.00	0.31	0.00	0.00	1.00	0.19	1.00	0.04	0.05	0.89	0.46	1.00	0.01	0.00	0.17	1.00	0.06	0.00	0.00	0.20	1.00	0.93	0.00
Financial situation (H)	0.16	0.00	0.89	0.00	0.11	0.00	0.06	0.00	0.00	0.24	0.15	1.00	0.00	0.07	0.15	0.02	0.06	0.58	1.00	0.00	0.47	0.00	0.34	0.00	0.17	0.13	0.30	0.64	0.20	0.07	0.00
Education (F)	0.56	0.11	0.20	0.00	0.11	0.09	0.00	0.04	0.33	0.15	0.10	0.06	0.09	0.19	0.10	0.08	0.05	0.09	0.33	0.00	1.00	0.06	0.34	0.06	0.06	0.04	0.20	0.40	0.30	0.07	0.00
Homeowner (H)	0.08	0.06	0.00	0.00	0.00	0.00	0.12	0.00	0.11	0.16	0.13	0.00	0.09	0.00	0.16	0.04	0.05	0.16	0.00	0.16	0.10	0.19	0.00	0.00	0.00	0.00	0.20	0.20	0.00	0.07	0.04
Education (M)	0.02	0.00	0.20	0.10	0.06	0.73	0.06	0.00	0.22	0.00	0.05	0.00	0.09	0.16	0.05	0.00	0.05	0.00	0.21	0.04	0.10	0.00	0.69	0.00	0.00	0.00	0.10	0.00	0.30	0.07	0.04
Low-skilled non-manual occ. (F)	0.00	0.00	0.20	0.05	0.00	0.18	0.06	0.00	0.11	0.46	0.00	0.00	0.09	0.00	0.00	0.04	0.05	0.09	0.00	0.00	0.10	0.06	0.17	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00
Female (I)	0.08	0.12	0.00	0.06	0.00	0.09	0.00	0.00	0.11	0.00	0.05	0.00	0.09	0.00	0.00	0.04	0.00	0.16	0.00	0.00	0.00	0.12	0.34	0.00	0.06	0.04	0.00	0.36	0.20	0.00	0.00
Act. status: Other inactive (F)	0.00	0.12	0.30	0.05	0.01	0.18	0.00	0.02	0.08	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.23	0.04	0.00	0.00	1.00	0.00	0.00	0.00	0.30	0.00	0.00	0.14	0.00
Make ends meet (H)	0.00	0.06	0.00	0.05	0.06	0.00	0.13	0.00	0.00	0.00	0.10	0.00	0.18	0.00	0.05	0.08	0.11	0.25	0.09	0.04	0.00	0.00	0.17	0.00	0.06	0.00	0.10	1.00	0.00	0.14	0.02
Born in Non-EU Country (I)	0.08	0.00	0.00	0.21	0.06	0.00	0.06	0.00	0.00	0.15	0.05	0.06	0.09	0.00	0.05	0.08	0.00	0.25	0.00	0.04	0.00	0.06	0.02	0.00	0.00	0.00	0.00	0.20	0.24	0.00	0.04
In retirement (F)	0.08	0.00	0.10	0.05	0.00	0.00	0.06	0.12	0.00	0.15	0.05	0.12	0.09	0.00	0.00	0.04	0.00	0.09	0.00	0.00	0.10	0.06	0.00	0.00	0.06	0.04	0.00	0.00	0.30	0.00	0.00
House worker (M)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.26	0.05	0.00	0.00	0.00	0.00	0.04	0.00	0.09	0.00	0.00	0.00	0.00	0.34	0.00	0.11	0.04	0.10	0.00	0.10	0.00	0.00
Skilled manual occ. (F)	0.00	0.04	0.00	0.00	0.00	0.09	0.03	0.00	0.11	0.00	0.00	0.06	0.00	0.14	0.05	0.04	0.00	0.09	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.10	0.60	0.20	0.00	0.00
	Panel B: Wave 2019																														
	AT	BE	BG	CH	CY	CZ	DE	DK	EE	EL	ES	FI	FR	HR	HU	IE	IS	IT	LT	LU	LV	MT	NL	NO	PL	PT	RO	SE	SI	SK	-
No. of adults (H)	0.67	1.00	0.52	0.12	0.14	0.17	1.00	0.68	0.00	0.56	1.00	0.00	1.00	0.73	1.00	1.00	1.00	0.00	0.10	0.09	1.00	0.13	0.00	1.00	1.00	0.00	0.62	0.02	0.74	0.36	
No. of children (H)	0.00	0.00	0.24	1.00	1.00	1.00	0.20	1.00	1.00	0.00	0.19	1.00	0.00	0.00	0.59	0.04	0.00	0.40	1.00	0.04	0.00	0.00	0.01	0.65	0.38	0.68	0.78	1.00	0.24	0.10	
Financial situation (H)	0.00	0.04	1.00	0.08	0.59	0.49	0.28	0.28	0.00	1.00	0.09	0.00	0.00	0.91	0.84	0.00	0.17	1.00	0.00	0.00	0.59	1.00	0.05	0.08	0.19	1.00	1.00	0.12	0.00	1.00	
No. of workers (H)	1.00	0.08	0.12	0.00	0.00	0.15	0.00	0.00	0.08	0.37	0.04	0.22	0.00	1.00	0.09	0.00	0.00	0.00	0.00	1.00	0.00	0.13	1.00	0.00	0.39	0.53	0.11	0.11	0.74	0.06	
Education (F)	0.00	0.04	0.06	0.08	0.27	0.08	0.20	0.00	0.08	0.12	0.04	0.00	0.04	0.18	0.09	0.07	0.05	0.12	0.07	0.03	0.17	0.00	0.00	0.09	0.06	0.26	0.11	0.11	0.50	0.13	
Education (M)	0.15	0.00	0.06	0.08	0.00	0.15	0.00	0.00	0.08	0.25	0.17	0.00	0.00	0.18	0.17	0.00	0.05	0.06	0.07	0.03	0.09	0.00	0.22	0.09	0.12	0.01	0.32	0.11	0.74	0.06	
Homeowner (H)	0.00	0.04	0.18	0.04	0.14	0.08	0.31	0.00	0.41	0.12	0.04	0.00	0.04	0.37	0.42	0.04	0.05	0.00	0.07	0.00	0.09	0.13	0.05	0.00	0.06	0.00	0.21	0.21	0.50	0.06	
Self-employed (M)	0.00	0.00	0.00	0.00	0.14	0.00	0.10	0.60	0.16	0.00	0.00	0.05	0.00	0.18	0.00	0.00	0.15	0.00	0.07	0.00	0.00	0.27	0.00	0.18	0.00	0.08	0.00	0.11	0.50	0.00	
Self-employed (F)	0.00	0.00	0.00	0.00	0.00	0.11	0.13	0.00	0.00	0.25	0.00	0.00	0.00	0.18	0.00	0.04	0.05	0.06	0.13	0.00	0.00	0.13	0.00	0.09	0.19	0.08	0.00	0.00	0.50	0.06	
Unemployed (F)	0.07	0.04	0.06	0.00	0.00	0.08	0.00	0.20	0.08	0.25	0.00	0.06	0.03	0.18	0.17	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.21	0.11	0.24	0.00	
House worker (M)	0.04	0.08	0.06	0.00	0.00	0.08	0.00	0.20	0.00	0.12	0.04	0.00	0.00	0.18	0.09	0.02	0.05	0.00	0.07	0.00	0.25	0.40	0.00	0.09	0.06	0.08	0.21	0.21	0.24	0.06	
Skilled manual occ. (F)	0.15	0.04	0.00	0.00	0.14	0.00	0.10	0.20	0.00	0.12	0.00	0.06	0.04	0.73	0.09	0.11	0.05	0.06	0.00	0.03	0.00	0.13	0.00	0.09	0.06	0.00	0.00	0.00	0.00	0.06	
Unknown country of birth (M)	0.00	0.00	0.12	0.08	0.00	0.00	0.20	0.00	0.00	0.03	0.00	0.13	0.00	0.18	0.09	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.11	0.00	0.00	
Part-time worker (F)	0.00	0.00	0.06	0.00	0.27	0.00	0.00	0.00	0.00	0.12	0.06	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.08	0.11	0.00	0.50	0.06	
Act. status: Other inactive (F)	0.00	0.00	0.06	0.08	0.22	0.00	0.00	0.40	0.00	0.00	0.04	0.06	0.00	0.18	0.09	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.11	0.00	0.24	0.00	

Table A.7: Top 15 Circumstances - XGBoost

This table presents the top 15 variables with the highest Variable Importance Score (VIS) from XGBoost for Waves 2011 and 2019. Panel A corresponds to Wave 2011, while Panel B corresponds to Wave 2019. Variables are sorted by their average VIS values, and a heatmap is used to visually represent the magnitude of the VIS, with darker shades indicating higher probabilities. (F) denotes Father, (M) denotes Mother, (H) represents Household characteristics, and (I) represents Individual characteristics.

	Panel A: Wave 2011																														
	AT	BE	BG	CH	CY	CZ	DE	DK	EE	EL	ES	FI	FR	HR	HU	IE	IS	IT	LT	LU	LV	MT	NL	NO	PL	PT	RO	SE	SI	SK	UK
Financial situation (H)	0.82	0.40	0.26	0.93	0.79	1.00	0.90	0.47	0.64	1.00	0.46	0.27	0.45	0.57	0.22	0.41	1.00	0.54	0.60	0.23	1.00	0.92	0.71	0.30	0.33	1.00	0.26	1.00	0.60	0.47	0.48
Education (F)	0.65	0.37	0.74	0.81	0.75	0.57	0.33	0.38	0.84	0.85	0.41	1.00	1.00	0.08	0.86	0.47	0.48	1.00	0.64	0.82	0.77	0.96	0.44	0.56	1.00	0.72	0.89	0.64	1.00	0.74	0.53
No. of children (H)	0.89	0.43	0.58	1.00	1.00	0.84	0.69	0.50	0.52	0.79	0.34	0.22	0.85	1.00	0.38	0.00	0.31	0.37	1.00	0.35	0.64	0.65	1.00	0.48	0.27	0.35	0.39	0.45	0.46	0.86	1.00
No. of adults (H)	0.58	0.64	0.26	0.62	0.47	0.42	0.34	0.33	0.55	0.42	1.00	0.56	0.64	0.54	0.07	0.61	0.71	0.38	0.42	0.47	0.23	1.00	0.10	0.84	0.26	0.18	0.21	0.15	0.55	1.00	0.76
No. of workers (H)	0.61	0.52	0.18	0.34	0.50	0.92	0.78	0.65	0.35	0.70	0.28	0.77	0.31	0.69	0.15	1.00	0.26	0.43	0.21	1.00	0.24	0.00	0.52	1.00	0.23	0.00	0.19	0.08	0.29	0.61	0.68
Skilled manual occ. (F)	0.35	0.07	0.22	0.41	0.23	0.21	0.26	0.40	0.08	0.31	0.29	0.54	0.58	0.12	0.10	0.30	0.29	0.32	0.14	0.19	0.22	0.52	0.19	0.12	0.46	0.31	0.08	0.06	0.15	0.23	0.35
Education (M)	0.72	0.13	1.00	0.45	0.77	0.67	1.00	1.00	1.00	0.00	0.58	0.34	0.65	0.57	1.00	0.43	0.22	0.00	0.38	0.51	0.83	0.00	0.38	0.56	0.00	0.00	1.00	0.72	0.78	0.42	0.45
Female (I)	0.21	0.15	0.06	0.16	0.17	0.88	0.31	0.19	0.29	0.26	0.06	0.74	0.18	0.31	0.02	0.22	0.96	0.16	0.16	0.07	0.57	0.25	0.40	0.37	0.10	0.05	0.10	0.33	0.21	0.14	0.17
Homeowner (H)	0.32	0.07	0.06	0.14	0.42	0.30	0.43	0.14	0.20	0.11	0.10	0.04	0.12	0.02	0.05	0.22	0.14	0.06	0.13	0.09	0.19	0.40	0.26	0.07	0.12	0.09	0.17	0.19	0.16	0.35	0.12
Self-employed (F)	0.35	0.08	0.01	0.21	0.47	0.16	0.10	0.84	0.08	0.39	0.14	0.06	0.28	0.03	0.15	0.03	0.32	0.07	0.00	0.39	0.00	0.48	0.18	0.11	0.19	0.05	0.27	0.14	0.16	0.03	0.32
House worker (M)	0.24	0.11	0.02	0.21	0.13	0.13	0.16	0.23	0.31	0.00	0.05	0.15	0.23	0.58	0.01	0.13	0.29	0.10	0.07	0.05	0.05	0.12	0.19	0.06	0.08	0.06	0.18	0.26	0.10	0.13	0.13
Born in Non-EU Country (I)	1.00	0.63	0.01	0.37	0.86	0.12	0.17	0.00	0.12	0.64	0.54	0.09	0.92	0.18	0.01	0.09	0.04	0.15	0.49	0.23	0.19	0.58	0.10	0.10	0.01	0.03	0.00	0.05	0.13	0.00	0.25
Make ends meet (H)	0.00	0.42	0.16	0.54	0.63	0.86	0.00	0.45	0.60	0.00	0.00	0.00	0.00	0.67	0.19	0.00	0.00	0.00	0.45	0.52	0.00	0.00	0.68	0.53	0.00	0.00	0.46	0.00	0.00	0.60	0.89
High-skilled non-manual occ. (F)	0.41	0.08	0.03	0.00	0.45	0.12	0.00	0.11	0.40	0.00	0.00	0.00	0.00	0.22	0.42	0.00	0.00	0.00	0.03	0.22	0.00	0.00	0.28	0.46	0.00	0.00	0.10	0.00	0.00	0.62	0.27
Self-employed (M)	0.11	1.00	0.01	0.04	0.13	0.06	0.07	0.21	0.02	0.23	0.07	0.05	0.07	0.04	0.00	0.05	0.06	0.04	0.02	0.06	0.01	0.06	0.23	0.09	0.00	0.12	0.24	0.04	0.09	0.00	0.27
	Panel B: Wave 2019																														
	AT	BE	BG	CH	CY	CZ	DE	DK	EE	EL	ES	FI	FR	HR	HU	IE	IS	IT	LT	LU	LV	MT	NL	NO	PL	PT	RO	SE	SI	SK	-
Education (F)	0.44	0.45	0.30	0.53	0.98	1.00	0.45	0.15	0.65	0.86	0.59	1.00	0.50	0.73	0.75	1.00	0.44	0.71	0.40	0.47	0.50	0.93	0.54	0.82	0.35	0.35	1.00	0.29	0.30	0.34	
Financial situation (H)	0.59	0.63	0.21	1.00	0.31	0.75	0.57	0.33	1.00	0.91	0.47	0.93	0.42	0.86	1.00	0.69	1.00	0.76	0.29	1.00	1.00	0.50	1.00	0.64	1.00	0.47	0.74	0.24	0.98	0.89	
No. of children (H)	0.80	1.00	0.32	0.82	0.81	0.62	1.00	0.11	0.71	1.00	0.27	0.87	1.00	1.00	0.98	0.87	0.74	0.74	1.00	0.36	0.43	0.43	0.87	0.61	0.37	0.25	0.58	0.26	0.75	1.00	
No. of adults (H)	0.86	0.67	0.03	0.31	0.35	0.76	0.80	0.05	0.72	0.10	0.40	0.71	0.37	0.54	0.35	0.68	0.62	0.77	0.33	0.17	0.47	0.19	0.54	1.00	0.21	0.21	0.38	0.03	0.59	0.41	
Education (M)	0.30	0.00	1.00	0.85	0.00	0.86	0.40	0.11	0.76	0.24	0.20	0.57	0.00	0.43	0.43	0.00	0.39	0.85	0.33	0.47	0.68	0.20	0.61	0.95	0.12	0.14	0.30	1.00	1.00	0.41	
No. of workers (H)	0.31	0.26	0.06	0.36	0.00	0.55	0.11	0.31	0.57	0.16	0.25	0.52	0.16	0.62	0.34	0.00	0.00	1.00	0.13	0.51	0.25	1.00	0.30	0.60	0.18	0.26	0.41	0.08	0.70	0.55	
Female (I)	0.50	0.21	0.01	0.32	0.19	0.32	0.27	0.37	0.66	0.26	0.10	0.70	0.26	0.10	0.32	0.22	0.29	0.22	0.06	0.15	0.29	0.34	0.54	0.72	0.07	0.06	0.12	0.36	0.17	0.09	
House worker (M)	0.35	0.54	0.01	0.13	0.12	0.19	0.10	0.07	0.54	0.12	0.09	0.13	0.13	0.10	0.13	0.19	0.31	0.12	0.20	0.06	0.54	0.15	0.20	0.03	0.05	0.03	0.11	0.28	0.08	0.25	
Homeowner (H)	0.22	0.21	0.03	0.45	0.09	0.22	0.24	0.01	0.19	0.32	0.06	0.30	0.17	0.11	0.44	0.53	0.37	0.03	0.11	0.13	0.17	0.02	0.47	0.20	0.06	0.09	0.19	0.49	0.31	0.40	
Skilled manual occ. (F)	0.28	0.27	0.07	0.00	0.44	0.15	0.25	0.09	0.35	0.28	0.09	0.21	0.23	0.15	0.41	0.22	0.21	0.29	0.10	0.22	0.12	0.12	0.16	0.64	0.28	0.07	0.12	0.04	0.22	0.05	
Born in Non-EU Country (I)	0.68	0.60	0.00	0.11	1.00	0.08	0.15	0.00	0.26	0.51	0.78	0.22	0.31	0.11	0.05	0.19	0.64	0.06	0.43	0.08	0.18	0.25	0.11	0.00	0.05	0.00	0.04	0.75	0.59	0.00	
Self-employed (F)	0.15	0.06	0.01	0.24	0.24	0.09	0.25	0.30	0.27	0.24	0.06	0.19	0.04	0.17	0.03	0.17	0.19	0.16	0.26	0.03	0.16	0.03	0.11	0.69	0.07	1.00	0.00	0.31	0.12	0.06	
Born in EU Country (I)	0.37	0.04	0.00	0.32	0.38	0.11	0.00	1.00	0.00	0.10	0.04	0.02	0.04	0.00	0.05	0.31	0.57	0.00	0.15	0.00	0.00	0.28	0.02	0.00	0.02	0.00	0.03	0.06	0.00	0.13	
High-skilled non-manual occ. (F)	0.00	0.00	0.07	0.00	0.00	0.51	0.00	0.00	0.23	0.05	0.14	0.00	0.00	0.00	0.00	0.41	0.00	0.03	0.12	0.00	0.42	0.14	0.30	0.00	0.00	0.17	0.02	0.13	0.17	0.02	
Self-employed (F)	0.05	0.04	0.01	0.05	0.04	0.05	0.14	0.00	0.02	0.11	0.02	0.28	0.00	0.13	0.03	0.13	0.08	0.06	0.05	0.00	0.01	0.06	0.04	0.66	0.03	0.30	0.00	0.00	0.12	0.00	

Table A.8: Full Circumstances - Linear-BMA

This table presents results from the Linear-BMA for 2011 and 2019,highlighting the Posterior Inclusion Probability (PIP) and posterior means values for each circumstance. A heatmap is employed to visually depict the magnitude of PIP values. The grid's color scheme conveys the strength of the VIS within each countrywith white indicating PIP values below 0.5 and various shades of red indicating values between 0.5 (light) and 1 (dark) in six different panels. The estimates in the table report the posterior means for each variable. Panel A and D exhibit the findings related to father's circumstances in 2011 and 2019, Panel B and E display the results concerning mother's circumstances in 2011 and 2019, and Panel C and F focus on household and individual circumstances in 2011 and 2019.

Panel A

Country	Father's Citizen.			Father's Birth			Father's Education	Father's Skills			Father's Occupation					
	EU	Europe - No EU27	Outside Europe	EU	Europe - No EU27	Outside Europe		Low Skilled	Medium Skilled	High Skilled	Self-Employed	Unemployed	Retired	House worker	Other inactive	Father Unkown/dead
AT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.017	-0.01	#N/D	0.075	0	-0.111	-0.003	0	-0.025	-0.001
BE	0	-0.06	-0.002	0	-0.029	-0.2	0.013	0.018	0.1	0.125	-0.018	0	0	0	-0.009	0
BG	0	-0.004	0.001	0.001	-0.004	-0.001	0.112	-0.114	0.003	0.002	0.001	0	-0.003	-0.001	-0.002	#N/D
CH	0.021	-0.007	-0.01	#N/D	#N/D	#N/D	0.068	-0.106	-0.003	#N/D	0	-0.001	-0.001	-0.037	-0.016	-0.002
CY	-0.109	-0.303	-0.007	-0.111	-0.012	-0.04	0.065	-0.002	0.005	0.121	0.006	0	0	#N/D	-0.003	0.001
CZ	-0.001	0	0	-0.001	0	0	0.067	-0.009	0.002	0.023	0.1	-0.01	-0.001	#N/D	-0.003	#N/D
DE	-0.01	#N/D	#N/D	-0.001	#N/D	#N/D	0.064	-0.098	0	#N/D	0.018	-0.001	-0.001	-0.021	-0.001	-0.012
DK	-0.13	-0.009	0.009	-0.113	-0.013	#N/D	-0.001	-0.072	0.002	0.028	-0.113	-0.004	-0.003	-0.001	0.003	#N/D
EE	-0.136	#N/D	#N/D	-0.042	#N/D	#N/D	0.066	0	0.001	0.148	0.037	0.005	0	-0.001	-0.005	-0.001
EL	#N/D	#N/D	0	#N/D	#N/D	#N/D	0.207	-0.171	#N/D	#N/D	0.003	0	0.008	#N/D	0	-0.002
ES	#N/D	0	#N/D	#N/D	#N/D	#N/D	0.106	-0.151	0.001	#N/D	-0.114	-0.559	-0.007	-0.018	-0.014	-0.132
FI	-0.001	-0.001	-0.01	#N/D	#N/D	#N/D	0.071	0	-0.001	#N/D	0	-0.034	0	0.02	0	#N/D
FR	0.001	0.002	#N/D	#N/D	#N/D	#N/D	0.09	-0.098	0	#N/D	0.064	-0.005	-0.002	0.001	-0.035	0
HR	0.001	0	0.007	-0.004	0.004	0.007	0.105	0	0.001	0.054	0	-0.5	-0.006	-0.013	-0.008	0
HU	0.004	-0.028	0	0.014	-0.01	0	0.089	0.002	0.032	0.134	0	-0.004	0	0.001	-0.003	0
IE	#N/D	-0.174	#N/D	#N/D	#N/D	#N/D	0.081	-0.029	-0.006	#N/D	0	-0.191	-0.006	-0.003	-0.016	-0.001
IS	-0.003	0	#N/D	#N/D	#N/D	#N/D	0.075	0.003	-0.012	#N/D	0	0.001	-0.002	#N/D	0.001	0
IT	#N/D	0	#N/D	#N/D	#N/D	#N/D	0.209	-0.065	0	#N/D	0	-0.59	-0.004	0	-0.007	#N/D
LT	0.003	0.001	0.001	-0.015	0	0.004	0.179	-0.002	0	0.001	0.006	0.002	0.013	0.004	-0.001	0.001
LU	0	-0.012	0	-0.003	-0.006	0.002	0.095	-0.012	0.025	0.103	0	0	-0.001	-0.003	0	-0.002
LV	-0.007	#N/D	#N/D	#N/D	#N/D	#N/D	0.157	0	0.001	#N/D	-0.002	-0.001	0.003	-0.003	0	-0.036
MT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.15	-0.019	#N/D	#N/D	0	-0.006	0.002	-0.015	-0.01	-0.001
NL	0	-0.001	-0.143	0	-0.005	-0.001	0.031	-0.048	0.046	0.05	0	-0.008	-0.084	0.004	-0.116	#N/D
NO	-0.002	0	-0.03	-0.001	-0.007	-0.092	0.001	-0.006	-0.001	0.087	-0.002	0.001	0	-0.193	#N/D	0.006
PL	0.048	-0.001	-0.009	0.011	-0.727	-0.002	0.146	-0.154	-0.06	#N/D	-0.091	-0.004	-0.004	-0.013	-0.006	-0.208
PT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.163	-0.199	#N/D	#N/D	0	-0.017	-0.294	0	-0.367	-0.195
RO	0	0.001	0.001	0.003	0	0.001	0.184	0.005	0.009	0.004	-0.144	-0.209	-0.124	-0.262	0.151	-0.001
SE	0	-0.004	#N/D	#N/D	#N/D	#N/D	0.001	0	-0.006	#N/D	0	-0.008	-0.004	-0.011	-0.057	0.002
SI	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.093	-0.003	0.014	#N/D	-0.02	-0.052	-0.012	-0.001	-0.003	0
SK	0	-0.004	0.001	0	-0.045	#N/D	0.032	0.001	0.017	0.102	0.001	-0.009	0	0.002	-0.005	-0.002
UK	0.004	-0.002	-0.007	0.001	-0.003	0.006	0.018	-0.026	0.002	0.089	0	-0.018	0.003	-0.001	0.001	0

Table continued on next page ...

Table A.8 continued: Panel B

Country	Mother's Citizen.			Mother's Birth			Mother's Education	Mother's Occupation					
	EU	Europe - No EU27	Outside Europe	EU	Europe - No EU27	Outside Europe		Self-Employed	Unemployed	Retired	House worker	Other inactive	Mother Unkown/dead
AT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.074	0	-0.003	0.002	0	-0.009	0
BE	0	-0.204	-0.028	0	-0.021	-0.259	0.063	-0.025	0	-0.023	0	0	0
BG	0	0	#N/D	0.002	-0.002	#N/D	0.139	0	-0.001	0.001	0.001	0	#N/D
CH	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.059	0	0.003	-0.004	0.001	-0.002	-0.001
CY	-0.002	-0.071	-0.106	-0.001	-0.006	-0.216	0.088	0.027	-0.015	0.012	0.008	-0.007	-0.003
CZ	-0.003	0	-0.003	0	0	0.002	0.11	0.003	-0.001	-0.001	-0.021	-0.001	#N/D
DE	-0.007	#N/D	#N/D	#N/D	#N/D	#N/D	0.001	0.052	-0.348	0	0	0	0
DK	-0.003	-0.01	-0.653	-0.016	-0.014	0.003	0	-0.002	-0.001	-0.002	0	0	#N/D
EE	-0.015	#N/D	#N/D	0	#N/D	#N/D	0.107	0.002	0.007	0.001	-0.124	0	0.49
EL	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0	0.004	0.001	#N/D	-0.043	0
ES	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.092	0	-0.002	0.002	0.001	-0.01	0.001
FI	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0	-0.002	-0.01	-0.003	-0.271	0.003	#N/D
FR	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.052	0.004	-0.002	0	0	0	0.003
HR	0.002	-0.002	0.007	0	-0.005	0.007	0.205	-0.002	0	0.004	-0.007	-0.01	-0.005
HU	0.061	-0.027	0.16	0.036	-0.029	0.085	0.108	0	-0.016	-0.004	-0.067	-0.001	0
IE	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.089	0	0.019	-0.054	-0.019	0.001	0.001
IS	#N/D	0.002	#N/D	#N/D	#N/D	#N/D	-0.063	0	0.009	#N/D	0.003	0.001	0.006
IT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0	-0.001	0	-0.073	0	#N/D
LT	0.001	-0.001	-0.004	0.002	0.003	0	0.002	0.002	0.006	0.003	0	0	0.001
LU	0	-0.006	-0.005	-0.008	-0.018	0.016	0.111	0.001	0.001	0	0	0	0
LV	-0.001	#N/D	#N/D	#N/D	#N/D	#N/D	0.159	-0.008	-0.007	-0.005	0.002	-0.003	-0.036
MT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0	-0.003	-0.004	-0.023	-0.001	-0.001
NL	-0.006	-0.001	-0.005	-0.001	-0.007	0	0.031	0	-0.001	0.008	0	0	#N/D
NO	0	-0.004	0	0	-0.038	-0.001	0	0	0	0	0	-0.001	0.009
PL	0.001	0.109	0.001	0.004	#N/D	#N/D	#N/D	#N/D	-0.112	0	0	0	-0.001
PT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	-0.096	0.001	-0.004	0	0	-0.03
RO	0.011	-0.001	-0.004	0.006	-0.004	0.082	0.197	-0.215	-0.001	-0.002	-0.133	0	-0.003
SE	0	#N/D	#N/D	#N/D	#N/D	#N/D	-0.002	0.001	-0.002	-0.005	0.011	-0.244	#N/D
SI	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.096	0.001	-0.007	0	-0.008	-0.001	-0.001
SK	0	-0.017	-0.011	0	-0.02	#N/D	0.064	0.001	-0.006	0.002	-0.049	-0.024	0
UK	0.005	-0.007	-0.076	0	-0.003	0.016	0.107	0	-0.019	0.001	0	0	0.001

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Table A.8 continued: Panel C

Country	Household circumstances									Individual Circumstances		
	Ability to make ends meet	Financial situation of the household	Presence of Parents			Tenancy Status - Owner	Type of Household			Gender	Citizenship	
			Father	Mother	Orphanage		# of Adults	# of Children	# of Earners	Female	EU	NON-EU
AT	#N/D	0	#N/D	#N/D	-0.001	0.005	-0.001	-0.019	-0.001	-0.001	-0.234	-0.356
BE	0.04	0.001	-0.023	-0.009	-0.193	0.025	0	-0.012	0	-0.001	-0.001	-0.036
BG	0.002	0.06	#N/D	#N/D	#N/D	-0.021	-0.055	-0.092	0.043	0.008	-0.002	-0.003
CH	0.003	0	-0.001	-0.029	-0.006	0	-0.001	-0.025	-0.001	-0.024	0.001	-0.175
CY	0.003	0.031	-0.003	-0.02	0	0	0	0	-0.02	0	-0.001	-0.001
CZ	0	0	-0.001	-0.106	0.002	0	-0.001	-0.04	0	-0.036	0	0.001
DE	#N/D	0	-0.001	-0.091	-0.018	0.07	0	-0.001	-0.058	-0.02	#N/D	-0.057
DK	-0.001	-0.001	#N/D	#N/D	#N/D	0	0.001	-0.001	-0.003	0	-0.039	-0.004
EE	0.001	0.023	-0.735	-0.002	0	0.012	0	0	0.001	0.001	#N/D	0
EL	#N/D	0.003	0	#N/D	0.003	0	0	-0.033	-0.001	-0.001	0	-0.503
ES	#N/D	0.052	#N/D	#N/D	-0.001	0	-0.004	-0.003	0	0	-0.469	-0.584
FI	#N/D	0	-0.001	-0.004	0.006	0.001	-0.015	0	0	-0.001	0	-0.14
FR	#N/D	-0.001	-0.138	-0.098	-0.076	0.001	-0.005	-0.027	0	-0.033	0	-0.221
HR	0.007	0.011	-0.003	0	-0.001	-0.001	-0.002	-0.003	0.007	0	0	0
HU	0.021	0	0.001	-0.023	-0.001	-0.001	-0.001	-0.05	0.002	0	0.014	-0.137
IE	#N/D	0.002	#N/D	#N/D	-0.007	0.123	-0.022	#N/D	0	-0.003	-0.18	-0.032
IS	#N/D	0	0.001	-0.002	0.008	0.082	0	0	0	0.001	-0.001	-0.002
IT	#N/D	0.038	#N/D	#N/D	#N/D	0.003	-0.032	-0.066	-0.001	-0.007	-0.293	-0.257
LT	0.01	0.01	0	-0.007	0.001	0	0	-0.004	0	0	0.001	0
LU	0.01	0	0	-0.002	0	0.019	0	-0.016	-0.032	-0.004	-0.117	-0.344
LV	#N/D	0	0	#N/D	-0.202	-0.003	0	-0.032	0	0.01	#N/D	0
MT	#N/D	0	0.001	#N/D	0.002	0.016	0	0.002	#N/D	-0.017	#N/D	-0.087
NL	0	0	-0.001	-0.065	#N/D	0	0	-0.002	0	-0.003	-0.002	-0.022
NO	0	0	0.001	0	#N/D	0	0	0	-0.002	0	-0.001	-0.111
PL	#N/D	0.025	-0.001	#N/D	-0.001	0	-0.025	-0.022	0.001	0.001	0.002	0.007
PT	#N/D	0.069	#N/D	#N/D	-0.076	-0.001	-0.015	-0.026	#N/D	0	-0.002	-0.004
RO	0.005	0.066	0	0.009	-0.03	-0.092	0	-0.003	0	0	#N/D	0.001
SE	#N/D	-0.003	0.018	-0.002	-0.001	-0.007	0	0	0	0.021	-0.014	-0.014
SI	#N/D	-0.001	#N/D	#N/D	#N/D	0	0	0	0.017	0	#N/D	-0.157
SK	0	0.003	0.001	0	0.002	-0.019	-0.004	0	0	-0.001	0	-0.009
UK	0	0	0.001	0	-0.001	0.074	0	0	0	0	0.013	-0.162

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Table A.8 continued: Panel D

Country	Father's Citizen.			Father's Birth			Father's Education	Father's Skills			Father's Occupation						
	EU	Europe - No EU27	Outside Europe	EU	Europe - No EU27	Outside Europe		Manual occupation	Low-skilled non-manual	High Skilled - non-manual	Employed Part-time	Self-Employed	Unemployed	Retired	House worker	Other inactive	Father Unkown/dead
AT	#N/D	#N/D	#N/D	#N/D	#N/D	-0.281	0.002	-0.063	#N/D	#N/D	#N/D	0	-0.132	-0.004	#N/D	0.014	0
BE	#N/D	#N/D	#N/D	#N/D	0	#N/D	0.084	-0.018	0	#N/D	0	-0.002	-0.141	0	-0.007	-0.001	0
BG	-0.005	0	0.001	0.004	0	0	0.136	0.007	0.084	0.187	-0.018	0.001	-0.044	0.008	0.001	-0.028	-0.184
CH	-0.001	#N/D	-0.01	0	-0.001	-0.004	0.088	#N/D	0	#N/D	-0.001	0	-0.003	0.018	-0.001	#N/D	-0.044
CY	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.142	-0.107	#N/D	#N/D	-0.006	0.001	-0.005	-0.009	-0.037	#N/D	-0.006
CZ	0.001	-0.001	-0.003	-0.002	-0.003	-0.003	0.063	-0.002	0	0.052	0	0.001	-0.13	0	0	-0.001	0.001
DE	#N/D	#N/D	0	#N/D	#N/D	-0.002	0.005	-0.094	0	#N/D	0.001	0.001	-0.003	-0.001	-0.001	0.001	0.001
DK	#N/D	#N/D	#N/D	0	0.002	-0.708	0.001	-0.026	0	#N/D	0.001	-0.001	-0.016	-0.003	-0.006	0.004	-0.01
EE	0.002	-0.033	-0.001	0.001	-0.117	-0.002	0.002	0.002	0	0.162	-0.001	0	-0.05	-0.153	0	0.001	-0.001
EL	#N/D	#N/D	#N/D	-0.005	#N/D	-0.004	0.146	-0.097	#N/D	0	-0.149	-0.001	-0.003	0	0	-1.069	0.002
ES	-0.234	0.017	-0.02	-0.003	0.033	-0.02	0.112	-0.063	0.015	0.027	-0.024	0	-0.01	-0.001	0	0.001	-0.763
FI	#N/D	#N/D	#N/D	0	-0.001	0.001	0.006	-0.053	0	#N/D	-0.001	0	-0.033	-0.018	-0.016	0.002	-0.059
FR	#N/D	#N/D	#N/D	#N/D	-0.039	#N/D	0.082	-0.076	0	#N/D	0.001	0	-0.012	-0.001	-0.024	-0.001	-0.002
HR	0.001	#N/D	-0.001	0.001	#N/D	0	0.11	-0.025	0	#N/D	0.002	-0.119	-0.002	0.006	-0.007	0.003	-0.002
HU	#N/D	#N/D	-0.004	#N/D	#N/D	-0.351	0.116	0	0	#N/D	-0.001	0	-0.064	0.005	0.001	0.023	-1.104
IE	#N/D	#N/D	#N/D	#N/D	0.009	#N/D	0.107	-0.006	#N/D	0.109	-0.006	0.1	0	-0.005	-0.002	0.001	-0.004
IT	#N/D	#N/D	#N/D	#N/D	-0.001	#N/D	0.074	-0.11	-0.057	#N/D	-0.252	-0.026	-0.54	0	-0.433	0	-0.665
LT	0.763	-0.004	-0.002	0.002	0	-0.032	0.121	-0.1	-0.005	0.055	0.007	0.077	0.004	0.001	-0.001	0.004	0.015
LU	-0.094	0	-0.012	-0.001	-0.001	-0.026	0.116	-0.005	0	0.007	0.003	-0.081	0	-0.001	-0.001	0	-0.003
LV	-0.032	-0.001	0	0.002	-0.002	0.004	0.172	-0.016	0.002	#N/D	0.005	0.01	-0.009	-0.007	-0.001	0.005	#N/D
MT	-0.042	-0.002	-0.016	-0.2	-0.258	-0.016	0.07	-0.011	0.003	0.116	0.067	-0.004	-0.001	0	0	0.008	-0.001
NL	0.034	0	-0.331	0.03	0.001	-0.042	0.001	-0.089	0.003	0.02	0	0.002	-0.002	-1.032	-0.001	-0.002	0
NO	-0.013	-0.103	-0.106	-0.004	-0.006	-0.155	0	-0.001	-0.025	0.008	-0.001	0.001	-0.003	-0.003	0	#N/D	-0.002
PL	-0.001	0	0	0	0	0.002	0.057	-0.114	-0.014	#N/D	0	-0.091	-0.001	0	-0.006	0	0.001
PT	#N/D	#N/D	#N/D	-0.003	-0.343	-0.041	0.085	-0.234	-0.134	#N/D	-0.001	-0.072	-0.49	-0.136	-0.007	-0.03	-0.288
RO	#N/D	#N/D	-0.016	#N/D	0.008	-0.016	0.143	-0.023	0.245	0.316	-0.548	-0.323	-0.001	-0.012	0.002	-0.574	-0.055
RS	-0.003	-0.001	-0.001	0.005	0.117	0.007	0.231	0	0	0	-0.916	#N/D	-0.388	0	-0.001	-0.024	-0.327
SE	#N/D	9.582	9.491	-0.155	-9.368	-9.828	-0.005	0.001	0.002	-0.002	#N/D	0	-0.178	0.001	#N/D	#N/D	0.001
SI	#N/D	#N/D	-0.013	#N/D	#N/D	-0.006	0.015	-0.001	0.009	0.085	-0.001	-0.004	-0.002	0	-0.002	0	-0.004
SK	0	-0.002	-0.002	-0.001	0	0	0.064	-0.005	0.001	0.001	-0.225	-0.069	0	0.002	-0.002	0	-0.011

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Table A.8 continued: Panel E

Country	Mother's Citizen.			Mother's Birth				Mother's Education	Mother's Occupation						
	EU	Europe - No EU27	Outside Europe	EU	Europe - No EU27	Outside Europe	Mother dead/unknown		Employed Part-time	Self-Employed	Unemployed	Retired	House worker	Other inactive	Mother Unkown/dead
AT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	-0.001	0.03	#N/D	0	0	-0.001	#N/D	0.001	-0.029
BE	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	-0.022	#N/D	0	0	0	-0.002	-0.003	-0.001	-0.682
BG	-0.077	0	-0.002	0.001	0	0	-0.006	0.155	-0.058	0.001	-0.001	-0.022	0.002	-0.156	-0.397
CH	0.004	#N/D	-0.048	0.007	0	-0.083	-0.142	0.058	0	0	-0.001	0.002	0.001	0	0
CY	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	-0.001	#N/D	-0.015	0	-0.005	0.001	-0.005	0.001	0.016
CZ	0.002	0	-0.002	0	0	-0.002	-0.256	0.073	0	-0.001	-0.262	-0.002	-0.001	-0.002	-0.012
DE	#N/D	#N/D	#N/D	#N/D	#N/D	-0.001	-0.014	0.002	0.001	-0.001	-0.009	-0.001	-0.182	0	0.002
DK	#N/D	#N/D	#N/D	0.003	0.001	#N/D	-0.001	0	0.001	0.007	0	-0.003	-0.001	-0.034	-0.001
EE	0.006	-0.002	-0.002	0	-0.001	0	-0.02	0.086	0.001	0.006	-0.005	-0.004	-0.066	-0.047	0.004
EL	#N/D	#N/D	#N/D	#N/D	#N/D	-0.001	-0.006	0.056	0	0.005	0	-0.005	0	-0.012	0
ES	-0.181	-0.337	-0.527	-0.027	-0.352	-0.01	-0.36	0.1	0	0	-0.009	-0.002	-0.12	-0.001	-0.011
FI	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	-0.018	0.002	0	-0.002	-0.003	-0.017	0	0	0.004
FR	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	-0.056	#N/D	0	#N/D	0.004	0.001	-0.002	0	0.001
HR	0.002	#N/D	#N/D	0.001	#N/D	-0.001	-0.118	0.051	-0.001	-0.123	0	0.003	-0.001	-0.121	-0.005
HU	#N/D	#N/D	0.001	#N/D	#N/D	-0.016	-0.084	0.021	0.003	0	-0.015	-0.001	0.001	-0.036	-0.001
IE	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.082	0	0.008	-0.021	-0.011	-0.013	-0.003
IT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.021	0.008	0.002	-0.015	0	0.001	-0.001	-0.106	-0.283
LT	-2.084	-0.006	-0.01	0.429	-0.003	-0.067	-0.052	0.075	0	0	0	0.001	0.004	0	-2.353
LU	-0.02	0	-0.001	0.001	-0.001	-0.007	-0.156	0.098	0.001	0.052	0.003	0	-0.003	-0.006	0
LV	-0.01	0.001	-0.001	-0.004	0	0.009	-0.175	0.172	0	0.003	-0.005	0.029	0	-0.007	0
MT	-0.011	0.009	-0.005	-0.023	0.001	-0.002	-0.016	0.053	0.064	0.001	#N/D	-0.001	0.002	-0.008	0
NL	-0.001	-0.001	0.233	-0.001	0	0	0	0	0.005	0	-0.002	#N/D	0	-0.003	0.001
NO	-0.005	-0.061	-0.005	-0.001	-0.007	-0.019	-0.002	0.006	0	0	-0.001	-0.002	-0.001	-0.001	-0.003
PL	-0.001	#N/D	0	0	0	0	-0.397	0.134	0.001	-0.085	0	-0.002	0	-0.007	-0.006
PT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	-0.302	0.092	-0.014	0	-0.003	0	0.001	-0.002	-0.023
RO	-0.008	#N/D	-0.015	#N/D	#N/D	#N/D	0	0	-0.008	-0.318	0.001	-0.003	-0.001	-0.022	-0.24
RS	-0.002	-0.002	-0.05	0	0.021	#N/D	-0.001	0.007	-0.261	0	-0.004	0.004	-0.001	-0.001	-0.104
SE	-0.085	0	-0.011	-0.003	0.001	-0.006	0.008	-0.002	#N/D	-0.005	0.001	0	#N/D	-0.003	0.003
SI	#N/D	#N/D	-0.001	#N/D	#N/D	-0.096	-0.203	0.076	-0.009	0	0	0	0.003	-0.003	0
SK	0	-0.001	-0.003	-0.001	0.002	-0.001	0.001	0.059	-0.115	0	-0.104	0	-0.001	-0.139	-0.024

Table continued on next page ...

Table A.8 continued: Panel F

	Household circumstances								Individual Circumstances		
Country	Financial situation of the household	Presence of Parents			Tenancy Status - Owner	Type of Household			Gender	Citizenship	
		Father	Mother	Orphanage		# of Adults	# of Children	# of Earners	Female	EU	NON-EU
AT	0.033	#N/D	0.026	0.604	0.034	0.064	0.174	0.095	0.026	1	1
BE	1	#N/D	0.022	0.038	0.616	0.362	0.991	0.04	0.219	0.088	1
BG	1	0.011	0.042	0.014	0.092	0.028	1	0.02	0.012	0.01	0.009
CH	0.053	0.032	0.012	0.073	0.021	0.013	0.011	0.012	0.254	0.485	0.121
CY	0.042	#N/D	0.072	0.034	0.241	0.021	1	#N/D	0.018	1	1
CZ	0.016	0.075	0.454	0.104	0.306	0.485	0.529	0.019	0.996	0.158	0.023
DE	0.017	#N/D	#N/D	#N/D	0.994	0.034	0.015	0.014	0.319	#N/D	0.033
DK	0.021	0.028	0.024	0.022	0.02	0.022	0.054	0.084	0.025	0.11	0.027
EE	0.012	0.054	0.012	0.011	0.044	0.012	0.038	0.201	0.02	#N/D	0.011
EL	1	#N/D	0.015	0.011	0.063	0.009	0.557	0.012	0.039	0.365	1
ES	1	0.165	0.008	0.967	0.964	1	1	0.005	0.005	0.008	0.06
FI	0.022	0.085	0.366	0.023	0.024	0.075	0.03	0.015	0.012	0.016	1
FR	0.016	#N/D	0.59	0.021	0.991	0.958	1	0.014	0.836	0.042	1
HR	1	#N/D	0.011	0.077	0.185	0.041	0.013	0.011	0.011	0.012	0.014
HU	0.867	#N/D	0.013	0.778	0.762	0.015	0.97	0.069	0.055	0.02	0.029
IE	0.848	0.057	0.026	0.021	1	0.206	0.056	#N/D	0.072	1	0.999
IT	0.987	#N/D	0.037	0.025	1	0.677	0.106	#N/D	0.022	1	1
LT	0.014	0.026	0.01	0.01	0.01	0.009	0.135	0.01	0.023	0.043	0.01
LU	0.021	0.087	0.019	0.072	0.061	0.021	1	0.011	0.01	0.231	1
LV	0.13	#N/D	0.034	1	0.022	0.038	0.021	0.087	0.025	#N/D	0.025
MT	1	0.044	0.008	0.008	0.944	0.025	0.016	0.013	0.077	#N/D	0.026
NL	0.012	0.01	0.033	#N/D	0.045	0.01	0.015	0.012	0.019	0.393	0.723
NO	0.215	0.013	0.008	0.009	0.215	0.008	0.113	0.038	0.01	0.115	0.286
PL	0.999	#N/D	0.008	0.013	0.013	0.253	0.884	0.014	0.018	0.012	0.009
PT	1	#N/D	0.014	0.348	0.023	1	1	0.01	0.009	0.008	0.015
RO	1	0.013	0.014	0.928	0.016	0.012	0.999	0.353	0.014	#N/D	0.015
RS	1	0.011	0.037	0.01	0.334	0.011	0.05	0.993	0.018	0.01	0.053
SE	0.409	0.221	0.02	0.027	0.11	0.018	0.112	0.018	0.024	0.055	0.999
SI	0.103	0.181	0.905	0.066	0.099	0.029	0.017	0.07	0.011	#N/D	0.783
SK	1	0.016	0.057	0.013	1	1	1	1	0.104	0.051	0.012

Table A.9: Full Circumstances - C-Forest

This table presents the results from the C-Forest analysis for the years 2011 and 2019, highlighting the Variable Importance Score (VIS) values for each circumstance. A heatmap is employed to visually depict the magnitude of VIS values. The grid's color scheme conveys the strength of the VIS within each countrywith white indicating PIP values below 0.5 and various shades of red indicating values between 0.5 (light) and 1 (dark) in six different panels. Panel A and D exhibit the findings related to father's circumstances in 2011 and 2019, Panel B and E display the results concerning mother's circumstances in 2011 and 2019, and Panel C and F focus on household and individual circumstances in 2011 and 2019.

Panel A

Country	Father's Citizen.			Father's Birth			Father's Education	Father's Skills			Father's Occupation					
	EU	Europe - No EU27	Outside Europe	EU	Europe - No EU27	Outside Europe		Manual occupation	Low-skilled non-manual	High Skilled - non-manual	Self-Employed	Unemployed	Retired	House worker	Other inactive	Father Unkown/dead
AT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.112	0.096	#N/D	0.101	0.024	#N/D	0.001	#N/D	0.04	0.01
BE	0.022	0.19	1	0.02	0.174	0.57	0.323	0.157	0.069	0.16	0.028	0.016	0.004	#N/D	0.037	0.01
BG	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.828	0.42	0.084	0.316	0.008	0.004	0.023	#N/D	#N/D	#N/D
CH	#N/D	#N/D	#N/D	0.15	0.314	0.169	1	0.987	0.051	#N/D	0.088	#N/D	0.059	#N/D	0.036	0.009
CY	0.362	0.294	0.954	0.305	0.492	0.739	0.785	0.283	0.056	0.486	0.054	#N/D	-0.023	#N/D	0.004	0.025
CZ	0.028	#N/D	#N/D	0.017	0.001	#N/D	0.666	0.349	0.055	0.403	0.045	#N/D	0.017	#N/D	0.037	#N/D
DE	0.023	#N/D	#N/D	0.046	#N/D	#N/D	0.586	1	0.065	#N/D	0.182	0.012	0.015	#N/D	0.008	0.218
DK	0.527	0.115	#N/D	0.261	0.098	#N/D	0.209	1	0.005	0.706	0.512	#N/D	-0.12	#N/D	#N/D	#N/D
EE	0.447	#N/D	#N/D	0.396	#N/D	#N/D	0.799	0.322	0.006	0.714	0.11	#N/D	-0.003	#N/D	0.098	0.011
EL	#N/D	#N/D	#N/D	#N/D	#N/D	0.133	1	0.561	#N/D	#N/D	0.093	#N/D	0.01	#N/D	0.029	-0.005
ES	#N/D	#N/D	#N/D	#N/D	0.009	#N/D	0.382	0.287	0.056	#N/D	0.058	0.026	0.011	-0.002	0.008	0.037
FI	#N/D	#N/D	#N/D	-0.063	0.134	0.122	0.268	0.408	-0.09	#N/D	0.022	0.12	-0.044	#N/D	-0.021	#N/D
FR	#N/D	#N/D	#N/D	0.05	0.029	#N/D	1	0.669	0.01	#N/D	0.105	-0.002	0.018	#N/D	0.045	0.042
HR	0.048	0.131	#N/D	0.004	0.08	#N/D	0.691	0.119	0.053	0.365	-0.003	0.783	-0.012	0.053	0.034	0.071
HU	0.011	-0.007	#N/D	0.008	-0.007	#N/D	1	0.289	0.053	0.591	-0.005	0.034	0.008	-0.01	0.027	0.012
IE	#N/D	#N/D	#N/D	#N/D	0.132	#N/D	1	0.5	0.124	#N/D	-0.001	0.328	-0.113	#N/D	0.08	-0.018
IS	#N/D	#N/D	#N/D	0.292	#N/D	#N/D	0.859	-0.12	0.655	#N/D	-0.122	#N/D	#N/D	#N/D	#N/D	0.081
IT	#N/D	#N/D	#N/D	#N/D	0.013	#N/D	1	0.311	0.03	#N/D	0.003	0.207	0	-0.003	0.02	#N/D
LT	#N/D	0.143	#N/D	#N/D	0.006	#N/D	1	0.326	0.006	0.466	0.036	#N/D	-0.009	#N/D	-0.068	0.094
LU	0.261	0.177	0.178	0.188	0.149	0.203	0.859	0.207	0.042	0.453	0.026	#N/D	0.003	#N/D	-0.004	0.012
LV	#N/D	#N/D	#N/D	0.191	#N/D	#N/D	0.832	0.147	0.011	#N/D	0.034	#N/D	-0.004	0.031	0.013	0.068
MT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	1	0.242	#N/D	#N/D	0.013	0.04	-0.019	#N/D	0.051	0.007
NL	0.015	0.046	0.263	-0.052	0.018	0.063	0.814	0.9	0.328	1	-0.008	0.119	0.316	-0.043	0.22	#N/D
NO	-0.023	-0.391	0.937	0.071	0.05	0.825	0.656	0.566	-0.008	1	0.008	#N/D	0.05	#N/D	#N/D	0.028
PL	#N/D	0.061	#N/D	0.028	0.012	#N/D	1	0.716	0.088	#N/D	0.337	-0.034	0.012	0.028	0.019	0.059
PT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	1	0.693	#N/D	#N/D	0.031	#N/D	0.036	#N/D	0.039	0.109
RO	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	1	0.162	0.066	0.309	0.847	0.002	0.058	0.116	#N/D	-0.001
SE	#N/D	#N/D	#N/D	0.217	0.049	#N/D	-0.223	-0.29	-0.168	#N/D	-0.219	#N/D	-0.031	#N/D	#N/D	#N/D
SI	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.7	0.233	0.085	#N/D	0.114	0.067	0.049	0.018	0.052	0.027
SK	-0.093	#N/D	#N/D	0.007	#N/D	#N/D	1	0.651	0.135	0.793	-0.026	#N/D	-0.072	#N/D	0.003	0.13
UK	-0.006	0.098	0.133	0.004	0.038	0.439	0.636	0.549	0.052	0.665	0.044	0.139	0.072	#N/D	-0.023	-0.002

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Table A.9 continued: Panel B

Country	Mother's Citizen. EU	Mother's Citizen. Europe - No EU27	Mother's Citizen. Outside Europe	Mother's Birth EU	Mother's Birth Europe - No EU27	Mother's Birth Outside Europe	Mother's Education	Mother's Occupation Self-Employed	Mother's Occupation Unemployed	Mother's Occupation Retired	Mother's Occupation House worker	Mother's Occupation Other inactive	Mother's Occupation Mother Unkown/dead
AT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.23	0.02	#N/D	0.01	0.04	0.02	0.01
BE	0.03	0.20	0.99	0.02	0.24	0.57	0.25	0.03	#N/D	#N/D	0.02	#N/D	#N/D
BG	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	1.00	0.00	0.01	#N/D	0.00	0.00	#N/D
CH	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.58	0.07	#N/D	#N/D	0.01	-0.01	-0.01
CY	0.19	0.27	1.00	0.14	0.33	0.62	0.43	0.02	#N/D	#N/D	0.05	0.02	0.01
CZ	0.02	0.04	#N/D	0.05	-0.01	#N/D	1.00	0.03	#N/D	0.01	0.13	-0.05	#N/D
DE	#N/D	#N/D	#N/D	0.05	#N/D	#N/D	0.05	0.05	0.04	0.01	0.12	-0.01	0.02
DK	0.08	0.04	#N/D	0.38	-0.01	#N/D	0.23	-0.18	#N/D	0.09	-0.04	-0.04	#N/D
EE	0.22	#N/D	#N/D	0.49	#N/D	#N/D	1.00	#N/D	#N/D	0.04	0.28	-0.06	0.03
EL	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.04	#N/D	#N/D	#N/D	#N/D	#N/D
ES	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.26	0.02	#N/D	#N/D	0.02	0.01	0.01
FI	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.02	0.00	0.10	#N/D	1.00	-0.06	#N/D
FR	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.77	0.04	#N/D	#N/D	0.08	0.00	0.01
HR	#N/D	0.32	#N/D	0.00	0.13	#N/D	1.00	0.00	0.09	0.00	0.17	-0.06	0.04
HU	0.02	0.00	#N/D	0.02	#N/D	#N/D	0.93	0.00	0.00	0.00	0.16	0.00	0.00
IE	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.86	-0.02	0.16	#N/D	0.13	#N/D	-0.02
IS	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	1.00	-0.20	#N/D	#N/D	0.27	-0.05	#N/D
IT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.02	0.02	0.00	0.09	0.01	#N/D
LT	#N/D	0.11	#N/D	#N/D	0.14	#N/D	0.74	-0.03	#N/D	#N/D	-0.03	#N/D	-0.05
LU	0.24	0.18	0.14	0.07	0.21	0.23	1.00	0.00	#N/D	#N/D	0.03	-0.01	0.00
LV	#N/D	#N/D	#N/D	0.13	#N/D	#N/D	1.00	-0.01	#N/D	-0.01	-0.01	#N/D	#N/D
MT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	-0.01	#N/D	-0.01	0.08	#N/D	0.00
NL	0.06	0.04	0.12	0.08	-0.03	0.07	0.73	-0.06	#N/D	#N/D	0.03	0.00	#N/D
NO	-0.05	#N/D	0.28	-0.01	0.21	0.14	0.06	-0.02	#N/D	-0.05	0.15	#N/D	#N/D
PL	#N/D	#N/D	#N/D	0.00	0.00	#N/D	#N/D	#N/D	0.01	#N/D	0.03	0.01	0.00
PT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.12	#N/D	0.01	0.00	-0.01	0.01
RO	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.98	0.81	0.01	0.01	0.24	-0.02	0.01
SE	#N/D	#N/D	#N/D	-0.22	#N/D	#N/D	-0.28	-0.40	#N/D	#N/D	0.29	1.00	#N/D
SI	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	1.00	0.01	0.02	0.00	0.16	0.03	-0.01
SK	-0.10	#N/D	#N/D	-0.07	#N/D	#N/D	0.88	0.02	0.11	#N/D	0.25	0.17	0.02
UK	-0.04	0.05	0.11	0.09	0.05	0.56	1.00	0.11	0.31	#N/D	-0.03	0.03	#N/D

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Table A.9 continued: Panel C

	Household circumstances									Individual Circumstances		
Country	Ability to make ends meet	Financial situation of the household	Presence of Parents			Tenancy Status - Owner	Type of Household			Gender	Citizenship	
			Father	Mother	Orphanage		# of Adults	# of Children	# of Earners	Female	EU	NON-EU
AT	#N/D	0.03	#N/D	#N/D	0.01	0.03	0.01	0.06	0.02	0.03	0.18	1.00
BE	0.18	0.13	-0.01	0.02	0.01	0.06	0.01	0.05	0.01	0.00	0.02	0.46
BG	0.12	0.21	#N/D	#N/D	#N/D	0.03	0.11	0.52	0.05	-0.01	#N/D	0.01
CH	0.23	0.00	-0.03	0.08	0.06	0.06	0.06	0.22	0.04	0.04	0.07	0.65
CY	0.30	0.31	0.01	0.06	0.00	0.07	0.02	0.02	0.12	-0.01	0.09	0.83
CZ	0.02	0.00	0.05	0.05	#N/D	0.05	0.00	0.25	0.03	0.08	0.05	-0.07
DE	#N/D	0.13	-0.01	0.12	0.09	0.38	0.00	0.05	0.41	0.03	#N/D	0.09
DK	0.05	0.00	#N/D	#N/D	#N/D	0.10	-0.03	0.02	0.21	-0.14	0.33	0.21
EE	0.04	0.18	0.14	0.03	0.00	0.05	0.01	0.05	0.12	0.03	#N/D	0.10
EL	#N/D	0.09	0.00	#N/D	0.03	0.00	0.11	0.16	0.18	-0.01	0.03	0.80
ES	#N/D	0.15	#N/D	#N/D	0.00	0.01	0.04	0.04	0.02	0.00	0.20	1.00
FI	#N/D	0.06	#N/D	0.07	#N/D	0.01	0.38	-0.01	0.20	-0.02	0.03	0.29
FR	#N/D	0.08	0.03	0.09	0.06	0.09	0.05	0.49	0.08	0.02	0.04	0.64
HR	0.19	0.34	0.07	0.02	-0.06	0.01	0.07	0.22	0.45	-0.06	0.02	0.06
HU	0.17	0.12	0.01	0.00	0.00	0.02	0.00	0.64	0.12	0.00	0.01	0.01
IE	#N/D	0.33	#N/D	#N/D	-0.01	0.72	0.40	#N/D	0.12	0.06	0.44	0.09
IS	#N/D	0.26	#N/D	-0.57	#N/D	0.95	0.13	0.13	-0.18	-0.09	0.06	0.14
IT	#N/D	0.30	#N/D	#N/D	#N/D	0.01	0.08	0.45	0.07	0.01	0.08	0.26
LT	0.47	0.55	-0.09	0.07	#N/D	0.07	-0.05	0.22	0.02	-0.08	#N/D	-0.01
LU	0.15	0.07	0.02	0.03	0.00	0.07	0.02	0.08	0.12	0.01	0.43	0.57
LV	#N/D	0.07	-0.02	#N/D	#N/D	0.08	0.01	0.33	0.02	0.12	#N/D	0.06
MT	#N/D	0.07	0.03	#N/D	0.01	0.05	-0.02	0.04	#N/D	0.04	#N/D	0.01
NL	0.24	0.08	0.06	-0.08	#N/D	-0.05	0.03	0.16	0.06	0.14	-0.02	0.25
NO	-0.01	0.03	0.16	#N/D	#N/D	-0.03	-0.11	0.03	0.03	-0.09	-0.06	0.69
PL	#N/D	0.22	0.00	#N/D	0.00	0.09	0.08	0.14	0.08	0.00	#N/D	-0.02
PT	#N/D	0.90	#N/D	#N/D	0.04	0.02	0.04	0.22	#N/D	-0.01	0.02	0.01
RO	0.46	0.32	#N/D	0.04	#N/D	0.08	0.02	0.17	0.01	-0.03	#N/D	#N/D
SE	#N/D	0.18	0.15	-0.19	#N/D	0.22	0.09	-0.33	-0.36	0.85	0.12	0.19
SI	#N/D	0.03	#N/D	#N/D	#N/D	-0.01	0.01	0.06	0.13	0.00	#N/D	0.53
SK	0.13	0.16	0.04	-0.03	#N/D	0.18	0.05	0.02	0.13	0.03	0.03	#N/D
UK	0.08	0.08	-0.04	-0.09	0.02	0.27	0.09	0.00	0.00	-0.04	0.14	0.46

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Table A.9 continued: Panel D

Country	Father's Citizen.			Father's Birth			Father's Education	Father's Skills			Father's Occupation						
	EU	Europe - No EU27	Outside Europe	EU	Europe - No EU27	Outside Europe		Manual occupation	Low-skilled non-manual	High Skilled - non-manual	Employed Part-time	Self-Employed	Unemployed	Retired	House worker	Other inactive	Father Unkown/dead
AT	#N/D	#N/D	#N/D	#N/D	#N/D	0.44	0.03	0.12	#N/D	#N/D	#N/D	0.04	0.02	0.02	#N/D	#N/D	#N/D
BE	#N/D	#N/D	#N/D	#N/D	0.02	#N/D	0.25	0.08	0.02	#N/D	#N/D	0.01	0.03	0.00	0.01	#N/D	0.00
BG	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	1.00	0.46	0.09	0.58	0.03	0.01	0.08	0.03	0.02	#N/D	#N/D
CH	0.23	#N/D	0.14	0.10	0.09	0.11	0.84	#N/D	-0.09	#N/D	-0.01	0.04	#N/D	#N/D	#N/D	#N/D	#N/D
CY	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	1.00	0.77	#N/D	#N/D	0.02	0.02	0.03	#N/D	0.04	#N/D	#N/D
CZ	0.00	-0.03	#N/D	0.00	-0.01	#N/D	1.00	0.36	0.03	0.64	#N/D	0.03	0.08	#N/D	0.01	#N/D	#N/D
DE	#N/D	#N/D	0.04	#N/D	#N/D	0.95	1.00	0.81	0.06	#N/D	0.00	0.02	0.09	0.02	0.02	#N/D	#N/D
DK	#N/D	#N/D	#N/D	0.01	-0.03	1.00	0.00	0.36	0.07	#N/D	#N/D	0.11	0.02	0.01	#N/D	#N/D	#N/D
EE	0.17	0.26	0.02	-0.02	0.22	#N/D	0.31	0.30	0.04	1.00	#N/D	-0.10	0.05	-0.13	0.03	#N/D	#N/D
EL	#N/D	#N/D	#N/D	0.00	#N/D	-0.01	1.00	0.45	#N/D	0.14	0.06	0.08	0.03	0.00	-0.01	0.15	#N/D
ES	0.16	0.06	0.82	0.13	0.07	0.56	0.46	0.17	0.04	0.19	0.00	0.01	0.02	0.01	0.01	#N/D	#N/D
FI	#N/D	#N/D	#N/D	-0.02	0.35	0.31	0.11	0.41	0.01	#N/D	-0.12	0.08	0.14	0.17	0.06	#N/D	0.16
FR	#N/D	#N/D	#N/D	#N/D	0.04	#N/D	0.56	0.36	0.02	#N/D	-0.06	0.03	0.02	0.01	0.03	#N/D	0.01
HR	#N/D	#N/D	#N/D	0.01	#N/D	#N/D	1.00	0.39	0.00	#N/D	#N/D	0.44	0.08	-0.01	0.02	-0.08	0.02
HU	#N/D	#N/D	0.11	#N/D	#N/D	0.11	1.00	0.12	0.01	#N/D	#N/D	-0.01	0.03	0.02	-0.02	#N/D	#N/D
IE	#N/D	#N/D	#N/D	#N/D	0.04	#N/D	1.00	0.16	#N/D	0.52	0.05	0.24	0.03	-0.04	0.03	#N/D	#N/D
IT	#N/D	#N/D	#N/D	#N/D	0.20	#N/D	0.59	0.27	0.05	#N/D	0.18	0.10	0.12	-0.01	0.10	#N/D	0.53
LT	#N/D	-0.03	0.20	#N/D	-0.02	#N/D	1.00	0.69	-0.03	0.66	#N/D	0.22	-0.07	#N/D	0.02	#N/D	#N/D
LU	0.34	0.22	0.47	0.20	0.17	0.56	1.00	0.25	0.04	0.30	#N/D	0.11	#N/D	0.00	0.03	#N/D	#N/D
LV	-0.03	0.25	0.06	-0.04	0.18	#N/D	0.96	0.48	0.00	#N/D	#N/D	0.10	0.06	0.04	0.09	#N/D	#N/D
MT	0.08	0.12	0.09	0.16	0.20	0.09	0.86	0.44	0.12	1.00	#N/D	0.05	0.06	#N/D	0.04	0.04	0.02
NL	-0.06	0.02	1.00	0.11	0.02	0.20	0.11	0.27	0.02	0.58	0.01	0.01	-0.03	0.04	-0.02	#N/D	#N/D
NO	0.22	0.26	1.00	0.15	0.13	0.99	0.02	0.03	-0.02	0.10	-0.01	0.00	#N/D	#N/D	-0.01	#N/D	#N/D
PL	#N/D	-0.02	#N/D	-0.01	0.01	#N/D	0.77	0.71	0.08	#N/D	-0.02	0.44	0.01	-0.01	0.03	-0.02	0.02
PT	#N/D	#N/D	#N/D	0.01	0.07	0.01	0.55	0.81	0.11	#N/D	0.00	0.04	0.09	0.01	0.01	#N/D	0.04
RO	#N/D	#N/D	0.03	#N/D	#N/D	0.02	0.77	0.37	0.14	0.49	0.05	1.00	0.00	-0.03	#N/D	0.21	0.05
RS	-0.02	0.03	#N/D	0.01	0.09	#N/D	1.00	0.12	0.07	0.17	0.21	#N/D	0.34	0.02	#N/D	0.09	0.07
SE	#N/D	0.05	1.00	0.07	0.02	0.75	-0.03	-0.01	-0.01	0.00	#N/D	0.04	0.01	0.00	#N/D	#N/D	#N/D
SI	#N/D	#N/D	0.46	#N/D	#N/D	0.54	0.86	0.50	0.19	1.00	#N/D	0.02	0.03	0.03	0.13	#N/D	#N/D
SK	0.02	#N/D	#N/D	0.01	#N/D	#N/D	0.60	0.24	0.05	0.30	0.17	0.06	0.01	#N/D	0.04	#N/D	#N/D

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Table A.9 continued: Panel E

Country	Mother's Citizen.			Mother's Birth				Mother's Education	Mother's Occupation						
	EU	Europe - No EU27	Outside Europe	EU	Europe - No EU27	Outside Europe	Mother dead/unknown		Employed Part-time	Self-Employed	Unemployed	Retired	House worker	Other inactive	Mother Unkown/dead
AT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	-0.01	0.13	#N/D	-0.01	#N/D	#N/D	#N/D	0.06	#N/D
BE	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.01	#N/D	0.00	0.01	0.00	#N/D	0.00	0.08	0.19
BG	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.02	0.97	0.02	0.02	0.00	#N/D	#N/D	0.09	0.02
CH	0.23	#N/D	0.20	0.19	0.04	0.21	0.02	1.00	-0.05	-0.01	#N/D	#N/D	#N/D	0.03	#N/D
CY	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.01	#N/D	0.03	0.03	#N/D	#N/D	#N/D	0.03	#N/D
CZ	0.01	-0.01	#N/D	0.00	-0.01	-0.01	0.06	0.73	-0.03	0.01	0.14	#N/D	0.01	0.06	#N/D
DE	#N/D	#N/D	#N/D	#N/D	#N/D	0.04	0.20	0.20	0.15	-0.14	0.18	#N/D	0.08	-0.08	-0.03
DK	#N/D	#N/D	#N/D	0.09	-0.07	#N/D	#N/D	-0.03	-0.18	0.05	#N/D	0.04	#N/D	0.00	#N/D
EE	0.02	0.16	0.08	0.01	0.03	0.01	0.04	0.50	-0.07	-0.04	0.01	#N/D	0.01	0.01	0.03
EL	#N/D	#N/D	#N/D	#N/D	#N/D	-0.01	0.01	0.45	0.00	0.05	0.01	-0.13	#N/D	0.07	0.04
ES	0.11	0.05	1.00	0.10	0.06	0.73	0.03	0.21	0.00	0.01	0.01	#N/D	#N/D	0.07	#N/D
FI	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.13	0.23	-0.05	0.21	0.06	0.11	-0.07	0.00	-0.08
FR	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.02	#N/D	0.02	#N/D	0.01	#N/D	0.01	0.06	0.00
HR	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.05	0.82	#N/D	0.25	0.02	0.03	#N/D	0.59	#N/D
HU	#N/D	#N/D	0.02	#N/D	#N/D	0.02	0.13	0.82	0.04	-0.05	#N/D	#N/D	0.03	0.22	0.11
IE	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.08	0.01	#N/D	#N/D	0.02	0.12	#N/D
IT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.01	0.40	0.03	0.05	#N/D	-0.01	0.01	0.32	0.05
LT	#N/D	0.02	0.06	#N/D	-0.02	#N/D	0.00	0.81	-0.06	-0.01	#N/D	#N/D	0.01	0.02	#N/D
LU	0.17	0.22	0.34	0.11	0.22	0.38	0.02	0.59	0.01	-0.01	#N/D	#N/D	0.01	0.11	0.04
LV	#N/D	0.06	-0.05	-0.03	0.06	0.05	0.08	1.00	#N/D	0.05	0.00	0.26	#N/D	0.06	#N/D
MT	0.15	0.06	0.03	0.15	-0.03	0.02	0.03	0.57	0.07	0.04	#N/D	#N/D	#N/D	0.06	#N/D
NL	0.27	-0.16	0.50	0.05	0.08	0.05	0.00	-0.01	0.13	-0.09	#N/D	#N/D	-0.04	0.17	#N/D
NO	0.13	0.21	0.83	0.08	0.17	0.60	0.02	0.02	-0.09	-0.03	#N/D	#N/D	0.01	-0.02	-0.03
PL	#N/D	#N/D	#N/D	0.01	-0.01	#N/D	0.04	1.00	0.00	0.64	0.01	-0.02	0.03	0.04	0.00
PT	#N/D	#N/D	#N/D	#N/D	#N/D	#N/D	0.07	0.33	0.03	0.02	0.02	-0.01	0.00	0.10	#N/D
RO	#N/D	#N/D	0.01	#N/D	#N/D	#N/D	0.02	0.32	0.02	0.71	0.00	#N/D	0.02	0.04	0.31
RS	-0.03	0.01	0.05	-0.02	0.05	#N/D	0.02	0.41	#N/D	0.00	0.07	-0.01	#N/D	0.20	#N/D
SE	0.10	0.03	0.89	0.01	0.03	0.80	#N/D	0.09	#N/D	-0.01	#N/D	#N/D	#N/D	0.10	0.00
SI	#N/D	#N/D	0.58	#N/D	#N/D	0.75	0.09	0.90	0.07	0.02	-0.01	0.01	0.03	0.15	#N/D
SK	0.03	#N/D	#N/D	0.00	#N/D	#N/D	0.09	0.57	0.14	0.00	0.09	#N/D	0.08	0.42	0.05

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Table A.9 continued: Panel F

Country	Financial situation of the household	Presence of Parents			Tenancy Status - Owner	Type of Household			Individual Circumstances		
									Gender	Citizenship	
		Father	Mother	Orphanage		# of Adults	# of Children	# of Earners	Female	EU	NON-EU
AT	0.02	#N/D	0.02	0.09	0.03	0.03	0.06	0.02	-0.02	0.21	1.00
BE	0.13	#N/D	0.01	0.01	0.06	0.07	0.12	0.05	0.02	0.02	1.00
BG	0.41	0.01	0.01	#N/D	0.02	0.03	0.38	0.02	0.00	#N/D	#N/D
CH	0.06	-0.02	0.01	0.03	0.15	0.03	0.06	0.05	0.08	0.36	0.25
CY	0.23	#N/D	-0.01	-0.01	0.06	0.02	0.30	#N/D	0.03	0.46	0.92
CZ	0.06	0.05	0.03	#N/D	0.06	0.14	0.18	0.07	0.09	0.04	-0.02
DE	0.07	#N/D	#N/D	#N/D	0.79	0.15	0.17	-0.07	0.17	#N/D	0.12
DK	0.05	0.07	0.08	#N/D	0.03	-0.05	0.08	0.42	-0.27	0.63	0.13
EE	-0.04	-0.01	0.04	#N/D	-0.04	-0.04	0.00	0.17	-0.05	#N/D	0.02
EL	0.36	#N/D	0.03	0.02	0.09	0.02	0.15	0.02	-0.01	0.03	0.55
ES	0.32	0.01	0.01	0.02	0.05	0.06	0.06	0.02	0.00	0.09	0.49
FI	-0.06	-0.02	0.44	#N/D	0.01	0.03	0.09	0.08	-0.14	-0.06	1.00
FR	0.05	#N/D	0.03	-0.01	0.14	0.11	0.21	0.03	0.01	0.02	1.00
HR	0.76	#N/D	-0.03	0.00	0.06	0.00	0.04	0.28	0.00	-0.02	0.02
HU	0.35	#N/D	0.04	#N/D	0.13	-0.01	0.58	0.27	0.03	-0.03	-0.04
IE	0.19	#N/D	0.01	#N/D	0.88	0.06	0.05	#N/D	0.04	0.31	0.14
IT	0.72	#N/D	0.02	0.03	0.30	0.09	0.14	#N/D	0.03	0.39	1.00
LT	0.11	0.03	0.05	#N/D	-0.01	-0.08	0.10	-0.03	-0.02	#N/D	-0.06
LU	0.09	0.03	0.01	0.00	0.07	0.06	0.37	0.00	-0.02	0.27	0.90
LV	0.11	#N/D	0.06	#N/D	0.06	-0.05	0.15	0.29	0.02	#N/D	0.07
MT	0.40	0.06	0.05	#N/D	0.30	0.14	0.04	-0.04	0.02	#N/D	0.14
NL	0.02	0.02	-0.02	#N/D	-0.02	0.03	0.10	0.08	0.04	0.60	0.58
NO	0.14	-0.01	-0.04	#N/D	0.26	0.03	0.22	0.08	-0.01	0.19	0.66
PL	0.23	#N/D	0.01	-0.01	0.01	0.07	0.13	-0.01	0.05	#N/D	-0.05
PT	1.00	#N/D	0.02	0.01	0.02	0.09	0.39	0.06	0.01	0.00	0.04
RO	0.36	0.02	-0.03	#N/D	0.02	0.02	0.20	0.25	0.00	#N/D	#N/D
RS	0.46	0.03	-0.01	0.03	0.13	-0.01	0.08	0.64	0.02	-0.02	0.10
SE	0.03	0.03	0.01	#N/D	0.02	0.00	0.01	-0.01	0.01	0.04	0.54
SI	0.08	0.07	0.14	#N/D	0.13	-0.02	0.13	0.35	-0.07	#N/D	0.84
SK	0.56	0.07	0.08	#N/D	0.19	0.15	1.00	0.51	0.07	-0.01	#N/D

References

Breiman, Leo. , 2001, random forests. *Machine Learning* 45, 5–32.

Brunori, Paolo, Hufe, Paul, and Mahler, Daniel. , 2023, the roots of inequality: estimating inequality of opportunity from regression trees and forests. *The Scandinavian Journal of Economics* 125, 900–932.

Chen, T., and Guestrin, C.. , 2016, xgboost: a scalable tree boosting system. in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* 785–794 New York, NY, USA. ACM.

Chipman, Hugh A., George, Edward I., and McCulloch, Robert E.. , 2010, bart: bayesian additive regression trees. *The Annals of Applied Statistics* 4, 266–298.

Feldkircher, Martin, and Zeugner, Stefan. , 2015, bayesian model averaging employing fixed and flexible priors: the bms package for r. *Journal of Statistical Software* 68.

Hastie, Trevor, Tibshirani, Robert, and Friedman, Jerome. , 2009, . *the elements of statistical learning: data mining, inference, and prediction.* Springer Science & Business Media, New York 2nd edn.

Hernández, Belinda, Raftery, Adrian E, Pennington, Stephen R, and Parnell, Andrew C. , 2018, bayesian additive regression trees using bayesian model averaging. *Stat. Comput.* 28, 869–890.

Moser, Mathias, and Hofmarcher, Paul. , 2014, model priors revisited: interaction terms in bma growth applications. *Journal of Applied Econometrics* 29, 344–347.

Yao, Yi-Ching. , 1984, estimation of a change-point in multiple regression models. *Statistics & Probability Letters* 2, 21–26.