Research conceptualising resilience primarily focuses on how past and current events or perceptions of the future determine fertility decision-making, emphasising adaptive responses to various threats. We employ data from the second wave of the Gender and Generation Program Survey (2024) concerning the following countries: Austria, Croatia, Czechia, Denmark, Estonia, Finland, Germany, Netherlands, Norway and United Kingdom. We deploy machine learning to analyse fertility intentions in relation with the personal resources and challenges faced by couples. Our results confirm the universal importance of certain factors, such as age and partnership status or the number of children already in the household.

Keywords: resilience, fertility intentions, GGP

INTRODUCTION

The concept of resilience is understood as an individual personality trait, encompassing personal, social, and environmental factors that shape one’s ability to adapt and recover (Fonagy et al., 1994, Aassve and Bastianelli, 2024). Previous research has identified resilience as an individual’s ability to positively adapt to some risk or adversity (Rutter, 2012). In the context of fertility choices, resilience refers to the capacity of individuals and couples to formulate plans for future childbearing, even under conditions of uncertainty. Moreover, resilient individuals and couples are able not only to make such plans but also to carry them out, whereas those with lower resilience may struggle to translate intentions into concrete actions.

A growing body of literature highlights that uncertainty is central to understanding fertility intentions, especially in times of crisis. Studying how individuals and families make fertility decisions under conditions of uncertainty is therefore crucial for understanding both demographic resilience and the long-term ability of societies to adapt.

However, resilience in fertility decision-making is not only an individual or family matter but also has broader societal implications. The ability of individuals and couples to form and implement fertility plans determines whether children are born, thereby influencing population renewal, intergenerational relations, and the long-term resilience of societies (Schoen et al., 1999; Sobotka, 2017). Previous research highlights that fertility decisions are embedded in wider social and institutional contexts, and that the ability to pursue fertility intentions is shaped by both individual resources and structural conditions (Morgan & Bachrach, 2011; Vignoli et al., 2020c). In this sense, understanding fertility intentions through the lens of resilience directly connects micro-level decision-making with broader demographic and social outcomes (Bengtson & Putney, 2006; Lesthaeghe, 2010). In this study, we analyze fertility plans through the lens of the interplay between individual- and family-level characteristics and broader country-level conditions, which together can foster or constrain resilience.

Our study builds on these insights by examining fertility intentions in the context of the COVID-19 pandemic, which created widespread uncertainty and tested both individual and societal resilience, but also by the lens of individual and household characteristics. Using recent data from the Gender and Generations Programme, we explore data from large set of European countries— Austria, Croatia, Czechia, Denmark, Estonia, Finland, Germany, Netherlands, Norway and United Kingdom —

to identify the individual- and family-level factors associated with resilience in fertility planning, and to assess how these patterns vary across different country contexts.

We explore resilience in fertility decision-making by identifying key factors that shape fertility intentions at the individual level. We analyse how the interplay of individual factors contributes to resilience at the personal level. We conduct our discussion in the context of the intensity of the COVID-19 pandemic measured by number of deaths at the time of the survey. We examine short-term fertility intentions using a machine learning approach (random forest). To date, few studies have utilized machine learning to gain a better understanding of fertility (Li & Xu, 2022; Stulp et al., 2023; Xu et al., 2024). Although, this tool provides much-needed flexibility in linking personal characteristics to outcomes, without requiring additional functional form assumptions. Moreover, development in explainable machine learning allows looking into the black box, and recovering interesting patterns.

Our contribution is the following. First, we analyze fertility intentions in the context of crisis (COVID-19) exploring the interplay between micro- and macro-level factors (individual and family characteristics, and country-level statistics). Second, we use novel method in this topic, machine learning, to indicate not only direction, but mainly, importance of each factor for fertility intentions certainty. Third, we explore the interactions between micro- and macro-level factors to fully describe how the resilience of individuals and families in the context of fertility intentions is shaped.

We find that the most important factors for predicting positive or negative fertility intentions—rather than uncertainty about short-term fertility—are the number of children, age (both the individual's and their partner's), and, to a lesser extent, type of relationship (married versus informal) and country of residence. The indicator of the current crisis stage (number of COVID-19 deaths) was less influential than, for example, education level, but more so than employment status or life satisfaction.

The article is structured as follow: in the next sections, we provide a literature review, data and method description, we elaborate about the results, and provide discussion and conclusion remarks.

LITERATURE REVIEW

The theoretical framework of fertility intentions

The Theory of Planned Behaviour (TPB) (Ajzen, 1991; Ajzen & Klobas, 2013) is frequently applied to explain fertility intentions, which are central to fertility decision-making. Following Klobas (2011), TPB is an appropriate model for aspects of human fertility that fall within an individual's control and involve conscious decision-making. This raises the question on whether the framework when studying fertility intentions in the face of societal crises, such as pandemic or war, which escape individual control. According to TPB, intentions are a driving force behind any action. Intentions are shaped by personal characteristics, attitudes, norms, and perceived behavioural control. This implies that both the availability of resources and a person's subjective sense of their ability to act, determined by perceived obstacles and constraints, play a crucial role (Ajzen & Fishbein, 2005; Fahlén & Oláh, 2018).

Fahlén and Oláh (2018) applied the TPB framework to understanding the interplay between individual life situations and institutional factors that shape people's perceived behavioural control, which can influence their sense of risk and security regarding their current situation and prospects. In our study, we employ a similar approach; however, we limit ourselves to individual factors that can play a decisive role in both perceived security and a sense of risk and security in the face of crises such as the Covid-19 pandemic, and consequently in the shape positive or negative fertility intentions.

Fertility Intentions and Resilience

Recent crises, such as the COVID-19 pandemic and the war in Ukraine, have heightened concerns regarding employment, health, and family security, thereby influencing fertility plans (Gatta et al., 2022; Vignoli et al., 2020a; Vignoli et al., 2020c; Chłoń-Domińczak et al., 2024). However, the effects were not homogeneous. Luppi et al. (2020) show that, while the pandemic induced downward revisions of fertility plans in Italy, Germany, France, Spain, and the United Kingdom, the variation across groups and countries was substantial. Raybould et al. (2023) observed both pro-natal and anti-natal shifts in the UK, resulting in only modest net changes.

Studies on the impact of the COVID-19 pandemic on social behaviour have provided new insights into social resilience. Resilience is recast as the ability of individuals and social entities to respond to challenges, enabling them to cope and adjust to adverse events (Pereirinha & Pereira, 2021). The global nature of the pandemic enabled the analysis of social resilience at various levels: international, national, local, household, and individual.

Studies indicating decline in fertility following crises (Luppi et al., 2020; Furceri et al., 2024), do not imply that social resilience can be directly translated into individual (family) resilience. Family resilience research tends to focus on intra-family coping mechanisms. In contrast, social resilience studies emphasize broader socioeconomic risks. In short, there is a disconnect in how resilience is conceptualized in relation to fertility (Bawati et al., 2024). Economic and social uncertainties may influence fertility decline not only through individual and familial challenges but also through systemic, community-level disruptions. Our study builds on these trends, focusing on factors that determine fertility intentions, and highlighting differences and similarities at the country level.

Economic uncertainty

In addition to the uncertainty about health and life caused by the pandemics, economic uncertainty is a key factor in determining fertility decisions (Comolli, 2017; Fahlén & Oláh, 2018; Vignoli et al., 2022; Kreyenfeld et al., 2023). Unemployment is considered a crucial marker of economic uncertainty in studies on fertility intentions (Novelli et al., 2021). Busetta et al. (2019) found that the higher the level of permanent unemployment, the lower the woman's fertility intentions. Among couples, the joblessness of man appears as a more significant driver of partner’s fertility intentions, even more than her own status. One can hypothesize that being unemployed reduces the opportunity cost for woman, such as in Adsera (2004). However, evidence remains mixed. A recent meta-analysis suggests that the negative effect of unemployment dominates in Europe (Alderotti et al., 2021).

Perceived resilience to job loss is a strong predictor of fertility intentions, as individuals who feel confident in their ability to handle potential economic setbacks are more likely to plan for parenthood. Unlike perceived employment stability, which has a limited impact, resilience shapes fertility decisions independently of external labour market conditions (Gatta et al., 2022). Moreover, while economic crises may strain family resources, resilient families demonstrate the ability to adapt and sustain support for their children despite financial challenges (UNICEF, 2025). In the context of fertility, resiliency in the face of crises, goes beyond individual's ability to cope with economic uncertainty, Comolli (2023) highlights various social phenomena affecting communities, morality, and social interactions. The study demonstrates that a deteriorating social climate and increasing uncertainty are associated with lower and more uncertain intentions for first and second births. Within this framework, uncertainty is not entirely rational. It concerns not only the actual circumstances faced by individuals, but also personal perceptions of the future (Neyer et al., 2022). Narratives about the future play a crucial role in shaping their actions, as they are deeply embedded in cultural and social environments (Vignoli et al., 2020c). Moreover, in times of global uncertainty, people react to more than just their current situation and limitations; visions of the future create a sense of distance from everyday life, which strongly influences fertility decisions, either hindering or encouraging them (Vignoli et al., 2022).

Vignoli, Drefahl and Desantis (2012) and Vignoli, Tocchioni, and Mattei (2020) find that job uncertainty helps to explain a first-birth postponement among women and men, particularly among women with higher education. Economic uncertainty reduces also the desire for a (additional) child (Ranjan, 1999). However, empirical results demonstrate that the links between economic uncertainty and fertility intentions are more complex (Alderotti et al., 2021). Whether uncertainty leads to a decline in positive fertility intentions is gender specific and is moderated by factors such as the type of welfare state (Fahlen & Olah, 2018). The Covid-19 pandemic has undoubtedly left its mark on the global economy, giving economic uncertainty a different dimension.

Health uncertainty

The health condition of individuals and uncertainty about it in the future cannot be neglected in the context of fertility intentions. A poor health status, infertility issues, chronic and mental illnesses determine planning and having children (Cvancarova et al., 2009; McGrath et al., 1999, Chen et al., 2001; Langeveld et al., 2002). This context is especially important for women (Dow & Kuhn, 2004, Fair et al., 2000, Langeveld et al. 2002) as it is strongly related to the time of pregnancy and delivery. However, men can be also exposed to health risks that make conceiving and raising children difficult or impossible (Cheng & Ng, 2007; Hammoud et al., 2008). These studies highlight the negative relationship between obesity and fertility for both genders.

Besides being an immediate predictor, concerns over long-term health can also influence fertility choices. Katz (2006) highlights that individuals can be exposed to health risks, which hinder individuals' ability to raise a child. These risk factors can lower fertility intentions. These risk factors have two elements in common: they are individual and, often, their life cycle patterns are known and anticipated. COVID-19, which is the immediate context of our research, introduces a new form of health risk. This health risk was common to all population, it was impossible to anticipate, and the consequences were uncertain. Wang, Gozgor & Lau (2022) show that COVID-19 pandemic-related health uncertainty was associated with a decrease in fertility rates; however, once the risk of the pandemic receded fertility rates appeared to recover, see Sobotka et al (2024).

In our analysis, we take into account subjective health status as a variable possibility explaining differences in certainty about fertility plans, for both genders.

Socio-demographic factors

Finally, fertility uncertainty can be analyzed through social and demographic characteristics, which may influence resilience in the face of socioeconomic crises to varying degrees. The question of who is unsure about their fertility intentions is key to understanding the source of such uncertainty. Fertility intentions are used, among others, to make population projections. Identifying socio-demographic characteristics of uncertain individuals helps to understand the challenges and character of declaration of fertility intentions, for example whether it is permanent or temporary. Jones (2017) finds that uncertainty is more likely among older women (above 30 years old), having one or more children, having strong desire against pregnancy and assessing own partner fertility plans as uncertain. Having certain features of human capital (Becker, 2009) may also increase individual resilience to various risk factors.

Experiencing parenthood offers firsthand insight into the costs and benefits of raising children, as well as an individual's capabilities as a parent. Consequently, both fertility intentions and realizations of childless individuals may differ from those of already parents. In Poland, Grzenda (2024) shows that even though intentions of parents and childless individuals were similar, realizations of these intentions were not.

One of the characteristics of the second demographic transition (Dirk, 1987) was the rejection of traditional values in favour of liberal ones. This manifested, among others, in an increase in cohabitation, as well as the rising share of children born out of wedlock. However, according to research (Wagner et al., 2019), the absence of a partner remains one of the main factors leading to childlessness. Therefore, in our study, we analyse factors such as life satisfaction and being in a formal relationship (marriage). We also focus on religiosity, which impacts short-term fertility intentions in Europe is ambiguous (Spéder & Kapitány, 2015).

To sum up, in our study we address two research questions. First: which individual characteristics such as age, parental status, formal relationship, employment, financial and housing uncertainty, life satisfaction, education, religiosity, subjective health matter for uncertainty in short-term fertility intentions in comparison to large macro-level crisis such as COVID-19 pandemics and what is the direction of relationship. Second: what are most important interactions between those factors and direction of correlations.

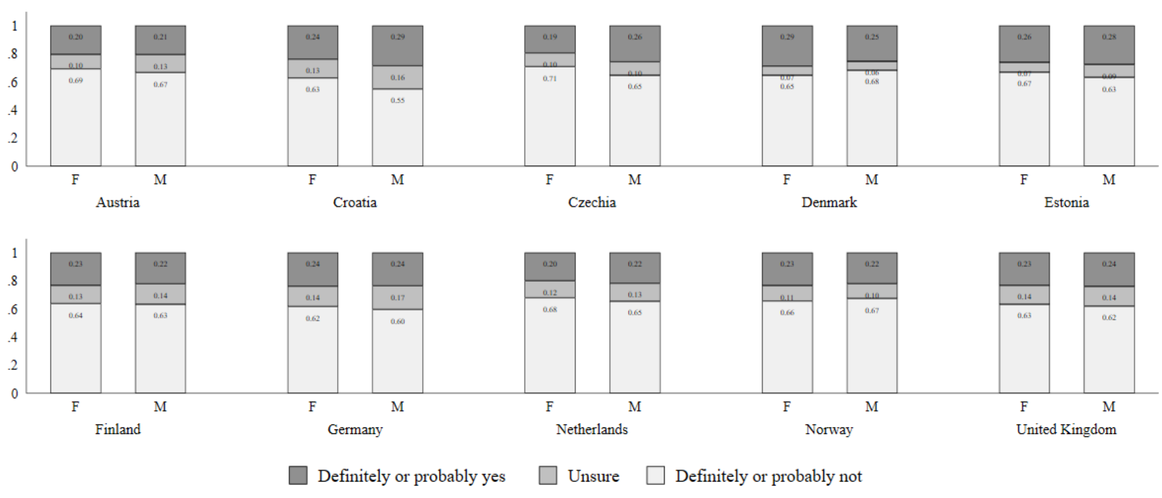
DATA

This study used data from the second wave of the Gender and Generation Programme Survey (GGP, 2024). We examined ten countries: Austria, Croatia, Czechia, Denmark, Estonia, Finland, Germany, Netherlands, Norway and United Kingdom. The choice of countries was based on data availability, geographical location and the intensity of the Covid-19 pandemic. The survey was developed as to allow comparative analysis. Care was taken to harmonize both questions, and possible answers.

The GGS survey typically covers individuals aged 18 to 79. Our study focuses on fertility intentions of couples, and we therefore included respondents aged 20-50 who currently have a partner. We focus on heterosexual couples, as we expect that the possibilities and constraints faced by these couples are similar across countries. provided information on their fertility intentions and whether they had children. By focusing on people aged 20 to 50 we are able to capture (almost) the entire reproductive period for men and women, and certainly the time when couples make decisions regarding their fertility. We exclude from the sample observations that do not provide information on their fertility intentions, or who lack information on basic demographic characteristics (age, gender, etc.). Table A1 in the Appendix shows the resulting samples after including each criterion.

For exploring certainty in the short-term fertility intentions, we selected variable with an answer to a question: "*Do you intend to have a/another child during the next three years? Please take into account only biological children.*" Respondents could choose one of six possible answers: "*Definitely not*", "*Probably not*", "*Unsure*", "*Probably yes*", "*Definitely yes*", and "*Currently expecting a child*". For this study, individuals who selected "*Currently expecting a child*" were excluded from the analysis. When constructing the dependent variable, we combined the "*Definitely not*" and "*Probably not*" responses, as well as the "*Definitely yes*" and "*Probably yes*" responses, resulting in a dependent variable with three levels.

Figure 1: Fertility intentions by gender and country of residence



Note: figure presents the distribution of answers to the question “Do you intend to have a child in the next three years?” by country and gender. Female respondents are indicates with the letter “F” and Male respondents with “M.” Numbers indicate fraction of individuals in each category, they might not add up to one due to rounding. Source: own elaboration based on GGS data, see text for more details.

Figure 1 summarizes the distribution of the dependent variables across countries. The distributions of fertility intentions appear similar. In all countries, the proportion of respondents with uncertain fertility intentions ranges between 7 and 15 percent, where the lowest values correspond to Denmark and Estonia. Around 60 percent of respondents in each country does not want to have a (an additional child). The proportions are similar for men and women. The remaining 25 to 30 percent of individuals express positive fertility intentions. The very low fertility intentions are partially driven by sample composition.

Our analysis includes several markers for uncertainty, both objective and subjective. Among the objective, we include the labour market status of respondent and their partner, where the former is more detailed. We also include a measure of their income, which indicates to what extent is household income sufficient to make ends meet. Answers to this question reflect both objective and subjective elements. Moreover, we use subjective health status as a proxy for health uncertainty, as it reflects individuals' perceived well-being and potential future health risks, which are crucial for fertility decisions. While objective health measures provide valuable insights, fertility planning is often influenced by personal health perceptions and anticipated limitations. This approach aligns with previous research highlighting the role of self-assessed health in fertility choices.

We also include two measures of housing uncertainty. During the questionnaire, respondents were asked about their household situation, and particularly whether they owned their current residence. Couples who are not owners might be less certain about their future. Respondents also informed about their intention to move. This variable shows lack of satisfaction with current living conditions. For these couples, moving to a new residence might be a necessary step before becoming parents.

To capture uncertainty and stage of the crisis due to COVID-19 pandemic we merged the data with COVID-19 deaths at the time when the survey was conducted. To ensure comparability, number of deaths has been standardized at the country level. We expect that a higher number reflects a greater disruption in respondents' lives. [1]

Besides these variables, the model also includes several additional controls. These include gender of the respondent, migrant status, number of children in the household,[2] religiosity, a measure of generalized trust, a measure of how much individuals plan for their future, and a measure of life satisfaction. All models also account for country fixed effects. Descriptive statistics of all variables included in the model, and the correspondent levels, are presented in Table A2 in the Appendix. We also display the number of missing values. We do not proceed to impute missing values, as the method does not require complete observations. Only in the case of religiosity and subjective health, we created a separate category of no answer to collect the missing observations.

METHODS

To assess which factors are important for short-term fertility plans, and how, we decided to use a machine learning method – random forest.

Random forest is a method developed for classification tasks, i.e. tasks in which we want to learn the most likely outcome given a set of characteristics. This method

[1] In some countries, the survey also includes direct questions on how much people believe their lives (and society) had change as a result of the pandemic. Unfortunately, these questions were asked only in some countries, and their formulation was not consistent.

[2] This variable is recoded to contain four levels: zero, one, two, and three or more.

represents an improvement over decision trees, as it reduces the risk of overfitting and makes the predictions more robust to the database used. In essence, the technique consists of building multiple decision trees and selecting as a prediction the modal output (Breiman, 2001).

The construction of decision trees involves constructing a random subset of the data, chosen with replacement. In this database, we fit a tree by creating nodes that split the data into branches. These splits are chosen to minimize the Gini impurity criteria in each of the resulting child nodes. Each tree grows until it reaches a stopping criterion, such as the maximum depth (number of splits) or each leaf has reached the smallest sample size allowed. In both cases, no further splits are possible.

Clearly the depth of the tree and the minimum size of the leaf determine which patterns can be recovered. Greater depths (or smaller leaves) increase the complexity of the model and allow capturing more intricate patterns. However, deeper trees (also smaller leaves) are also more prone to overfitting, in which case results will lack robustness. The output of the estimation process is a mapping from a vector of characteristics (of dimension k, where k is the number of variables) to an outcome vector. This outcome vector can contain the probabilities of observing each outcome (no, uncertain, yes), or a prediction of the most likely outcome (mode).

Selecting the right hyperparameters

A crucial initial step concerns then the estimation of hyperparameters, the maximum depth, minimum leaf sizes, and the number of estimators used in each estimation. We search parameters over a broad parameter space using a random search algorithm and five-fold cross-validation on the training sample (90% of all observations). We select the parameters that maximize the average F_1 score. This criterion is defined as

$$F_1=\frac{1}{K}\sum_{i=1}^{K}\frac{2TP_i}{2TP_i+FN_i+FN_i}$$

Where K indicates the number of classes, i.e. 3, TP stands for True positives, FN for false negatives and FP for false positive. The F_1 score is the harmonic mean of precision and recall. The main advantage of this criterion is that it gives equal weights to each outcome of the classification problem. This feature is especially important when classes are not balanced. As seen in Figure 1, most respondents (around 60% in each country) did not plan to have a child in the next three years. The remaining 40% were evenly split across between those who plan, and those who do are uncertain.

Given the randomness involved, we bootstrap the entire process ten times, each time selecting a different (random) sample to train the model. Finally, we opted to have a minimum leave size of one, a depth of 143, and 168 trees in the forest. The performance of the model is presented in Table B1 in the Appendix, split between the test and training samples. In the train sample, the fit is almost perfect, as only a few predictions diverge from their actual values. In the test data, the parameters show an acceptable accuracy: 71% of correct predictions. The prediction ability differs across classes, and the least numerous ("uncertain") seldom gets predicted, only 1% of observations are classified in this group. The recall for this category is around 3%, considerably lower than the more numerous categories. Appendix Table B2 shows the recall and precision for each category, as well as the average values.

RESULTS

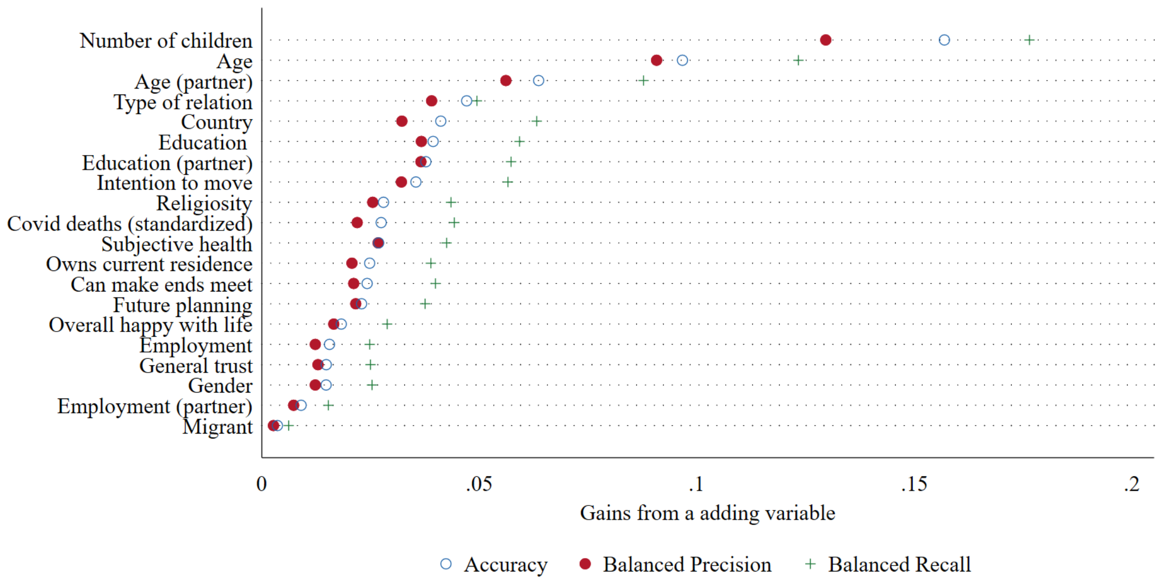
We split the section into two parts. In the first part, we consider which characteristics serve to differentiate fertility intentions by fitting a single model to all available databases. This model includes country and gender as additional predictors. In the second part, we focus more explicitly on whether predictors of fertility intentions are different for men and women, and across countries.

What drives fertility intentions?

In the main model the dependent variable has three categories, one for each intention: Negative, those who do not want to have (more) children; Uncertain; Positive, those who would like to have additional children. As discussed in the data section, the model contains twenty different predictors, which differ in their ability to predict the outcome variable. To evaluate which variables matter the most, we employ permutation methods. The method consists of comparing the predictive power of the fitted model to an artificial model where a given variable has been replaced with random numbers (from the same distribution). The difference between the two predictions shows how a given variable improves the performance of the model. We employ three different performance measures: accuracy, balanced precision and balanced recall.[3]

[3] Accuracy denotes the ratio of correct predictions to total predictions. Precision shows the ability of the model to predict an outcome, i.e. the proportion of times that a prediction of a given class is correct. Balanced precision is an average of precision for each level of the dependent variable. Balanced recall denotes the average sensitivity. In both, balanced precision and balance recall all levels of the dependent variable have the same importance.

Figure 2. Permutation importance



Notes: Dots indicate the average gains in different performance measures from including a variable in the model, gains are defined as the difference between the full model and a model where a given variable has been replaced by random numbers. We repeat the procedure 10 times for each variable.

We observe that the most important variable is the presence of other children in the household, followed by age and partner's age. These results are not too surprising, as fertility intentions change over the life cycle, and couples who already have achieved their preferred family size might not be planning for future children. Age and partner's age also exhibit a high correlation in our sample, which can explain why model's performance decreases to a similar extent when these variables are excluded.

Type of relationship (formal versus informal), country of residence, education and whether individuals want to move, appear to distinguish fertility intentions of respondents. But their contribution is minor in relation to the variables discussed before. The number of deaths at the time of the interview is very close to this group, suggesting that fertility intentions were affected by the pandemic. Markers of uncertainty concerning the housing status (ownership and moving intentions) are in the same range of values.

At the very bottom of Figure 2 we find two personal traits: gender and migrant status. The low importance of migrant status suggests that migrants react similarly to non-migrants when faced with similar conditions. However, it could also reflect insufficient variation of this variable. Around 10 percent of individuals are migrants, so randomizing the values affects a small proportion. In the case of gender, we are more confident to state that men and women react similarly when facing similar circumstances.

Figure 2 does not express the direction of the effects. While we know that age is an important variable, it does not indicate how it operates. To understand how this variable affects the predicted probabilities, we proceed to estimate partial dependency function. The partial dependency function is a counterfactual exercise, where we assign to each individual the same level of a given variable (e.g. we treat everyone as if they had higher education) and compute the predicted probability. We repeat this exercise for all levels of the (relevant) predictors. The results are presented in Table 3. For ease of interpretation, the table also includes the observed proportions in the first row. The table is split into two parts. On the first three columns, the partial dependence is obtained from the full sample. On the second set of columns, the results pertain the subsample of individuals who are young (i.e. aged between 20 and 40 years old) with fewer than two children. We focused on this subsample as they are more diverse in their fertility intentions. The order of variables is consistent with their importance as presented in Figure 2.

Table 1. Predicted probabilities by variables

Short-term fertility intentions: do you plan to have a child?	All			Restricted sample: below 40 and with less than 2 children		
	Yes	Uncertain	No	Yes	Uncertain	No
Mean	0.242	0.123	0.634	0.453	0.188	0.360
Number of children						
0-Childless	0.408	0.068	0.523	0.408	0.068	0.523
1-One	0.468	0.038	0.494	0.468	0.038	0.494
2-Two	0.026	0.023	0.951			
3-Three or more	0.004	0.005	0.991			
Age (respondent)						
1-[20-24]	0.275	0.050	0.675	0.452	0.081	0.466
2-[25-29]	0.329	0.072	0.599	0.550	0.124	0.326
3-[30-34]	0.339	0.073	0.587	0.583	0.126	0.291
4-[35-39]	0.284	0.053	0.663	0.534	0.092	0.374
5-[40-49]	0.128	0.021	0.851	0.238	0.026	0.735
Age (partner)						
1-[20-24]	0.253	0.056	0.691	0.461	0.088	0.450
2-[25-29]	0.300	0.070	0.629	0.547	0.115	0.338
3-[30-34]	0.316	0.068	0.616	0.584	0.109	0.306
4-[35-39]	0.285	0.059	0.656	0.553	0.100	0.347
5-[40-49]	0.203	0.027	0.769	0.408	0.047	0.545
Type of relation						
1-Partner	0.257	0.095	0.648	0.483	0.155	0.362
2-Married	0.370	0.049	0.581	0.708	0.052	0.240
Country						
Austria	0.257	0.062	0.681	0.257	0.062	0.681
Croatia	0.283	0.064	0.652	0.283	0.064	0.652
Czechia	0.281	0.062	0.656	0.281	0.062	0.656
Denmark	0.319	0.031	0.650	0.319	0.031	0.650
Estonia	0.292	0.048	0.660	0.292	0.048	0.660
Finland	0.258	0.069	0.674	0.258	0.069	0.674
Germany	0.250	0.077	0.673	0.250	0.077	0.673
Netherlands	0.263	0.063	0.674	0.263	0.063	0.674

Norway	0.281	0.066	0.653	0.281	0.066	0.653
Education						
1-Primary	0.254	0.064	0.682	0.254	0.064	0.682
2-High-School	0.270	0.068	0.662	0.270	0.068	0.662
3-Bachelor	0.277	0.059	0.664	0.277	0.059	0.664
4-More than BA	0.290	0.050	0.661	0.290	0.050	0.661
Education (partner)						
1-Primary	0.260	0.069	0.671	0.260	0.069	0.671
2-High-School	0.266	0.074	0.660	0.266	0.074	0.660
3-Bachelor	0.274	0.066	0.661	0.274	0.066	0.661
4-More than BA	0.282	0.063	0.655	0.282	0.063	0.655
Religiosity						
1-No	0.249	0.082	0.669	0.249	0.082	0.669
2-Intermediate	0.285	0.071	0.643	0.285	0.071	0.643
3-Yes	0.309	0.067	0.624	0.309	0.067	0.624
Subjective health						
1-Very good	0.274	0.074	0.652	0.274	0.074	0.652
2-Good	0.264	0.087	0.649	0.264	0.087	0.649
3-Fair	0.262	0.076	0.662	0.262	0.076	0.662
4-Bad	0.261	0.081	0.659	0.261	0.081	0.659
Owns current residence						
0-No	0.255	0.092	0.653	0.477	0.150	0.374
1-Yes	0.275	0.087	0.638	0.509	0.128	0.363
Can make ends meet						
1-With great difficulty	0.257	0.090	0.652	0.482	0.140	0.378
2-With difficulty	0.258	0.091	0.651	0.483	0.140	0.377
3-With some difficulty	0.259	0.093	0.647	0.483	0.144	0.373
4-Fairly easily	0.260	0.095	0.645	0.481	0.148	0.371
5-Easily	0.260	0.094	0.646	0.481	0.148	0.371
6-Very easily	0.264	0.088	0.648	0.492	0.139	0.369
Future planning						
1-I plan	0.266	0.088	0.646	0.495	0.139	0.366
2-somehow	0.261	0.093	0.646	0.486	0.145	0.368
3-neither nor	0.258	0.098	0.644	0.480	0.154	0.366
4-rather not	0.255	0.094	0.651	0.474	0.147	0.379
5-Take each day	0.252	0.092	0.656	0.469	0.145	0.386
Overall happy with life						
0-No	0.257	0.100	0.644	0.472	0.150	0.377
1-Yes	0.268	0.102	0.630	0.491	0.151	0.358
Employment						
1-Working	0.264	0.097	0.639	0.264	0.097	0.639
2-Unemployed	0.248	0.082	0.670	0.248	0.082	0.670
3-Inactive	0.230	0.049	0.721	0.230	0.049	0.721
4-Leave	0.265	0.078	0.657	0.265	0.078	0.657
General trust						

1-Most people can be trusted	0.260	0.099	0.642	0.475	0.150	0.375
2-Need to be very careful	0.258	0.103	0.639	0.475	0.156	0.369
Gender						
0 - Man	0.256	0.104	0.640	0.468	0.158	0.374
1 - Woman	0.260	0.100	0.641	0.479	0.154	0.367
Employment (partner)						
0-Not employed	0.249	0.097	0.654	0.458	0.147	0.395
1-Work	0.260	0.109	0.632	0.471	0.163	0.367
Migrant						
0-No	0.259	0.111	0.630	0.468	0.166	0.366
1-Yes	0.258	0.106	0.635	0.472	0.162	0.365

Notes: Table shows partial dependence functions for variables in the model.

The number of children was the most important feature in Figure 2, and Table 1 reproduces this result. There is a dramatic difference in the partial dependence functions for zero or one child, against two or more. In the former, the partial probability of expressing positive fertility is around 20 percentage points, whereas among those with two or more children it falls to less than 5 percentage points. This pattern corresponds to the two-child ideal.

When it comes to predictors, we observe that as people age, they are more likely to state positive fertility intentions until they become 35 years old. Then there is a sharp decline in the predicted probabilities. People older express very little uncertainty, and they tend to express negative intentions. This pattern matches well with observed fertility realization, i.e. there is a sharp decline after turning forty years old. We observe a similar pattern when considering the age of the partner, though responses are flatter, see also Figure B2 in the Appendix. If decisions were made jointly, we would expect these patterns to overlap more.

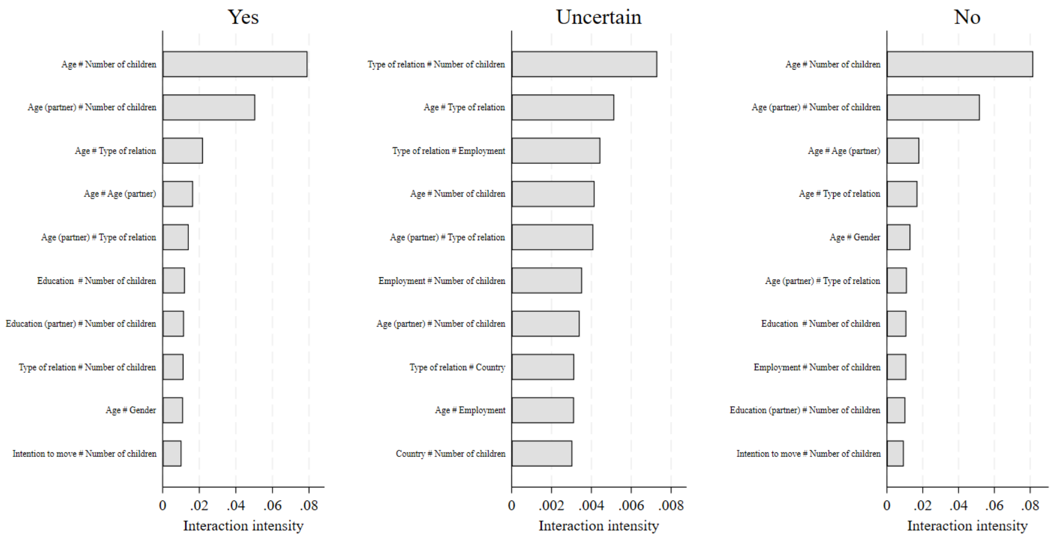
Other variables affect the probabilities in the expected direction. Being married is associated with a lower uncertainty, and higher positive fertility intentions, especially in the restricted younger sample. A more secure economic position, exemplified by the labor market status or household financial situation, is associated with a more positive fertility intention. In the restricted sample, the difference in the probability of stating a positive fertility intention between *Inactive* and *Working* is as high as five percentage points, a more than 10% increase from average values. Similarly, if we consider education, we observe that higher education is related almost monotonically with the probability of expressing desire to have children. This would be expected if people with higher education have access to resources that increase their resilience to uncertainty. We can also observe an important role of having a better health status in expressing positive fertility intentions. Somehow surprisingly, household financial situation play a minor role in the model, while households with higher income are more likely to express positive fertility intentions the difference between more and less affluent households is of around one percentage point.

Relevant interactions: micro- and macro-level factors

In the previous section, we used partial dependence functions to recover the direction of each variable. In this section, we expand its use to identify and explore relevant interactions. We follow the procedure laid out in Greenwell et al. (2018). The intuition behind their approach is simple. If the effects of variable X1 (X2) vary across different levels of variable X2 (X1), then there is an interaction between these two variables. Greenwell et al. (2018) propose to measure dispersion of the effects of X1 within levels of X2 using the range. And then, they use the standard deviation of these ranges to aggregate across levels of X2. An essential component of this method is the partial dependence function of the prediction with respect to the two variables under study. This measure does not indicate the direction of the interaction;

it only shows where there is greater dispersion of the predicted probabilities. We compute this "interaction intensity" measure separately for each level of the dependent variable.

Figure 3: Important interactions for each response



Notes: Own elaboration. Interaction intensity obtained following Greenwell et al. (2018). We compute the interaction intensity separately for each answer.

In Figure 3, we show the most important interactions in the model. The horizontal axes show the amount of dispersion of effects when we hold features constant. Each graph shows interactions for fertility intention. The figures for "Yes" and "No" are very similar, and in fact the first five interactions are identical. This suggests that these interactions trade between these two outcomes, i.e. that "Uncertainty" varies less across these variables. The most important interactions in "Uncertainty" include some of the same variables ("Age", "Number of children"), but they also include new variables: employment and religiosity. The narrower range of these interactions reflects the lower frequency of this outcome was less frequently selected.

The most important interactions are between variables with a steeper partial dependence to begin with: age, number of children and age of the partner. In fact, as shown in Figure B2 these variables command the larger interactions overall, followed closely by education, employment, religiosity and country. On the other side of the spectrum, variables such as gender and migrant status present very weak interactions overall. The only exception is an interaction between age and gender, which reflect the fact that men can plan to have children at higher ages than women.

DISCUSSION

Due to different demographic, economic, social, and cultural conditions in individual countries, resilience in fertility planning may take different forms. In the context of uncertainty in fertility intentions, examining the differences between individual and family characteristics provides insights into how families respond to crises and what resources help them maintain reproductive plans.

As highlighted in the previous research, demographic characteristics are associated with fertility plans in diverse ways across countries (Luppi et al., 2020). Our study confirms this by showing that only already having children and age of the respondent and their partner are universally important in predicting certainty about fertility plans. This finding reflects a strong role of the planed size of the family (mainly, 2+2 or 2+1) and awareness of biological constraints: with increasing number of children and with age, individuals and couples tend to be more decisive about not planning (more) children in the near future.

At the same time, empirical research suggests that characteristics related to global crises, but measured at the individual level such as economic or health conditions, can also affect resilience in fertility decision-making (Busetta et al., 2019; Wang, Gozgor & Lau, 2022). Yet, some studies have found little evidence that crisis-driven economic uncertainty leads to abandoning or postponing fertility plans (Luppi et al., 2020). Our findings align more closely with the latter: while we incorporated indicators of household, health, and pandemic-related uncertainty, these turned out to be less important for the certainty of fertility plans than expected. Notably, gender did not significantly influence outcomes, suggesting that fertility decisions, and uncertainties, are often shared within couples, pointing to resilience as a joint family process rather than an individual trait.

Summing up, we find that only a small number of variables matter strongly, and consistently for short-term fertility plans. Men and women are most likely to plan children in their 30s, with increasing age associated with greater certainty, but mostly due to a decision not to have additional children. Religiosity plays a role in differentiating between those with positive versus negative intentions: religious individuals are more likely to express fertility plans, while those with low religiosity are more likely to opt against childbearing. Importantly, religiosity may reflect not only beliefs but also community embeddedness and social support, which can mitigate the effects of uncertainty and enhance resilience.

Our approach emphasizes the *importance* of different factors rather than their directional interpretation. This novelty allows us to highlight how some features such as age, marital status, and religiosity contribute more strongly than others to resilience in fertility intentions. At the same time, our study has limitations. First, we analyze associations rather than causal mechanisms, meaning we cannot directly identify the drivers of uncertainty. Second, we capture country-level differences but not specific policies implemented during the pandemic, which may have shaped resilience at the societal level. Incorporating such policy measures in future work would help clarify how institutional responses interact with family-level resilience.

CONCLUSIONS

Understanding fertility intentions is crucial for projecting population dynamics, yet the growing prevalence of uncertainty in fertility plans adds complexity to this task. By focusing on individuals who are unsure about their childbearing plans, this study contributes to understanding how resilience operates at the intersection of individual, family, and societal factors.

Our results indicate that only two characteristics are significantly important for shaping fertility intentions - age and number children already born. Other factors, such as educational attainment and labor market status, play a limited role, suggesting that even individuals with stable employment and higher education may remain uncertain about their fertility plans during crises. Religiosity and marital status, however, emerge as important correlates: being religious and being married are both associated with positive fertility intentions, while marriage additionally reduces uncertainty. These findings point to the relevance of both personal resources and social embeddedness in supporting resilience.

From a broader perspective, our findings offer lessons about how families adapt to crises and under what conditions they can sustain reproductive plans and create supportive environments for children. Families with stable partnerships and strong community ties are better able to buffer uncertainty and maintain fertility intentions, thereby securing more favorable conditions for childbearing and child development. At the same time, societal conditions matter: while the direct effect of the COVID-19 crisis was modest in our models, the pandemic context shaped the environment within which families made decisions, illustrating the interplay between individual/family resilience and societal resilience.

Finally, our results highlight that uncertainty itself should be treated as a key outcome. Monitoring uncertainty in fertility intentions provides valuable insights into how individuals and families experience crises and how fragile or resilient their reproductive plans are under stress. Policymakers aiming to support family resilience should therefore not only promote favorable structural conditions (e.g., childcare provision, income security, accessible health services) but also pay attention to how uncertainty affects family planning and children's well-being.

In conclusion, resilience in fertility intentions is co-constructed by individuals, families, and societies. By analyzing both certainty and uncertainty in fertility planning during the COVID-19 pandemic, we show that family adaptation is rooted in a combination of personal resources, household stability, and supportive societal contexts. Recognizing and strengthening this interplay is key to enabling families to adapt to crises, sustain fertility plans, and ensure good conditions for children's growth and development.

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Appendix A: Additional sample description

Table A1. Sample sizes

	All	20<age<49	with partner	Fertility intentions	Basic demographics
Austria	8 266	5 817	4 217	3 961	3 839
Croatia	7 487	5 995	4 284	3 959	3 875
Czechia	5 594	3 487	2 790	2 646	2 626
Denmark	8 269	7 672	5 380	5 020	4 980
Estonia	9 252	6 631	4 951	4 623	4 577
Finland	3 388	2 928	2 107	1 988	1 959
Germany	22 048	20 796	15 650	15 512	14 807
Netherlands	8 078	5 440	3 806	3 571	3 504
Norway	5 374	4 311	3 070	2 747	2 733
United Kingdom	7 875	5 483	3 417	3 152	3 104

Notes: Table presents the sample size in each country upon applying the restrictions listed in the text. The last column presents the final database used in the analysis. Overall, the sample contains 46 004 observations.

Table A2. Descriptive statistics

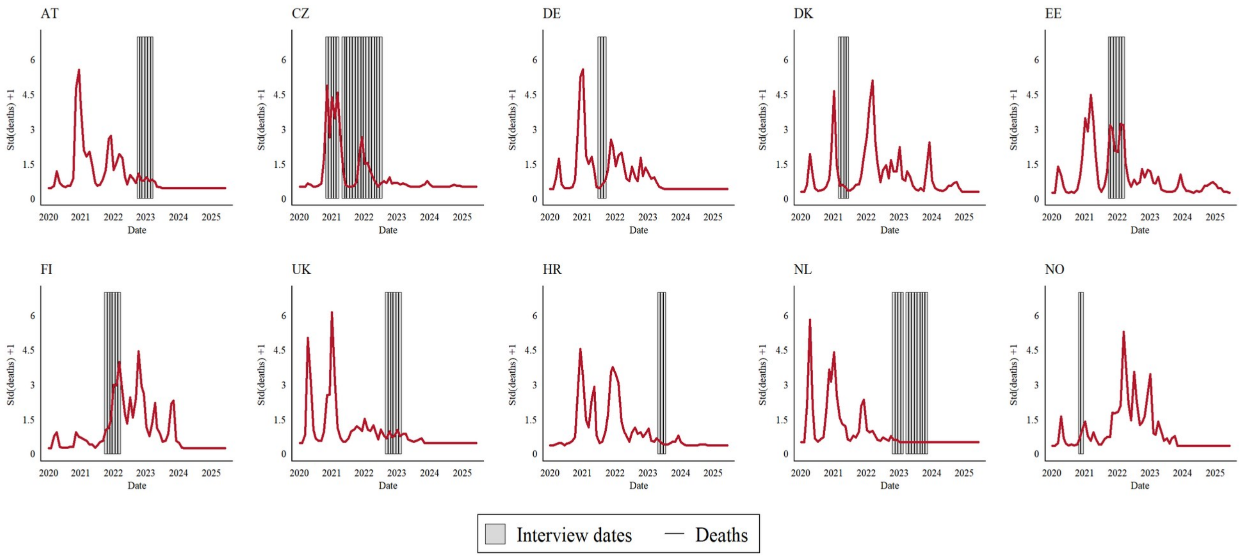
	Fertility intentions			
	Definitely or probably not	Unsure	Probably or definitely yes	Total
Age	38.37	32.04	31.61	35.98
	(8.02)	(6.44)	(5.32)	(7.94)
Gender				
Man	38.69	42.58	40.14	39.51
Woman	61.31	57.42	59.86	60.49
Migrant				
No	89.43	88.17	87.58	88.83
Yes	10.57	11.83	12.42	11.17
Education				
Primary	5.14	4.54	3.32	4.63
High-School	42.99	42.32	34.29	40.82
Bachelor	28.67	28.55	31.33	29.29
More than BA	23.21	24.59	31.07	25.25
Number of children				
Childless	25.87	54.91	60.73	37.76
One	15.51	22.71	29.74	19.79
Two	41.34	17.57	7.78	30.40
Three or more	17.27	4.81	1.76	12.04

Subjective health				
Very good	24.47	26.46	30.96	26.26
Good	49.73	49.62	48.80	49.50
Fair	21.36	20.19	17.15	20.21
Bad	4.43	3.73	3.08	4.02
Religiosity				
No	64.99	65.08	64.35	64.85
Intermediate	11.43	11.06	10.52	11.17
Yes	23.58	23.85	25.13	23.98
Employment				
Working	81.68	75.50	79.08	80.30
Unemployed	2.65	3.16	2.78	2.74
Inactive	6.63	6.05	4.67	6.09
Leave	4.37	7.82	8.56	5.80
No answer	4.68	7.47	4.91	5.08
Can make ends meet				
With great difficulty	2.04	2.20	1.67	1.97
With difficulty	4.69	5.27	4.07	4.61
With some difficulty	15.86	16.41	12.96	15.24
Fairly easily	26.55	24.68	23.72	25.64
Easily	22.17	20.79	23.21	22.25
Very easily	16.45	15.86	21.10	17.49
No answer	12.24	14.78	13.28	12.80
Overall happy with life				
No	31.88	33.96	28.95	31.43
Yes	58.67	54.24	61.16	58.73
No answer	9.44	11.80	9.89	9.84
General trust				
Most people can be trusted	43.20	36.71	43.32	42.43
Need to be very careful	43.36	46.98	42.64	43.64
No answer	13.43	16.31	14.04	13.93
Future planning				
I plan	16.30	16.39	19.65	17.12
somehow	17.83	18.13	20.53	18.52
neither nor	27.44	27.22	25.82	27.03
rather not	19.77	17.64	15.99	18.61
Take each day	6.70	6.37	5.27	6.32
No answer	11.94	14.25	12.73	12.41
Owns current residence				
No	33.75	55.59	50.73	40.48
Yes	66.25	44.41	49.27	59.52
Intention to move				
Definitely not	40.06	20.87	23.27	33.69
Probably not	28.95	23.88	22.01	26.67
Unsure	11.52	20.97	14.03	13.28
Probably yes	11.02	20.07	21.94	14.74
Definitely yes	7.96	13.73	18.26	11.13
No answer	0.48	0.48	0.49	0.48

Type of relation				
Partner	38.91	65.72	58.88	46.97
Married	61.09	34.28	41.12	53.03
Age (partner)	39.28	32.33	31.92	36.68
	(9.44)	(7.16)	(6.09)	(9.17)
(proportion missing)	3.17	4.12	3.53	3.37
Education (partner)				
Primary	6.54	4.93	4.76	5.92
High-School	43.46	42.35	36.10	41.56
Bachelor	26.38	26.06	28.16	26.77
More than BA	21.01	23.05	28.68	23.09
No answer	2.61	3.60	2.30	2.66
Employment (partner)				
Not employed	9.93	11.25	9.99	10.11
Work	76.70	71.15	75.93	75.83
No answer	13.37	17.60	14.08	14.06
Country				
Austria	8.92	7.65	7.17	8.34
Croatia	7.87	10.02	9.08	8.42
Czechia	6.12	4.51	5.21	5.71
Denmark	11.21	5.70	12.42	10.83
Estonia	10.19	6.39	11.13	9.95
Finland	4.24	4.72	4.07	4.26
Germany	30.63	40.61	32.01	32.19
Netherlands	7.99	7.67	6.58	7.62
Norway	6.18	5.20	5.69	5.94
United Kingdom	6.64	7.54	6.63	6.75
Covid deaths (standardized)	-0.11	-0.21	-0.10	-0.12
	(0.74)	(0.64)	(0.76)	(0.73)

Note: Tables presents descriptive statistics used in the study. Column headers indicate values of the outcome variable. The category “No answer” was recoded to missing prior to the analysis.

Figure A1: Deaths by Covid during the sample period



Notes: The picture plots the standardized number of Covid deaths in each country (we add one for visualization). The vertical bars indicate dates on which at least an interview took place.

Deriving covariates for the model

We derive the following variables.

Age and partner's age are based on the variables *dem02y* (own year of birth) and *dem22y* (year of birth partner) and *intdatey* (Year of interview).

Number of children is based on the variables *dem42* (Biological children with current partner) and variables *lhi08_xx* (number of children with partner xx).

Education and partner's education. These variables are based on *dem07isced* and *dem25isced*. We merged the categories: *Primary* and *Lower secondary* (Primary), *Upper secondary* and *Post secondary non tertiary* (*High school)*, *Short cycle tertiary* and *Bachelor* (B.A.), and *Master* and *PhD* (More than BA)

Employment is based on the variable *dem06*. The following categories were merged: *Employed, Self-Employed, Helping family member, Military* (Employed); *Unemployed* and *Other* (Unemployed); *In education, Retired, Homemaker, Ill or disabled* (Inactive), *On maternal or paternity leave, on parental leave* (Leave).

Employment partner is based on *wrk32*. We merged the following categories: *not in paid job, but looking…, Not in paid job, not looking* ("Not employed"), *In paid employment* ("Working").

Subjective health is based on *wel06*. We merged the last two categories *Bad* and *Very bad* (Bad).

Future Plan is based on *att02*, which is on a 0-10 scale. We create the levels "I plan" (values 0/2), "Somehow" (values 3/4), "Neither nor"(values 5/6), "Rather not" (values 7/8), and "I take each day" (values 9/10)

Religiosity is based on *att10*, which is on a 0-10 scale. We create the levels "No" (values 0/4), "Intermediate" (level 5), "Yes" (values 6/10).

Happy with life: is based on *wel08*, which is on a 0-10 scale. We create the levels "No" (values 0-7), "Yes" (values 8-10)

The following variables were not modified: Gender (based on *dem02*), Migrant origin (based on *dem03),* Intention to move (based on *dem19*).

Appendix B: Additional model characteristics.

Table B1: Confusion matrix

Train data

	hat(No)	hat(Unsure)	hat(Yes)
No	23385	0	4
Unsure	109	4859	15
Yes	74	0	9742

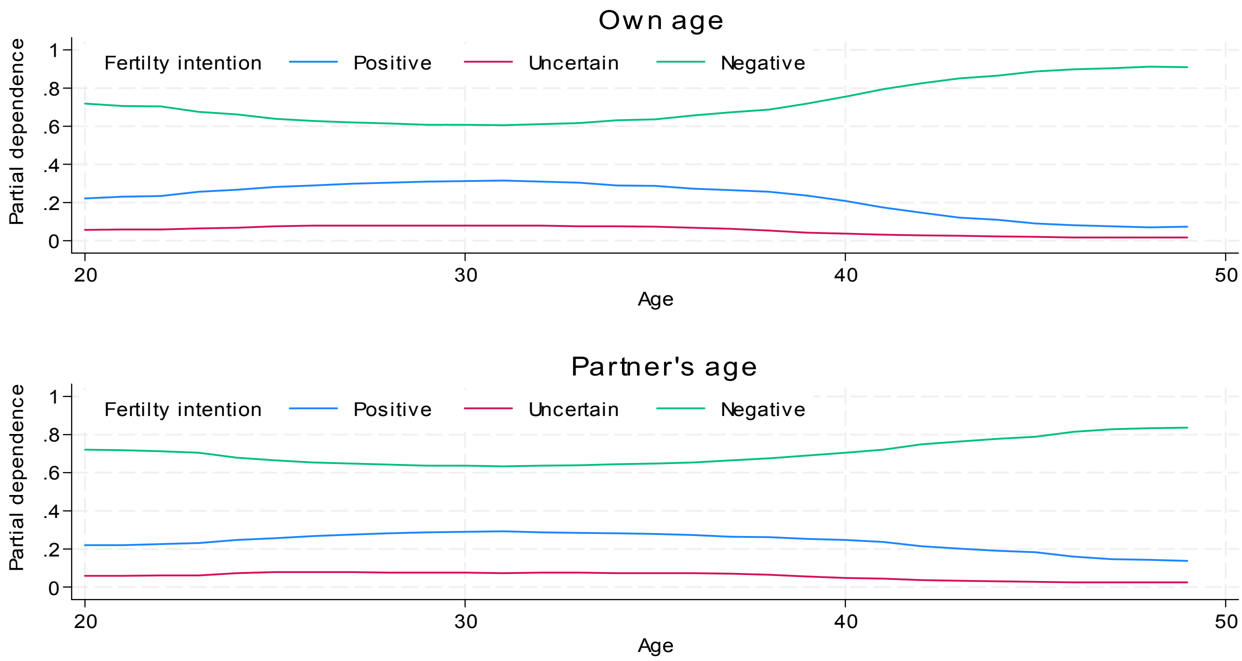
Test data

	hat(No)	hat(Uncertain)	hat(Yes)
No	2368	16	287
Uncertain	323	19	224
Yes	329	14	756

Table B2: Goodness of fit

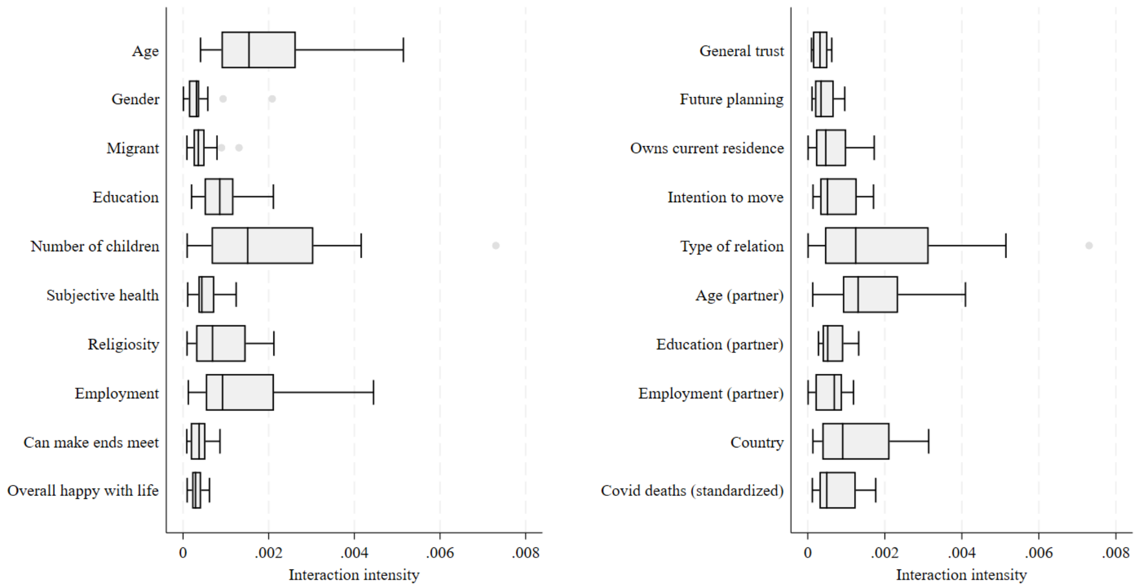
	Average	No	Uncertain	Yes
Accuracy	0.725			
Recall	0.590	0.887	0.034	0.688
Precision	0.536	0.784	0.388	0.597

Figure B1: Partial dependence plots: age and partners' age.



Notes: the figure shows the partial dependence of fertility intentions with respect to own age (and partners' age). Source: Own elaboration based on GGS data.

Figure B2: Distribution of interaction intensity for each variable



Notes: Own elaboration. Boxplots show the intensity of interactions between the variable in the row, and all other variables.