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Leaving uncertainty behind: A cross-country analysis of fertility intentions

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Abstract

We conceptualize individual-level resilience as the ability of men and women to form plans about future fertility, either in positive or negative terms. We study which factors predict fertility intentions with an emphasis on interactions between micro and macro factors based on the second wave of the Gender and Generation Program Survey (2024) concerning ten developed European countries using Random Forest. Our model shows that factors linked to resilience are valuable predictors of fertility intentions, particularly factors defined at the individual level: difficulties across life domains (such as health, or housing) predict greater uncertainty in fertility intentions; whereas variables associated with family resources, such as education or religiosity, predict more positive fertility intentions. Variables at an aggregate level, such as the intensity of the pandemic, are weaker predictors. Our model does not find large interactions between micro and macro variables.

Keywords:
resilience, fertility intentions, GGP

JEL Classification:
J11, J13

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INTRODUCTION

Resilience, understood as the capacity to adapt and maintain functioning under conditions of adversity, has been studied at the individual, family, and societal levels (Fonagy et al., 1994, Rutter, 2012, Aassve and Bastianelli, 2024). In the context of fertility choices, resilience refers to an individual or couple's ability to formulate and implement clear plans for future childbearing even under conditions of uncertainty. Lower resilience is therefore reflected in both the inability to implement desired fertility plans, and in a higher level of uncertainty surrounding these plans.

Studying how individuals and families make fertility decisions under conditions of uncertainty is crucial for understanding both demographic resilience and the long-term ability of societies to adapt. The ability of individuals and couples to form and implement fertility plans determines whether children are born, which influences 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 analyse 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. Our analysis incorporates individual and household characteristics to better understand sources of heterogeneity. We analyse data from ten developed European countries collected within the Gender and Generations Programme (GGP). The data was collected during the pandemic and allows identifying the individual – and family-level factors associated with resilience in fertility planning, and to assess how these patterns vary across countries. We complement GGP data with a country level measure of pandemic intensity; the standardized number of deaths related to COVID-19 at the time of the interview.

A key challenge in this study is that theory offers limited insight into how family resources interact with contextual factors, and provides little guidance on whether these interactions matter. Standard regression approaches require pre-specifying a functional form and an interaction structure; if the true pattern is more complex, results will be sensitive to these choices. To address this limitation, we use random forests (Breiman, 2001). This machine learning algorithm has valuable advantages. Unlike more traditional approaches, it does not require imposing assumptions on the data generation process. In our case, the validity of the estimation does not rest on a particular likelihood function. Instead, random forests provide a non-parametric approach to recover underlying probabilities. Random forests naturally incorporate interactions between variables by identifying which variable combinations better distinguish between outcomes. Finally, recent developments in explainable machine learning helped to better understand how the model makes predictions. Given these advantages, it is not surprising that machine learning methods are gaining traction in the analysis of fertility (Li & Xu, 2022; Stulp et al., 2023; Xu et al., 2024) and, in demographics more generally (Bjerre 2022).

Our contribution is the following. First, we analyse fertility intentions in the context of a global health crisis exploring the interplay between micro- and macro-level factors (individual and family characteristics, and country-level statistics). Second, we exploit novel developments in explainable machine learning to identify what variables and interactions help in predicting certainty in fertility intention. 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.

Life-course variables, whose importance is well established in prior research, are treated here as a benchmark, allowing us to assess whether other factors provide additional explanatory power beyond standard demographic gradients. Our results show that fertility resilience is shaped not only by these baseline characteristics, but also—importantly—by household-level resources and vulnerabilities, which provide additional explanatory power beyond standard demographic characteristics. In particular, variables related to education and health status play a more substantial role than employment status or subjective life satisfaction in predicting fertility intentions.

At the same time, the intensity of the COVID-19 crisis plays only a secondary role in explaining variation in the certainty of fertility intentions. Moreover, we find little evidence of systematic interactions between pandemic exposure and household resources. This suggests that, to the extent that the pandemic depressed positive fertility intentions, its effects were broadly shared across population groups rather than strongly differentiated by individual-level advantages or disadvantages.

The article is structured as follows: in the next sections, we provide a literature review, data and method description, elaborate on 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. 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, serve to understand fertility intentions (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. In our empirical analysis, we adopt a similar framework but focus on individual factors that shape perceived security and risk during crises such as the COVID-19 pandemic. We explore how these factors help to predict 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 population groups and countries was substantial. Raybould et al. (2023) observed both pro-natal and anti-natal shifts in the United Kingdom, resulting in only modest net changes. These findings suggest that crises, by themselves, do not fully determine fertility intentions. Individual and societal context matter for fertility planning.

Studies on the impact of the COVID-19 pandemic on social behaviour have provided new insights into social resilience. Resilience is framed 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 a 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, such as the severity of the COVID-19 pandemic. Our analysis builds on these trends, focusing on factors that determine fertility intentions and highlighting differences and similarities at the country level.

Against this background, our study explicitly incorporates a cross-national measure of the intensity of the COVID-19 crisis, captured by the number of pandemic-related deaths, and examines how macro-level uncertainty interacts with individual and family resources in shaping fertility intentions.

Economic uncertainty

In addition to the uncertainty about health and life caused by the pandemic, 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 the man appears as a more significant driver of the partner's fertility intentions, even more than her own status. One can hypothesise that being unemployed reduces the opportunity cost for women, 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 manage 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 labor 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 an 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 also reduces 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 also be 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 their ability to raise a child and 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 the entire 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).

Health-related uncertainty and fertility intentions are closely intertwined across the life course. Health status (and uncertainty) changes with age: approaching the end of the reproductive life span significantly increases the likelihood of experiencing uncertainty about childbearing plans. As shown by Jones (2017), uncertainty is more common among women above age 30, those who already have one or more children, individuals expressing a strong desire against pregnancy, and those who perceive their partner's fertility plans as uncertain. The uncertainty in fertility intentions is a volatile and transitional state between clearly positive and clearly negative intentions (Kuhnt et al., 2021). Increasing age not only raises the odds of being uncertain but also contributes to the postponement of (additional) births. In the context of late parenthood, such delays may lead to fewer births than originally intended, as biological fecundity declines with age and social norms still set informal limits on acceptable parenthood timing.

Personal and family resources

Individual and family resources play a leading role in enabling individuals to leave uncertainty behind when forming fertility intentions, as they directly reflect both personal circumstances and the immediate family context in which fertility decisions are embedded. Broader demographic transitions have profoundly reshaped family behaviours across Europe. The second demographic transition marked a shift from traditional to more liberal values (van de Kaa, 1987), reflected in the spread of cohabitation, delayed parenthood, and a growing share of non-marital births. These changes have fundamentally altered the conditions under which fertility intentions are formed.

Partnership status constitutes one of the most important personal and family resources for fertility planning, and one of the most important transformations of the second demographic transition. Even though births in weaker unions are more likely than before the transition, stable relationships and marriage still provide additional support for childbearing intentions. The absence of a partner remains a key factor contributing to postponed or unrealised fertility (Wagner et al., 2019). Sturm, Koops, and Rutigliano (2023) show that the lack of a suitable partner is the most frequently reported reason for unmet fertility intentions, while being in a partnership is positively associated with the intention to have a child. Importantly, this association varies over the life course: the influence of partnership strengthens from early adulthood as individuals approach socially defined fertility deadlines, but after a country- and gender-specific age threshold, it may weaken, remain stable, or even reverse. This highlights the age- and context-dependent nature of partnership effects on fertility planning.

Fertility decision-making within couples is not merely the sum of two individual intentions but a fundamentally interactive process shaped by the resources, preferences, and biographical contexts of both partners. Stein, Willen, and Pavetic (2014) conceptualise the transition to parenthood as a joint decision in which each partner's fertility intentions both influence and are influenced by the other's preferences. Their findings show that the life-course situations of both partners, considered relationally, play a crucial role in shaping fertility plans. While male partners often exert a stronger direct influence on the dynamics of decision-making, female partners display overall stronger effects and retain veto power over the final fertility decision.

Parenthood experience itself constitutes another resource that shapes subsequent fertility intentions. Becoming a parent provides direct insight into the costs and benefits of raising children as well as into one's own capabilities in the parental role. Moreover, as parents reach their optimal family size, they might shift to negative fertility intentions. Notwithstanding, evidence from Poland shows that the fertility intentions of parents and childless individuals were similar, but parents were more able to implement their fertility plans (Grzenda, 2024).

Personal values and subjective well-being further shape fertility intentions. Religiosity and value orientations influence reproductive plans, although empirical findings for Europe are mixed, particularly with respect to short-term fertility intentions (Spéder & Kapitány, 2015). Religiosity constitutes an important personal resource shaping fertility intention, yet its influence varies across national contexts. In more traditional gender regimes, religiosity tends to exert a stronger influence on fertility intentions than in more gender-egalitarian societies, although this pattern is not universal (Bein et al., 2021). This indicates that the motivational role of religiosity in fertility planning depends not only on individual beliefs but also on the broader institutional and normative environment. In addition, life satisfaction and subjective well-being may affect individuals' readiness to have children and their perceived ability to realise fertility plans.

The fertility intentions are deeply embedded in broader family systems that shape individual attitudes toward childbearing and socially shared norms regarding reproduction. Mönkediek and Bras (2018) demonstrate that family systems influence fertility intentions both directly, by structuring household composition and intergenerational proximity, and indirectly, by shaping perceptions of the social and material conditions considered necessary for having children. Importantly, the effects of kin proximity are not uniform across the parity spectrum: while proximity to kin tends to reduce positive fertility attitudes among childless individuals, it has the opposite effect among parents, for whom nearby family networks appear to facilitate intentions to have additional children.

Certain features of human capital, such as education, skills, and career opportunities (Becker, 2009), may enhance individuals' capacity to manage risks related to childbearing. These characteristics can shape fertility intentions by providing individuals with greater resources to cope with socioeconomic or personal challenges. In line with this, Testa and Stephany (2017) show that both first and second birth intentions are positively correlated with educational attainment. However, this relationship, stronger for men than for women, tends to disappear once the normative value of a two-child family is reached.

Hypotheses

The literature review points to two sets of factors that shape fertility intentions. On one side, greater exposure to COVID-19 can create a shared environment of instability that limits the value of future planning and shifts fertility intentions away from positive outcomes. On the other side, individual and family characteristics, such as partnership stability, educational attainment, religiosity, and housing security, provide resources from which households can draw to define and maintain their fertility intentions.

It is less clear how the two sets interact to develop fertility intentions. On the one hand, couples that command more resources can buffer the fertility-depressing effects of the pandemic, while those with fewer resources are disproportionately affected. Alternatively, both factors can operate independently. Crisis exposure shifts intentions across the population, while resources shape the baseline level of fertility planning regardless of crisis intensity. These considerations lead to the following three hypotheses:

Hypothesis 1 (Crisis intensity): Greater exposure to the COVID-19 pandemic, measured by pandemic-related mortality, is associated with a shift away from positive fertility intentions and toward uncertainty. However, its predictive importance is weaker than that of individual and family-level resources.

Hypothesis 2 (Personal and family resources): Individuals with stronger personal and family resources are more likely to express positive short-term fertility intentions and less likely to remain uncertain about their childbearing plans.

Hypothesis 3 (interaction between context and resources)**:** The effect of pandemic intensity on fertility intentions varies by individual and family resources. Individuals with fewer resources display more uncertain intentions during periods of high pandemic mortality, as they lack the buffers needed to sustain reproductive plans.

DATA

This study used data from the second wave of the Gender and Generation Programme Survey (GGP, 2024). The survey was developed to allow comparative analysis. Care was taken to harmonize both questions and answers. The survey is conducted by an independent research team in each country under the coordination of an independent institution. So far, twenty countries run the survey, sixteen of them in Europe. In this research, we examined data from ten developed European countries for which data was initially released: Austria, Croatia, Czechia, Denmark, Estonia, Finland, Germany, the Netherlands, Norway, and the United Kingdom. These countries are at a similar development level but represent different welfare states. Our sample does not include France and Latvia because the documentation for these countries was not available at the time of writing the paper.

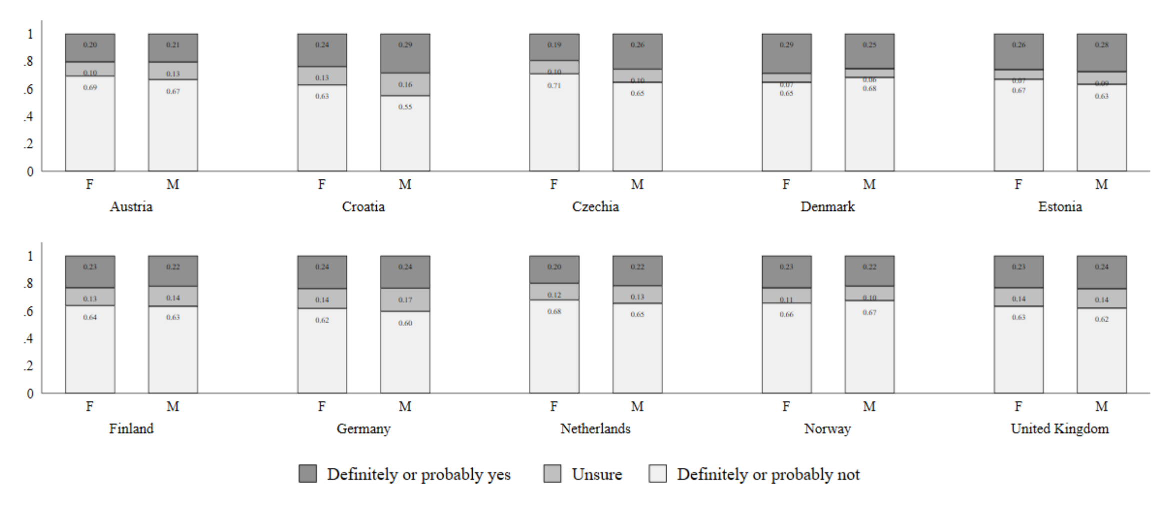
The GGS survey covers individuals aged 18 to 79. Our study focuses on fertility intentions of couples, and we therefore included respondents aged 20-50 who currently have a partner. We focus on heterosexual couples, as we expect that the possibilities and constraints faced by these couples are similar across countries.[1] By focusing on people aged 20 to 50, we can capture (almost) the entire reproductive

[1] Modeling the intentions of same-sex couples requires a different model altogether.

period for men and women[2]. We also restrict the sample to individuals who were not expecting a child at the time of the interview. We exclude from the sample observations that do not provide information on their fertility intentions or that lack information on basic demographic characteristics (such as age or gender). Table A1 in the Appendix shows how each criterion affects the sample size.

The question used to measure short-term fertility intentions reads: "*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 answers: "*Definitely not*", "*Probably not*", "*Unsure*", "*Probably yes*", "*Definitely yes*", and "*Currently expecting a child*". 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: the 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. "F" denotes answers from Female respondents, while M denotes answers from Male respondents. 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.

[2] In our data, the proportion of individuals expressing any non-negative intention after the age of 50 is low.

Figure 1 summarizes the distribution of the dependent variables across countries. 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 do 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 GGS includes several markers for uncertainty in economic and health domains. Among economic markers, we employ the labour market status of the respondent and their partner, and a measure of household income. Concretely, individuals indicate whether household income is sufficient to make ends meet. Answers reflect both objective and subjective elements.

From the health domain, we select subjective health status as a proxy for health uncertainty. This variable 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 influenced by personal health perceptions and anticipated limitations. This approach aligns with previous research highlighting the role of self-assessed health in fertility choices.

To capture uncertainty and the stage of the crisis due to the COVID-19 pandemic, we merged the GGS data with information on COVID-19 deaths collected by researchers from Johns Hopkins University (Dong and Gardner, 2020). We merge the databases using the month of the interview in GGS. Given that the number of deaths depends on population size, we standardized the variable at the country level before proceeding with the analysis. The standardization employs only information available to participants when taking the survey. We expect that a higher number reflects a greater disruption in respondents' lives. [3] We include deaths, and not cases, in our model, because in the sample period, the disease became less severe. A higher case count during the first months implied much higher uncertainty than in subsequent years. Figure A1 in Appendix A displays the standardized number of deaths in each country from the early days of the pandemic till 2025. Grey areas indicate months for which GGP data was collected. This figure shows that there is substantial variation in the intensity of the pandemic across countries, and in some cases within countries as well (see Czechia).

We also include two measures of housing uncertainty. During the questionnaire, respondents indicated whether they owned their current residence and whether they had plans to move. Couples who are not owners might be less certain about their future. An intention to move suggests a lack of satisfaction with current living conditions. For these couples, moving to a new residence might be a necessary step before becoming parents.

Besides these variables, we construct an indicator of whether respondents have reached their preferred family size. This binary variable equals one for respondents who have fathered at least as many children as their declared ideal number of children. Couples who have already achieved their desired fertility ideals might be less affected by uncertainty in other life domains.

Finally, our model includes additional controls to address baseline differences. These include gender of the respondent, age, migrant status, number of children in the household,[4] religiosity, a measure of generalized trust, a measure of the extent to

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[3] In some countries, the survey also includes direct questions on how much people believe their lives (and society) had change because of the pandemic. Unfortunately, the questions were different, and harmonization was not possible.

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

which individuals plan for their future, and a measure of life satisfaction. The model includes country indicators to address stable country factors. Many variables in this set have been considered in previous research, such as age or previous fertility realizations. These variables provide a baseline to understand what shapes intentions beyond them. Descriptive statistics of all variables included in the model, and the corresponding levels, are presented in Table A2 in the Appendix. We also display the number of missing values. For categorical variables, we treat missing values as an additional category. The only continuous variable with missing values is age of the partner. We impute these missing values with median values.

METHODS

We analyse the relationship between short term fertility intentions and personal characteristics using random forests. Random forest is a machine learning method developed for classification tasks, i.e. tasks in which we want to learn the most likely outcome given a set of characteristics (Breiman,2001). This method represents an improvement over decision trees, as it reduces the risk of overfitting and makes the predictions more robust to the database used.

The estimation of random forests is based on a bagging procedure consisting of two steps. The first step requires bootstrapping. In this step, the model constructs random subsamples of the data, where observations are chosen with replacement. In each subsample, we fit a tree using a subset of the available parameters. Like in a regression tree, the algorithm identifies the splits that minimize the Gini impurity criteria in each of the resulting child nodes. Each tree grows until it reaches a stopping criterion, such as reaching the maximum depth (number of splits) or until each leaf has reached the smallest sample size allowed. These two parameters, 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 are also more prone to overfitting, in which case results will lack robustness.

The second step, aggregation, consists of combining the predictions of the different trees for each parameter combination. The outcome can either be a vector of probabilities of observing each outcome (negative, uncertain, positive), or a prediction of the most likely outcome (the outcome with the largest probability) across different trees. The aggregation step ensures that even if individual trees are overfitted, the final prediction is robust. The current analysis will focus on the predicted probabilities, as recovering the modal category in each leave will overpredict the most frequent category, at the expense of the others.

There are other algorithms available to combine predictions from trees, such as boosting. These algorithms can increase the accuracy of predictions via sequentially fitting smaller trees. These algorithms might require a larger number of trees to tap into these accuracy gains (Hastie et al, 2017). In addition, boosting appears less robust to the selection of hyperparameters. Finally, it is unlikely that random forests overfit the data in classification problems (Hastie et al, 2017).

Selecting the right hyperparameters

As discussed in the previous section, a first step is the selection 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 the harmonic mean of precision and recall. This criterion 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 between those who plan and those who 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, the optimal minimum leave size was equal to three, depth to 102, and 71 trees in the forest for the entire data. Table B1 in the Appendix presents performance measures of the model for both 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: 74% of correct predictions. The prediction ability differs across classes: the model seldom predicts the least numerous class ("uncertain"). Only 1% of observations are predicted to fall in this group. The recall for this category is also lower than for categories denoting certain intentions. Appendix Table B2 shows the confusion matrices for the train and test subsamples.

Interpreting machine learning models

Random forests and machine learning methods, more generally, offer flexibility at the cost of interpretability. In recent years, this criticism has led to the development of tools that provide a look into the black box (Molnar 2025). These tools differ in their scope. Some explainers are local, i.e. they produce explanations for particular feature combinations; other explainers are global, they describe the overall working of the model. While both are useful, our analysis of the model rests on three different global explainers.

First, to assess the importance of predictors in the model, we use Permutation Feature Importance. The method consists of comparing the predictive power of the model in actual data to predictions on a database where a variable has been replaced with random numbers (drawn from the same distribution). If the model relies on the information contained in that variable, then its reshuffling should decrease the quality of the predictions. We employ three different performance measures: accuracy, balanced precision, and balanced recall.[5] We present the changes in positive terms, i.e. the gain in precision from having used the "true" information. While intuitive, the method has two downsides. First, if two features (X1 and X2) are highly correlated, then the exclusion of one (X1) need not affect the quality of predictions, as the model still relies on the information contained in the second variable (X2) (Ragodos et al 2024, Molnar 2025) Second, if the empirical frequency of a given feature is low (for example being a migrant), then randomizing the information contained has only limited effects on the total sample, even if this variable is locally relevant.

Second, we study how features affect predictions using Partial Dependency Profiles (PDP). Obtaining PDPs is a counterfactual exercise, where we assign to everyone the same level of a given variable (e.g. we treat everyone as if they had higher education) and compute the predicted probability of each outcome. We repeat this operation for all levels of the predictors. PDPs are comparable to average partial effects in traditional non-linear models. The main difference is that predictions are not embedded in a parametric model. A known limitation of PDPs is that they can

[5] 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.

generate predictions for covariate combinations that do not exist empirically. This issue arises when predictors are strongly correlated, for example, when considering the age of both partners, or when considering the education levels of each partner. PDPs should be interpreted with caution.

Third, we expand PDP to detect interactions between features using the approach described in Greenwell et al. (2018). An interaction is indicated when the PDP of variable X1 (X2) varies across the levels of variable X2 (X1), suggesting that the model captures a dependency between these variables in predicting the outcome. If the PDP of X1 is flat across levels of X2, then these two variables enter the model additively. Interaction strength is quantified using the dispersion of the partial dependence profile of X1 within each level of X2 and then aggregating this dispersion across levels using the standard deviation of ranges. Higher values indicate stronger interactions.

This measure of interaction strength shares the same limitations as PDPs, since it is computed from the same counterfactual predictions. Additionally, because interaction strength is computed pairwise across all variable combinations, the number of interactions grows fast. If the model contains n predictors, we need to consider $n \times (n-1)/2$ interactions.

While progress in machine learning interpretability has been remarkable, the measures listed before have some limitations. A feature can be important for a particular model, while at the same time it is irrelevant in the underlying data generating process (Ragodos et al 2024). Feature importance, PDP and interaction strengths reflect both underlying fundamentals, as well as inner workings of the model. We opt to be cautious and interpret our results as measures of the information employed by the model.

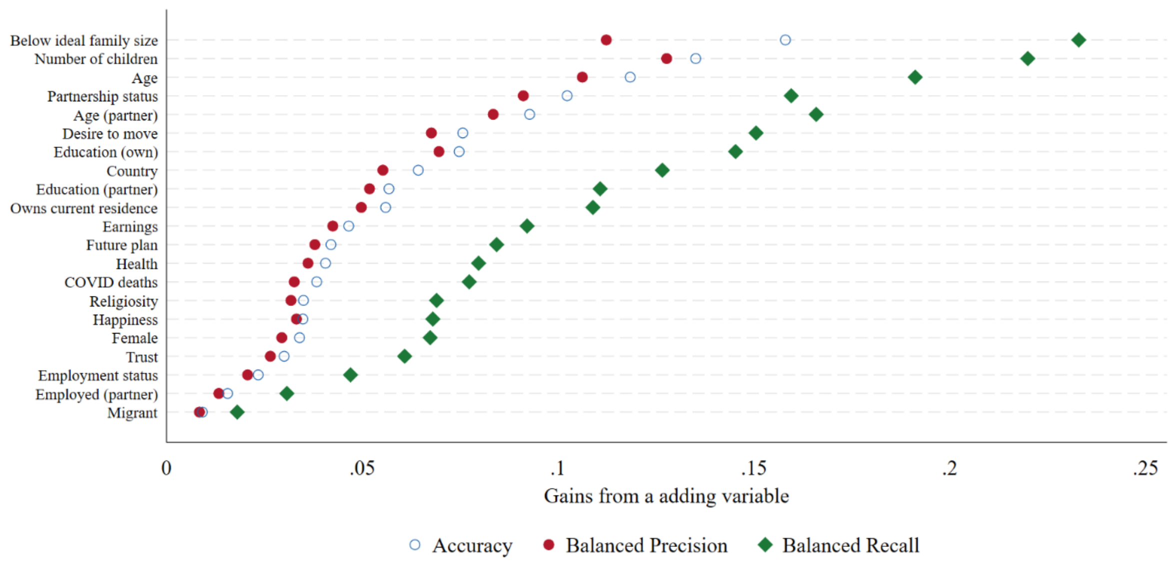
RESULTS

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 predicts fertility intentions?

In the main model, the dependent variable has three categories, one for each intention: Negative, those who do not intend to have a child in the next three years; Uncertain, for those who are not sure; Positive, for those who would like to have a (additional) child. As discussed in the data section, the model contains twenty-one different variables, which differ in their ability to predict fertility intentions. These differences are shown in Figure 2, which presents the Permutation Feature Importance for all variables in the model.

Figure 2: Permutation importance



Notes: Dots indicate the average gains in each performance measure 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 draws from the same distribution. We repeat the procedure ten times for each variable.

According to this measure, the most important predictors are those related to previous fertility choices. Having achieved the desired number of children is the most important, and a closely related variable, the actual number of children, is second in line. Reshuffling the information on these variables leads to a decline in the proportion of correct predictions (*accuracy*) from around 0.9 (see Table B1 in the appendix) to around 0.75. Similarly, the model identifies two other variables connected to the stage in the life cycle, *age* and *partner's age,* as relevant for model predictions. These findings replicate patterns already known in the literature. We treat the results for these well-established characteristics as benchmarks for interpreting the importance of the remaining variables.

The next set of factors highlights resources available to couples. Permuting the type of relationship (formal versus informal), and education (of each member) leads to a reduction in the proportion of correct predictions of between five and ten percentage points, or around two thirds of the decline observed for the variables in the first group. Country level variables appear in a third group. Reshuffling the country of residence or the intensity of the pandemic leads to a decline in accuracy of around five percentage points. In other words, the model relies on these data to predict fertility intentions to a lesser extent than individual factors. This provides initial evidence in favour of personal traits playing a bigger role than systemic factors in predicting fertility intentions.

At the bottom of Figure 2, we find two variables that our literature review suggested would be important: employment status and employment status of the partner. In our sample, around 90 percent of partners work, so it is possible that the lack of importance of this variable is related to the low proportion of observations that are reshuffled. The variable can still be relevant locally. However, one's own employment status is different, as it shows more levels and variation. One purely model-based explanation is that this variable is correlated with other features, such as earnings or education level. Once the model employs information from these variables, the role of labour market status is secondary. A more substantial explanation is linked to the context in which the data were collected. At the height of the COVID-19 pandemic, employment status may have become a less reliable indicator of economic security than usual. On the one hand, employed people could fear sudden interruptions in their work due to changes in regulations; on the other, people had access to additional income provided by the government.

How do variables affect predicted probabilities?

Figure 2 does not express how fertility intentions vary by levels of the predictors, and so it does not provide an answer to our second research hypothesis. To understand how each variable affects the predicted probabilities, we estimate the Partial Dependence Profiles. The results are presented in Table 1. For ease of interpretation, the table also includes the observed proportions in the first row. The table is split into two parts. In the first three columns, the partial dependence is obtained from the full sample. On the second set of columns, the results pertain to the subsample of young individuals (i.e. aged between 20 and 39 years old) with fewer than two children. We focused on this subsample as they are more diverse in their fertility intentions. We grouped variables into those describing the respondent, those describing the respondent’s partner, those describing the household, and those describing the aggregated conditions.

Table 1: Partial dependence profiles for each variable

	Full sample			Only respondents younger than forty with one or fewer children		
	Yes	Uncertain	No	Yes	Uncertain	No
Average	0.239	0.122	0.639	0.447	0.187	0.365
Individual characteristics						
01) Gender						
1-Men	0.235	0.133	0.631	0.429	0.195	0.377
2-Women	0.238	0.123	0.639	0.452	0.189	0.359
02) Age						
20	0.254	0.164	0.582	0.355	0.177	0.468
24	0.277	0.169	0.554	0.409	0.191	0.400
28	0.308	0.167	0.525	0.494	0.202	0.304
32	0.307	0.160	0.532	0.508	0.202	0.291
36	0.279	0.152	0.570	0.472	0.205	0.324
40	0.221	0.133	0.646	0.446	0.204	0.349
44	0.178	0.115	0.707			
48	0.165	0.109	0.726			
03) Migrant						
1-Yes	0.239	0.135	0.626	0.438	0.198	0.364
2-No	0.238	0.125	0.637	0.446	0.190	0.365
04) Education (own)						
1-Primary	0.229	0.132	0.639	0.428	0.196	0.377
2-High-School	0.227	0.128	0.645	0.430	0.195	0.375
3-Bachelor	0.242	0.127	0.631	0.450	0.188	0.361
4-More than BA	0.254	0.131	0.615	0.465	0.193	0.343
05) Employment status						
1-Working	0.239	0.122	0.639	0.452	0.187	0.360

2-Unemployed	0.231	0.137	0.632	0.428	0.192	0.380
3-Inactive	0.217	0.128	0.655	0.400	0.178	0.422
4-Leave	0.263	0.150	0.587	0.464	0.197	0.340
06) Health						
1-Very good	0.244	0.128	0.628	0.448	0.187	0.364
2-Good	0.236	0.126	0.637	0.442	0.193	0.366
3-Fair	0.232	0.129	0.639	0.437	0.195	0.368
4-Bad	0.231	0.129	0.640	0.432	0.193	0.374
07) Happiness						
1-Yes	0.243	0.122	0.635	0.458	0.184	0.358
2-No	0.226	0.128	0.646	0.425	0.195	0.380
08) Trust						
Most people can be trusted	0.238	0.120	0.642	0.447	0.181	0.372
Need to be very careful	0.235	0.127	0.638	0.443	0.193	0.363
09) Future plan						
1-I plan	0.241	0.121	0.637	0.453	0.182	0.365
2-Somehow	0.238	0.122	0.640	0.448	0.183	0.369
3-Neither nor	0.236	0.126	0.638	0.447	0.192	0.361
4-Rather not	0.232	0.126	0.642	0.436	0.192	0.372
5-Take each day	0.232	0.129	0.639	0.434	0.191	0.375
10) Religiosity						
1-No	0.231	0.122	0.647	0.432	0.189	0.379
2-Intermediate	0.243	0.131	0.626	0.458	0.196	0.346
3-Yes	0.251	0.129	0.621	0.471	0.191	0.338
11) Desire to move						
1-Definitely not	0.238	0.119	0.643	0.451	0.183	0.366
2-Probably not	0.229	0.128	0.643	0.431	0.192	0.376
3-Unsure	0.230	0.148	0.622	0.427	0.209	0.365
4-Probably yes	0.254	0.132	0.614	0.452	0.190	0.358

5-Definitely yes	0.257	0.129	0.613	0.464	0.184	0.353
Partnership status and characteristics						
12) Partnership status						
1-Partner	0.233	0.140	0.627	0.418	0.209	0.373
2-Married	0.297	0.103	0.600	0.598	0.139	0.263
13) Age (partner)						
20	0.262	0.169	0.569	0.379	0.195	0.426
24	0.276	0.170	0.554	0.405	0.204	0.391
28	0.311	0.162	0.527	0.478	0.197	0.325
32	0.313	0.157	0.530	0.495	0.194	0.311
36	0.258	0.137	0.606	0.483	0.197	0.321
40	0.243	0.137	0.620	0.456	0.202	0.342
44	0.220	0.129	0.652	0.435	0.201	0.363
48	0.209	0.129	0.662	0.422	0.204	0.374
14) Education (partner)						
1-Primary	0.233	0.128	0.639	0.430	0.194	0.376
2-High-School	0.230	0.127	0.643	0.435	0.195	0.370
3-Bachelor	0.238	0.126	0.635	0.447	0.189	0.364
4-More than BA	0.253	0.129	0.618	0.465	0.191	0.345
15) Employed (partner)						
1-Work	0.239	0.121	0.640	0.457	0.186	0.357
2-Not employed	0.226	0.130	0.644	0.422	0.189	0.389
Household characteristics						
16) Number of children						
0.0	0.282	0.126	0.592	0.454	0.185	0.360
1.0	0.285	0.143	0.572	0.492	0.205	0.304
2.0	0.170	0.144	0.686	.	.	.
3.0	0.173	0.131	0.696	.	.	.

17) Below ideal family size						
1-Yes	0.311	0.160	0.529	0.503	0.197	0.299
2-No	0.031	0.047	0.923	0.068	0.074	0.858
18) Earnings						
1-Very easily	0.243	0.121	0.636	0.457	0.183	0.360
2-Fairly easily	0.233	0.124	0.643	0.442	0.191	0.367
3-Easily	0.238	0.122	0.640	0.447	0.186	0.366
4-With difficulty	0.230	0.129	0.640	0.435	0.194	0.371
5-With some difficulty	0.236	0.129	0.636	0.442	0.190	0.368
6-With great difficulty	0.230	0.127	0.643	0.438	0.190	0.372
19) Owns current residence						
1-Yes	0.242	0.122	0.636	0.458	0.185	0.357
2-No	0.234	0.135	0.630	0.430	0.197	0.374
Macro characteristics						
20) Country						
AT	0.233	0.125	0.642	0.440	0.188	0.372
CZ	0.249	0.129	0.622	0.456	0.191	0.353
DE	0.220	0.136	0.644	0.422	0.201	0.377
DK	0.260	0.110	0.631	0.476	0.169	0.355
EE	0.258	0.115	0.627	0.463	0.176	0.361
FI	0.238	0.128	0.634	0.442	0.191	0.367
HR	0.248	0.134	0.618	0.455	0.189	0.356
NL	0.238	0.127	0.635	0.444	0.191	0.365
NO	0.242	0.127	0.631	0.453	0.190	0.357
UK	0.235	0.131	0.634	0.440	0.192	0.368
21) COVID deaths (standardized)						
-0.75	0.236	0.148	0.616	0.436	0.204	0.360
0.0	0.245	0.119	0.636	0.455	0.182	0.362
0.75	0.248	0.120	0.632	0.457	0.181	0.362
1.5	0.250	0.122	0.628	0.453	0.182	0.365

2.25	0.245	0.128	0.627	0.446	0.186	0.368
3.0	0.243	0.134	0.622	0.444	0.188	0.369

Notes: Table shows partial dependence profiles for variables in the model. Each cell presents the average predicted probability of each fertility intention (in column headers) if all observations had the same value of a variable. We consider the entire sample, and the sample of individuals who are younger than 40 years old and who have only a single child. The two models are fit independently.

Previous fertility choices and age are the most important features in Figure 2, and Table 1 reproduces this result. Whether someone has reached their ideal family size appears as the feature with the steepest PDP. The predicted probability of negative intentions is above 90 percent for respondents who completed fertility, and around 50 percent for those who did not. In the case of age, PDP also show an increase in negative fertility intentions as people get older, but the slope is not as steep. These predictions serve as a sanity check for our model. We are able to recover relationships that are established in the literature.

The most significant resource is marital status, which is a proxy for partnership stability. Being married is associated with lower uncertainty and higher positive fertility intentions, especially in the restricted younger sample. Among youth, the reduction in uncertain fertility intention related to marriage is around seven percentage points. Even in the context of the second demographic transition, marriage remains a relevant factor. Education and labour market status appear as valuable individual resources. Higher education and being employed are linked to higher probabilities of positive fertility intentions and lower negative intentions. However, the predicted uncertainty is stable across levels of those variables. This suggests that there is scope for supporting the fertility plans of individuals across the board.

Housing status predicts different fertility intentions. Owning the current residence reduces uncertainty, as it creates a more stable environment. However, satisfaction with the household also matters. And here the model identifies an interesting U-shaped pattern. It predicts lower uncertainty at both ends of the scale. On one end, it reflects that good housing conditions (definitely not moving) support fertility intentions. On the other hand, the desire to move might be fuelled by fertility intentions: people search for homes to realize the fertility plans.

Other resources operate in the direction anticipated from the literature review, and in H2. Predictions of positive fertility intentions are more common among religious individuals, among healthier individuals, and among people who plan for the future. However, differences in predicted probabilities across categories hover at around one percentage point. Uncertain intentions are stable across groups, suggesting that the model uses these variables to distinguish positive and negative intentions. This provides partial support for Hypothesis 2. Commanding more resources is associated with higher positive intentions, but unlike what we anticipated, it does not resolve uncertainty.

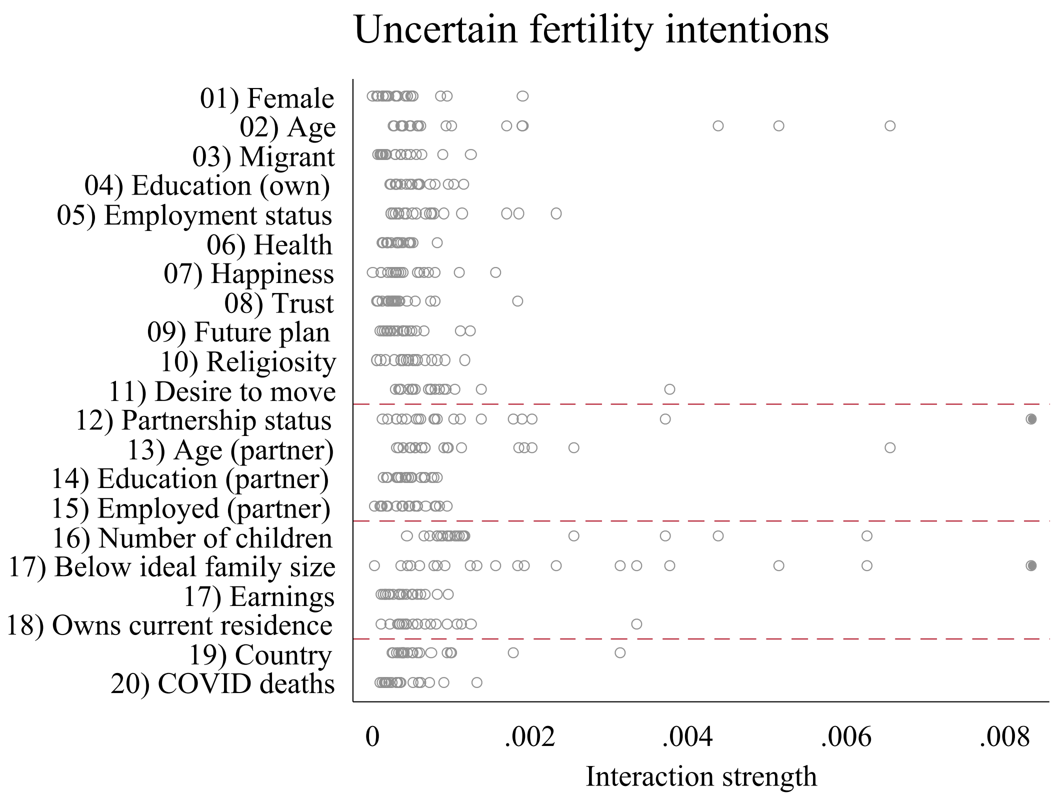
The intensity of the pandemic has an inverse U-shape relation with positive fertility intentions. At lower levels, the model predicts lower positive intentions and more uncertain intentions. These low values are characteristic of the Netherlands and Croatia, where the sample was collected late in the pandemic. Prolonged exposure to COVID-19 could have lasting effects on fertility intentions, even if at the time of the survey, the intensity is lower. For higher values of pandemic intensity, we observe both an increase in uncertainty and a decline in positive intentions, along with our hypotheses, though the profile is flat. Only among the youth, negative fertility intentions increase monotonically with the intensity of the crisis, but the difference is less than one percentage point. The pandemic has only a minor effect on how the model predicts fertility intentions. Moreover, this result should be treated with caution as values of pandemic intensity above occurred only in two countries: Czechia and Finland.

We also find evidence of cross-country heterogeneity. Countries in Western Europe are associated with lower positive intentions than Nordic countries (Denmark and Norway) and Eastern European countries (Czechia and Estonia). Interestingly, among the countries with lower positive intention among the youth, we can find Austria and the United Kingdom, two countries that addressed the COVID-19 challenge with widely different policies. While our interpretation focuses on the nature of the state and policies deployed during COVID-19, country indicators capture any time constant heterogeneity across countries, which could include social norms or parity structure.

Relevant interactions: micro- and macro-level factors

In the previous section, we used partial dependence profiles to recover how average predictions varied across levels of a given variable. This approach showed which variables helped to predict fertility intentions, and how steep the gradients are. As PDP are averaged across all other variables, they are not sufficient to express interactions as required by H3. In this section, we explore two-dimensional PDP, how the predictions change as we manipulate two variables. Exploring all 210 interactions is unfeasible. Instead, we use the method proposed by Greenwell et al (2018) to identify the stronger interactions, both in the model as a whole and among those including a specific predictor.

Figure 3: Interaction strength for predicting uncertain fertility intentions



Notes: Own elaboration. The strength of interactions for predicting uncertain fertility intentions is computed following Greenwell et al. (2018). Each dot represents an interaction between the variable in the row and other variable in the model. Values to the right indicate stronger interactions. The filled dot indicates the interaction between the variables *Partnership status* and *Below ideal family size*.

Figure 3 presents a bird's eye view of the strength of interactions for predicting uncertain outcomes. Each dot indicates a different interaction. The filled dot, for example, indicates the strength of interaction between the variables *Partnership status* and *Below ideal family size,* i.e. the strongest interaction for uncertain intentions. Figure A2 in Appendix A shows this interaction. When respondents achieved their ideal family size, the type of partnership did not affect uncertainty. Marital status only matters when individuals have not achieved their fertility plans.

Figure 3 shows that the model tends to interact different features with variables connected to previous fertility choices and age. By contrast, country level variables exhibit overall small interactions. The strongest interaction of a country is with whether an individual is below the ideal family size, and then with their marital status. The latter interaction is shown in Figure A3 in Appendix A. These interactions show that being in a married couple predicts lower uncertainty, and that uncertainty is higher in Germany. A comparison of Czechia and Estonia shows a similar uncertainty for married couples in both countries. However, among cohabiting couples, uncertainty is greater in Estonia. Differences are within one percentage point, or 10 percent of the average predicted uncertainty.

In the case of pandemic intensity, the most important interaction is also with having achieved the desired family size, and as in previous cases, only when couples have not achieved their preferred family size do we observe fluctuations in predicted uncertainty. Besides this variable, the next relevant interaction is with the *age of the partner*. This shows a large decline in predicted uncertainty for young couples at low values of intensity. When the partner is older, the decline is less pronounced, though it starts from a lower level.

The interactions between COVID-19 deaths and family resources/strains are even weaker: the predictions are not affected by conditioning on a second variable. We conclude that the model treats family resource variables and COVID-19 mortality as linearly additive in the prediction of uncertain fertility intentions. These results stand against H3. Couples with fewer resources are less likely to express positive intentions, and they are even less likely during pandemic crises. However, the predictions of the model do not suggest that uncertainty hits this couples especially strongly.

When we consider positive fertility intentions, the picture remains similar. Figure A5 in Appendix A shows the interaction strength for predicting positive fertility intentions. The interactions between family resources and country variables are also weaker than interactions with previous fertility realizations and age. Figures A6 in the Appendix display interactions between pandemic intensity and three resources: marital status, religiosity and own education. In the three cases, lines appear parallel, suggesting that the model employs these variables additively, and not multiplicatively.

DISCUSSION

This paper examines shortterm fertility intentions in the context of the COVID19 pandemic by conceptualizing resilience at the individual level as the capacity to formulate plans about future childbearing, either in positive or negative terms. Using data from the second wave of the GGP survey covering ten developed European countries and a machine learning approach based on random forests, we assess the relative importance of a wide range of individual, householdlevel, and contextual characteristics, treating basic demographic factors primarily as a baseline for fertility decisionmaking. The results indicate systematic differences in how these characteristics are associated with positive, negative, and uncertain fertility intentions across the studied contexts. Against this background, three main findings emerge from the analysis. First, consistent with prior research, demographic characteristics particularly age and number of children rank among the most important predictors of fertility intentions (Figure 2). Individuals at later stages of the life course and those with existing children exhibit systematically lower levels of fertility resilience. However, the results also show that these demographic gradients do not fully account for variation in outcomes. In particular, partnership status and housing stability display levels of predictive importance that are comparable to, and in some cases exceed, those of standard demographic variables (Figure 2). This finding provides strong support for Hypothesis 2, which posited that individuals with stronger personal and family resources would be more likely to express positive fertility intentions and less likely to remain uncertain about their reproductive plans. The results indicate that fertility resilience is shaped not only by life-course position but also by individuals' embeddedness in stable relational and living arrangements. Demographic variables thus appear to provide a baseline structure, while resource-related factors contribute additional explanatory power beyond these well-established patterns.

Second, economic variables contrary to expectations derived from the literature on fertility and economic uncertainty play a limited role in predicting fertility responses during the pandemic. Economic variables, including income loss and perceived financial strain, exhibit relatively low permutation importance (Figure 2), indicating that they contribute little to predictive performance. This finding stands in contrast to a large body of work emphasizing the central role of economic conditions in shaping fertility decisions. One possible interpretation is that the COVID-19 pandemic constituted a sufficiently large and pervasive shock to compress variation in economic experiences, thereby reducing the relative importance of marginal differences in income or financial stress. Another explanation is that policy interventions implemented during the pandemic may have mitigated short-term economic risks, weakening the link between economic conditions and fertility intentions. Finally, it is possible that in contexts of acute uncertainty, fertility decisions are driven less by immediate economic constraints and more by longer-term considerations such as partnership stability or housing conditions, which are more directly reflected in the variables that emerge as important in our models.

The results also provide partial support for Hypothesis 1 concerning the role of crisis intensity. Measures related to pandemic exposure, including excess mortality, are associated with shifts away from positive fertility intentions and toward uncertainty, but their relative predictive importance remains substantially weaker than that of demographic and household-level resources (Figure 2). This suggests that while the pandemic constituted an important contextual shock, its effects were filtered through individuals' social and family circumstances rather than operating as a dominant independent determinant of fertility responses.

Third, the analysis provides limited evidence of interaction effects between pandemic-related exposure and individual-level resources. Measures of interaction strength indicate that most interactions contribute only modestly to predictive performance (Figure 3), a pattern that is consistent across different fertility intention outcomes (Figures A5 and A6). While some specific interactions can be identified (Figures A2–A4), their overall contribution remains limited. These findings provide only weak support for Hypothesis 3, which proposed that the effect of pandemic intensity would vary depending on individuals' access to personal and family resources. Instead, the results suggest that the pandemic operated primarily as a broadly uniform shock, rather than one whose effects were systematically buffered or amplified by individual advantages. The findings are therefore more consistent with an additive framework, in which factors such as age, parity, partnership status, and housing conditions contribute independently to fertility responses.

The partial dependence profiles provide further insight into these relationships by illustrating how predicted fertility intentions vary across the range of key variables (Table 1). These profiles confirm the importance of life-course and household-level factors, while also highlighting the relatively weak and often non-linear associations for economic variables. Together, these patterns reinforce the interpretation that fertility resilience during the pandemic is shaped more by structural and relational contexts than by short-term economic conditions.

Taken together, these findings contribute to the literature by refining the current understanding of the factors associated with fertility intentions in the context of large-scale crises. While previous studies have highlighted the role of economic uncertainty, the present results suggest that, in the context of the COVID-19 pandemic, household-level resources and relational factors—particularly partnership status and housing stability—are more central in shaping fertility resilience. This shifts attention away from purely economic explanations and toward a broader framework in which fertility decisions are embedded in relational and material contexts that structure individuals' capacity to maintain or revise their reproductive plans.

From a methodological perspective, the use of permutation importance (Figure 2) and interaction strength measures (Figure 3) allows for a flexible comparison of predictors across domains. At the same time, these measures capture relative contributions to predictive accuracy rather than causal effects. The results should therefore be interpreted as identifying patterns in the data, rather than as evidence of underlying causal mechanisms.

The findings also have implications for policy. If fertility resilience during crises is more strongly associated with partnership stability and housing conditions than with short-term economic fluctuations, then policies focused exclusively on income support may be insufficient to sustain fertility intentions. Instead, interventions that improve access to stable housing, reduce uncertainty related to living arrangements, and support family formation may play a more important role. In this sense, policies targeting structural and relational dimensions of uncertainty may be more effective than those addressing only temporary income shocks.

Several limitations should be acknowledged. First, as noted in the methods section, the use of random forests entails important trade-offs. The explanatory measures derived from this framework conflate aspects of the model's internal structure with the underlying data-generating process. As a result, the findings should be interpreted in terms of associations and relative predictive importance rather than causal relationships. In addition, our analysis relies primarily on global explainers, which may obscure heterogeneous local patterns and interaction structures at more granular levels of the data.

Second, the relatively weak role of pandemic intensity may also reflect limited within-country variation. A naive strategy would be to exclude country fixed effects from the model; however, this would conflate the interpretation of pandemic intensity with broader institutional differences captured by cross-country variation in excess mortality. Conversely, augmenting the model with additional policy measures introduces similar identification challenges, as policy responses are themselves highly correlated with institutional context and pandemic severity. This limits our ability to fully disentangle health shocks from institutional and policy environments within the present framework.

Third, the model performs substantially better in predicting positive and negative fertility intentions than in predicting uncertainty. This limitation is partly mechanical, reflecting class imbalance in the outcome variable. However, it may also point to a more substantive issue: uncertainty is a conceptually more fluid and less well-defined category, potentially reflecting transitional states or ambivalence rather than a stable behavioral intention. Notably, the most important predictors appear to differentiate primarily between positive and negative intentions, while contributing relatively little to distinguishing uncertain responses. This suggests that uncertainty may require a distinct conceptual and empirical treatment beyond the standard classification framework used here.

Future research could extend this approach by combining machine learning methods with causal inference techniques, as well as by incorporating more detailed measures of expectations, uncertainty, and policy exposure. In addition, further work is needed to examine how the relative importance of predictors evolves over time, particularly as the longer-term consequences of the pandemic for fertility behavior become more apparent.

CONCLUSIONS

Understanding fertility intentions is crucial for projecting population dynamics, particularly in contexts marked by high levels of uncertainty. By focusing on individuals who are unsure about their childbearing plans, this study contributes to a better understanding of fertility resilience as the ability to form clear intentions under adverse conditions.

Our findings show that fertility resilience is shaped not only by standard life-course characteristics but also by household-level resources and relational contexts. Variables such as partnership status, religiosity, education, and housing conditions emerge as important predictors of fertility intentions, indicating that individuals embedded in more stable social and material environments are more likely to maintain clear reproductive plans. At the same time, economic variables such as employment status and financial strain play a comparatively limited role in predicting fertility intentions.

The analysis also shows that the intensity of the COVID-19 pandemic has only a secondary role in explaining variation in fertility intentions, and that its effects do not strongly interact with individual-level resources.

These findings have important implications for understanding fertility behavior in times of crisis. Rather than being driven primarily by short-term economic fluctuations, fertility intentions appear to be more closely linked to longer-term structural conditions related to partnership stability, housing, and social embeddedness.

From a policy perspective, this implies that supporting fertility resilience may require going beyond income stabilization policies. Interventions that reduce uncertainty related to housing, support stable family formation, and strengthen long-term planning capacity may be more effective in sustaining fertility intentions during periods of widespread uncertainty.

Overall, the results highlight that fertility resilience is shaped by the interplay between individual resources, household conditions, and broader societal contexts, and that uncertainty itself constitutes a key dimension of fertility behavior that deserves closer attention in both research and policy.

REFERENCES

Adsera, A. (2004). Changing fertility rates in developed countries. The impact of labor market institutions. Journal of Population Economics, 17(1), 17–43. doi:10.1007/s00148-003-0166-x

Ajzen, I. (1991). The Theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. doi: 10.1016/0749-5978(91)90020-T

Ajzen, I. and Fishbein, M. (2005). The influence of attitudes on behaviour. In: Albarracín, D., Johnson, B.T., and Zanna, M.P. (eds.). *The handbook of attitudes*. Mahwah: Lawrence Erlbaum: 173–221.

Ajzen, I., & Klobas, J. (2013). Fertility intentions: An approach based on the theory of planned behavior. *Demographic research*, *29*, 203-232. doi: 10.4054/DemRes.2013.29.8

Alderotti, G., Vignoli D., Baccini M., & Matysiak A. (2021). Employment Instability and Fertility in Europe: A Meta-Analysis. *Demography*, 58(3), 871–900. doi.org/10.1215/00703370- 9164737.

Bawati, A., Nieuwenhuis, R., Uzunalioglu, M., & Thaning, M. (2024). *Family and Social Resilience: a scoping review of the empirical literature*.

Becker, G. S. (2009). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago press.

Bein, C., Gauthier, A. H., & Mynarska, M. (2021). Religiosity and fertility intentions: can the gender regime explain cross-country differences? *European Journal of Population*, *37*(2), 443-472. doi: https://doi.org/10.1007/s10680-020-09574-w

Bengtson, V. L., & Putney, N. M. (2006). *Two Future 'Conflicts' Across Generations and Cohorts?'.* The futures of old age. London: SAGE Publications, 20-29.

Busetta, A., Mendola, D., & Vignoli, D. (2019). Persistent joblessness and fertility intentions. *Demographic Research*, *40*, 185-218. doi:10.4054/DemRes.2019.40.8

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32. doi: https://doi.org/10.1023/A:1010950718922

Bjerre, D. S. (2022). Tree-based machine learning methods for modeling and forecasting mortality. ASTIN Bulletin, 52(3), 765–787. doi:10.1017/asb.2022.11

Chłoń-Domińczak, A., Chełchowska, M., Grzenda, W., Kotowska, I.E., Maliszewska, A., Tymicki, K. (2024). Resilience as a theoretical foundation for fertility dynamics, *FutuRes research reports*.

Comolli, C. L. (2017). The fertility response to the Great Recession in Europe and the United States: Structural economic conditions and perceived economic uncertainty. *Demographic Research*, 36, 1549-1600. doi: 0.4054/DemRes.2017.36.51

Comolli, C. L. (2023). Social Climate, Uncertainty and Fertility Intentions: from the Great Recession to the Covid-19 Crisis. *European Journal of Population*, *39*(1), 35.

Cvancarova, M., Samuelsen, S. O., Magelssen, H., & Fossa, S. D. (2009). Reproduction rates after cancer treatment: experience from the Norwegian radium hospital. *Journal of Clinical Oncology*, 27(3), 334-343. doi: 10.1200/JCO.2007.15.3130

Chen, J.L., Phillips, K.A., Kanouse, D.E., Collins, R.L. & Miu, A. (2001). Fertility desires and intentions of HIV-positive men and women. *Family Planning Perspectives*, 33(4), 144–165. doi:10.2307/2673717

Cheng, J.Y.W. & Ng, E.M. (2007). Body mass index, physical activity, and erectile dysfunction: an U-shaped relationship from population-based study. *International Journal of Obesity*, 31(10), 1571–1578. doi: 10.1038/sj.ijo.0803639.

Dong E, Du H, Gardner L (2020) An interactive web-based dashboard to track COVID-19 in real time, *The Lancet Infectious Diseases*, 20, 533-534

Dow, K.J. & Kuhn, D. (2004). Fertility options in young breast cancer survivors: A review of the literature [Online exclusive]. *Oncology Nursing Forum*, 31(3), E46–E53. doi: 10.1188/04.onf.e46-e53

Fahlén, S., & Oláh, L. S. (2018). Economic uncertainty and first-birth intentions in Europe. *Demographic Research*, *39*, 795-834. doi: 10.4054/DemRes.2018.39.28

Fair, A., Griffiths, K. & Osman, L.M. (2000). Attitudes to fertility issues among adults with cystic fibrosis in Scotland. *Thorax*, 55(8), 672–677. doi: 10.1136/thorax.55.8.672

Fonagy, P., Steele, M., Steele, H., Higgitt, A., & Target, M. (1994). The Emanuel Miller memorial lecture 1992 the theory and practice of resilience. *Journal of child psychology and psychiatry*, *35*(2), 231-257.

Fostik, A. (2021). COVID-19 and fertility in Canada: a commentary. *Canadian Studies in Population*, *48*, 217-224. doi: https://doi.org/10.1080/00324728.2022.2134579

Furceri, D., Pizzuto, P., & Yarveisi, K. (2024). The effect of pandemic crises on fertility. *Journal of Population Economics*, *37*(1), 3.

Gatta, A., Mattioli, F., Mencarini, L., & Vignoli, D. (2022). Employment uncertainty and fertility intentions: Stability or resilience? *Population Studies*, *76*(3), 387-406. doi: https://doi.org/10.1080/00324728.2021.1939406

Generations and Gender Programme (2024), https://www.ggp-i.org/form/bibtex/add/

Greenwell, B., Boehmke, B., and McCarthy, A. (2018) "A Simple and Effective Model-Based Variable Importance Measure" arXiv. https://doi.org/10.48550/arXiv.1805.04755.

Grzenda, W. (2024). Short-term fertility intentions and outcomes: similarities and differences between childless women and mothers. *Journal of Family Studies*, *30*(5), 881–905. https://doi.org/10.1080/13229400.2024.2347326

Guetto, R., Bazzani, G., & Vignoli, D. (2022). Narratives of the future and fertility decision-making in uncertain times. An application to the COVID-19 pandemic. *Vienna Yearbook of Population Research*, *20*, 223-260. doi: 10.1553/populationyearbook2022.res1.6

Hammoud, A.O., Wilde, N., Gibson, M., Parks, A., Carrell, D.T. & Meikle, A.W. (2008). Male obesity and alteration in sperm parameters. Fertility and Sterility, 90(6), 2222–2225. doi: 10.1016/j.fertnstert.2007.10.011

Hastie, T., Tibshirani, R., and Friedman, J. (2017) *The Elements of Statistical Learning, 2nd edition*. Springer New York. doi: 10.1007/978-0-387-84858-7.

Jones, R. K. (2017). Are uncertain fertility intentions a temporary or long-term outlook? Findings from a panel study. *Women's Health Issues*, 27(1), 21-28. doi: https://doi.org/10.1016/j.whi.2016.10.001

Katz, P.P. (2006) Childbearing decisions and family size among women with rheumatoid arthritis. Arthritis Care & Research: Official Journal of the American College of Rheumatology, 55(2), 217–223. doi: 10.1002/art.21859

Klobas, J. (2011). The Theory of Planned Behaviour as a model of reasoning about fertility decisions. *Vienna Yearbook of Population Research*, *9*, 47–54. doi: http://www.jstor.com/stable/41342802

Kreyenfeld, M., Konietzka, D., Lambert, P., & Ramos, V. J. (2023). Second birth fertility in Germany: Social class, gender, and the role of economic uncertainty.

European Journal of Population, *39*(1), 5. doi: https://doi.org/10.1007/s10680-023-09656-5

Kuhnt, A. K., Minkus, L., & Buhr, P. (2021). Uncertainty in fertility intentions from a life course perspective: Which life course markers matter? *JFR-Journal of Family Research*, *33*(1), 184-207. doi:10.20377/jfr-426

Langeveld, N., Stam, H., Grootenhuis, M. & Last, B. (2002) Quality of life in young adult survivors of childhood cancer. *Supportive Care in Cancer*, 10(8), 579–600. https://doi.org/10.1007/s00520-002-0388-6

Li, M., & Xu, X. (2022). Fertility Intentions for a second child and their influencing factors in contemporary China. *Frontiers in Psychology*, *13*, 883317.

Luppi, F., Arpino, B., & Rosina, A. (2020). The impact of COVID-19 on fertility plans in Italy, Germany, France, Spain, and the United Kingdom. *Demographic research*, *43*, 1399-1412. doi:10.4054/DemRes.2020.43.47

Malicka, I., Mynarska, M., & Świderska, J. (2021). Perceived consequences of the COVID-19 pandemic and childbearing intentions in Poland. *Journal of Family Research*, *33*(3), 674-702. doi: https://doi.org/10.20377/jfr-666

Matysiak, A., & Vignoli, D. (2008). Fertility and women's employment: A meta-analysis. *European Journal of Population/revue Européenne De Démographie*, 24(4), 363–384. doi.org/10.1007/s10680-007-9146-2

McGrath, J.J., Hearle, J., Jenner, L., Plant, K., Drummond, A. & Barkla, J.M. (1999). The fertility and fecundity of patients with psychoses. *Acta Psychiatrica Scandinavica*, 99(6), 441–446. https://doi.org/10.1111/j.1600-0447.1999.tb00990.x

Molnar, C. (2025) Interpretable Machine Learning: A Guide for Making Black Box Models Explainable (third edition), Publisher: Christoph Molnar

Morgan, S. P., & Bachrach, C. A. (2011). Is the Theory of Planned Behaviour an appropriate model for human fertility? *Vienna Yearbook of Population Research*, *9*, 11–18.
doi: https://www.jstor.org/stable/41342798

Mönkediek, B., & Bras, H. (2018). Family systems and fertility intentions: Exploring the pathways of influence. *European Journal of Population*, *34*(1), 33-57. doi: https://doi.org/10.1007/s10680-017-9418-4

Novelli, M., Cazzola, A., Angeli, A., & Pasquini, L. (2021). Fertility intentions in times of rising economic uncertainty: Evidence from Italy from a gender perspective. *Social Indicators Research*, *154*, 257-284. doi: https://doi.org/10.1007/s11205-020-02554-x

Neyer, G., Andersson, G., Dahlberg, J., Ohlsson Wijk, S., Andersson, L., & Billingsley, S. (2022). Fertility decline, fertility reversal and changing childbearing considerations in Sweden: A turn to subjective imaginations? Stockholm Research Reports in Demography. Preprint. doi: https://doi.org/10.17045/sthlmuni.19698442.v2

Pereirinha, J. A. C., & Pereira, E. (2021). Social resilience and welfare systems under COVID-19: A European comparative perspective. *Global Social Policy*, *21*(3), 569-594. doi:10.1177/14680181211012946

Ranjan, P. (1999) Fertility Behaviour under Income Uncertainty. *European Journal of Population* **15**, 25–43. doi: 10.1023/A:1006106527618

Ragodos, R., Wang, T., & Feng, L. (2024). From Model Explanation to Data Misinterpretation: Uncovering the Pitfalls of Post Hoc Explainers in Business Research. arXiv preprint arXiv:2408.16987.

Raybould, A., Mynarska, M., & Sear, R. (2023). “The future is unstable”: Exploring changing fertility intentions in the United Kingdom during the COVID-19 pandemic. *Perspectives on Sexual and Reproductive Health*, *55*(4), 229-238. doi: https://doi.org/10.1111/psrh.12248

Schoen, R., Astone, N. M., Kim, Y. J., Nathanson, C. A., & Fields, J. M. (1999). Do fertility intentions affect fertility behavior? Journal of Marriage and the Family, 61(3), 790–799.

Sobotka, T. (2017). Post-transitional fertility: Childbearing postponement and the shift to low and unstable fertility levels. Demographic Research, 19, 1–54.

Sobotka, T., Zeman, K., Jasilioniene, A., Winkler-Dworak, M., Brzozowska, Z., Alustiza-Galarza, A., Németh, L. and Jdanov, D. (2024), Pandemic Roller-Coaster? Birth Trends in Higher-Income Countries During the COVID-19 Pandemic. Population and Development Review, 50: 23-58. doi:https://doi.org/10.1111/padr.12544

Spéder, Z., & Kapitány, B. (2015). Influences on the link between fertility intentions and behavioural outcomes. In D. Philipov, A. C. Liefbroer, & J. E. Kolbas (Eds.), *Reproductive decision-making in a macro-micro perspective* (pp. 79–112). Springer. doi:10.1007/978-94-017-9401-5

Stein, P., Willen, S., & Pavetic, M. (2014). Couples' fertility decision-making. *Demographic Research*, *30*, 1697-1732. doi: 10.4054/DemRes.2014.30.63

Stulp, G., Top, L., Xu, X., & Sivak, E. (2023). A data-driven approach shows that individuals' characteristics are more important than their networks in predicting fertility preferences. *Royal Society Open Science*, *10*(12), 230988.

Sturm, N., Koops, J. C., & Rutigliano, R. (2023). The influence of partnership status on fertility intentions of childless women and men across European countries. *European Journal of Population*, *39*(1), 20. doi: https://doi.org/10.1007/s10680-023-09664-5

Testa, M. R., & Stephany, F. (2017). The educational gradient of fertility intentions: a meta-analysis of European studies. *Vienna yearbook of population research*, *15*, 293-330. doi: 10.1553/populationyearbook2017s293

UNICEF. (2025). *Prospects for Children in 2025: Building Resilient Systems for Children's Futures*.

Van de Kaa, D. J. (1987). Europe's second demographic transition. *Population bulletin*, *42*(1), 1-59.

Vignoli, D., Bazzani, G., Guetto, R., Minello, A., & Pirani, E. (2020a). Uncertainty and narratives of the future: A theoretical framework for contemporary fertility. *Analyzing contemporary fertility*, 25-47. doi: https://doi.org/10.1007/978-3-030-48519-1_3

Vignoli, D., Guetto, R., Bazzani, G., Pirani, E., & Minello, A. (2020b). Uncertainty and narratives of the future: A theoretical framework for contemporary fertility. Population and Development Review, 46(3), 511–550.

Vignoli, D., Guetto, R., Bazzani, G., Pirani, E., & Minello, A. (2020c). A reflection on economic uncertainty and fertility in Europe: The narrative framework. *Genus*, *76*, 1-27. doi: https://doi.org/10.1186/s41118-020-00094-3

Vignoli, D., Tocchioni, V., & Mattei, A. (2020). The impact of job uncertainty on first-birth postponement. *Advances in Life Course Research*, *45*, 100308. Doi.org/10.1016/j.alcr.2019.100308.

Vignoli, D., Drefahl, S., & De Santis, G. (2012). Whose job instability affects the likelihood of becoming a parent in Italy? A tale of two partners. *Demographic Research*, *26*, 41–62. doi: http://www.jstor.org/stable/26349881

Vignoli, D., Minello, A., Bazzani, G., Matera, C., & Rapallini, C. (2022). Narratives of the future affect fertility: Evidence from a laboratory experiment. *European Journal of Population*, *38*(1), 93-124. doi: https://doi.org/10.1007/s10680-021-09602-3

Wagner, M., Huinink, J., & Liefbroer, A. C. (2019). Running out of time? Understanding the consequences of the biological clock for the dynamics of fertility intentions and union formation. *Demographic Research*, *40*, 1-26. doi:10.4054/DemRes.2019.40.1

Wang, Y., Gozgor, G., & Lau, C. K. M. (2022). Effects of pandemics uncertainty on fertility. Frontiers in Public Health, 10, 854771. doi: https://doi.org/10.3389/fpubh.2022.854771

Xu, X., Gauthier, A., Stulp, G., & van den Bosch, A. (2024). Understanding Narratives of Uncertainty in Fertility Intentions of Dutch Women: A Neural Topic Modeling Approach. *Social Science Computer Review*, 08944393241269406.

Zhao, B., Nguyen, V.K., Xu, M. *et al.* Random survival forest for predicting the combined effects of multiple physiological risk factors on all-cause mortality. *Scientific Reports* **14**, 15566 (2024). https://doi.org/10.1038/s41598-024-66261-0

Appendix A: Additional sample description

Table A1. Sample sizes

	All	20<age<50	with partner	Fertility intentions	Basic demographic s
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

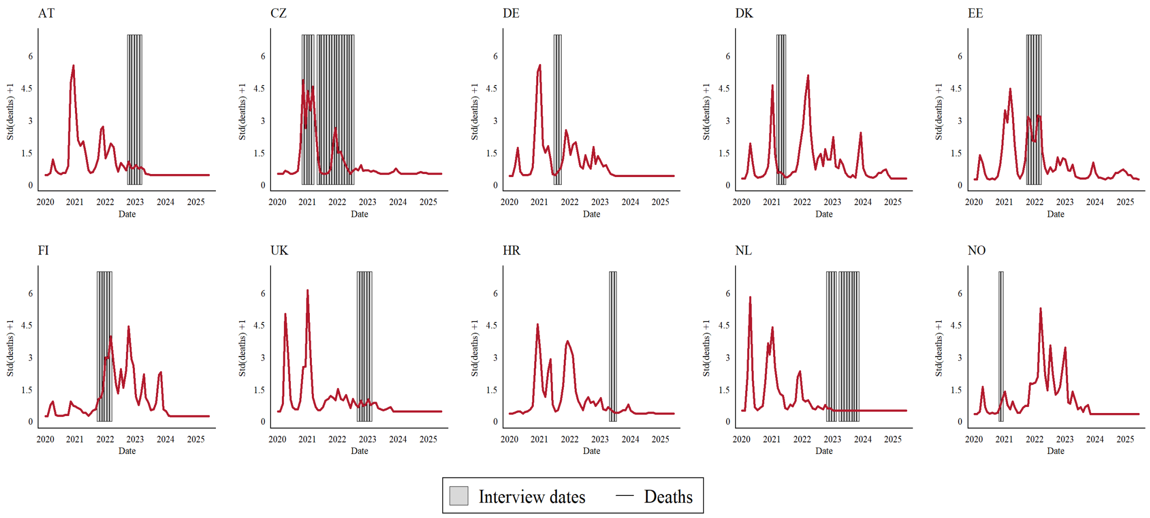
	Fertility intentions			
	Definitely or probably not	Unsure	Probably or definitely yes	Total
Age	38.37	32.04	31.61	35.98
	(8.02)	(6.44)	(5.32)	(7.94)
Gender				
Man	38.69	42.58	40.14	39.51
Woman	61.31	57.42	59.86	60.49
Migrant				
No	89.43	88.17	87.58	88.83
Yes	10.57	11.83	12.42	11.17
Education				
Primary	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)

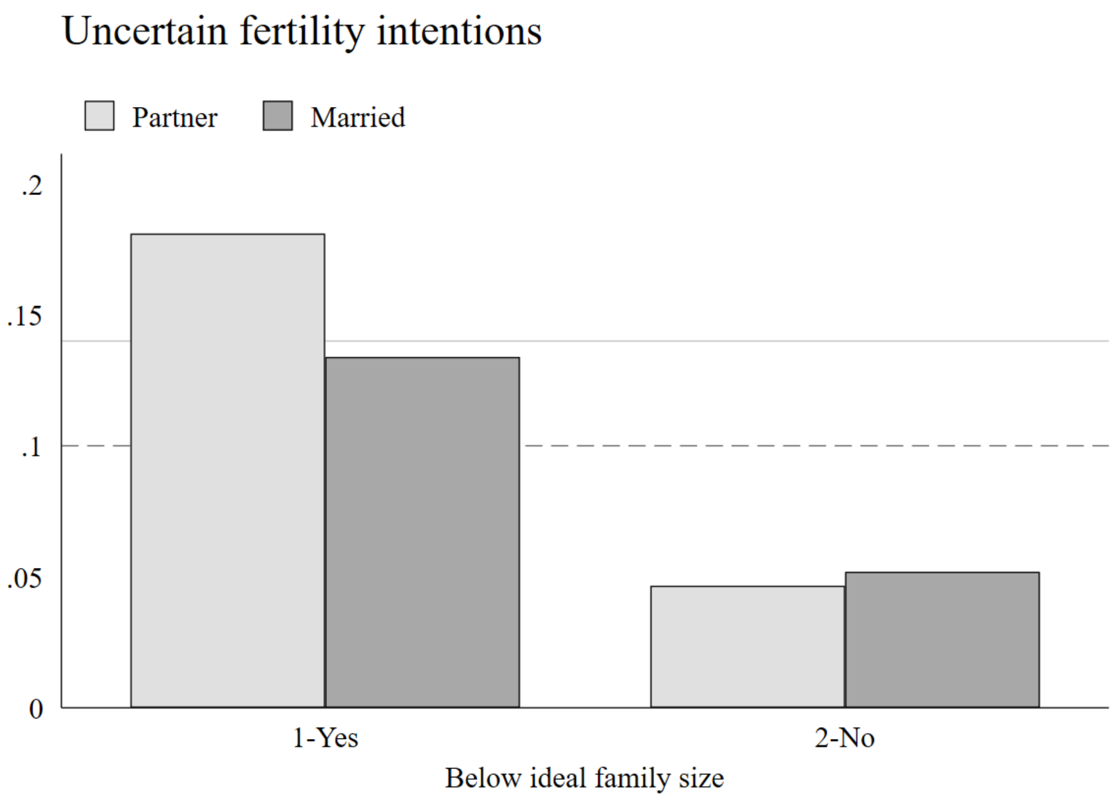
Note: Table presents descriptive statistics used in the study. Column headers indicate values of the outcome variable.

Figure A1: Deaths by COVID-19 during the sample period



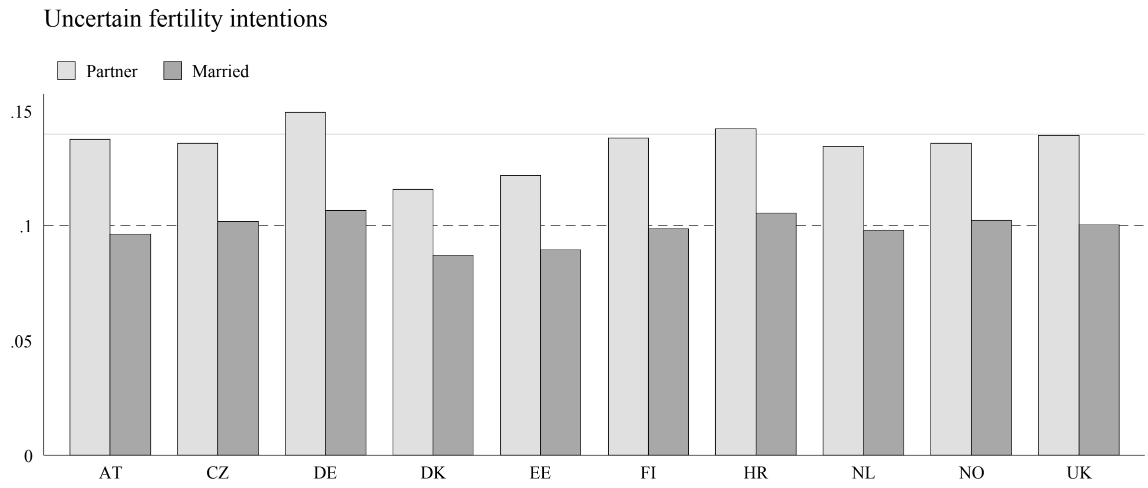
Notes: The picture plots the standardized number of COVID-19 deaths in each country (we add one for visualization). The vertical bars indicate dates on which at least an interview took place. Data from John Hopkins University.

Figure A2: An important interaction for Uncertain fertility intentions



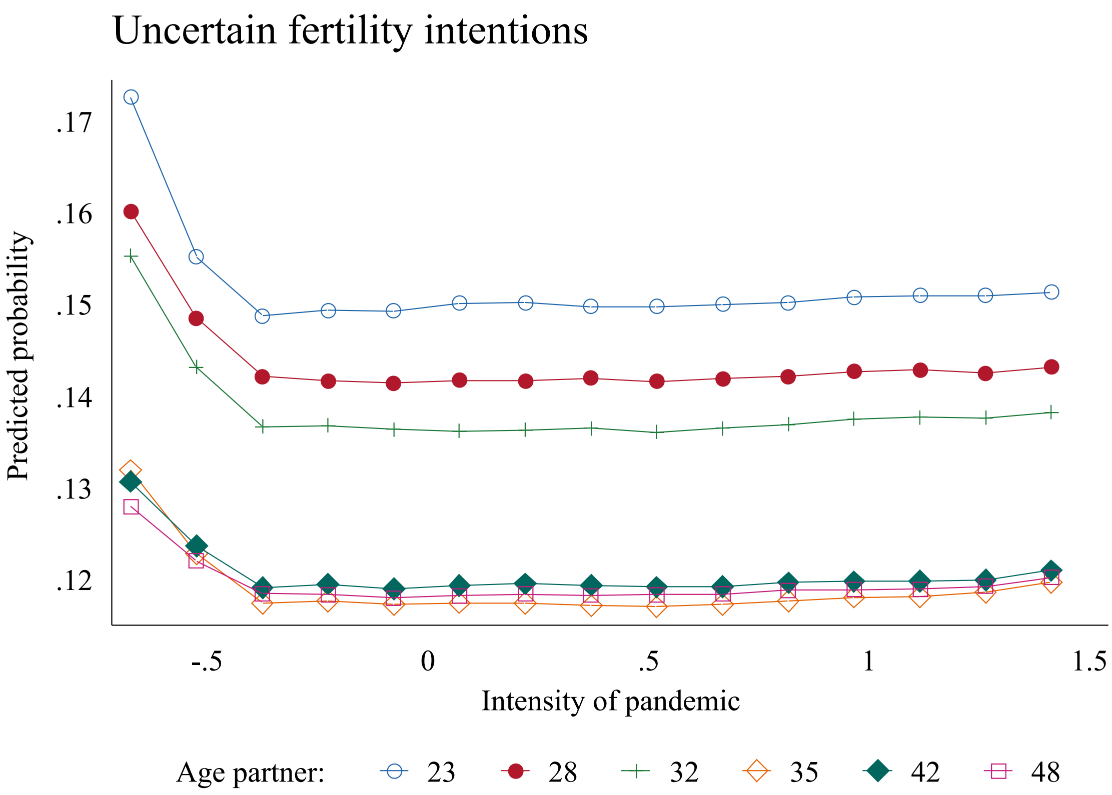
Notes: The figure shows the most important interaction in predicting uncertain fertility intentions. The height of the bar displays the PDP for each combination. The dash line presents the PDP for married individuals, and the solid line the PDP for cohabiting individuals.

Figure A3: Uncertainty fertility intentions vary by country and marital status



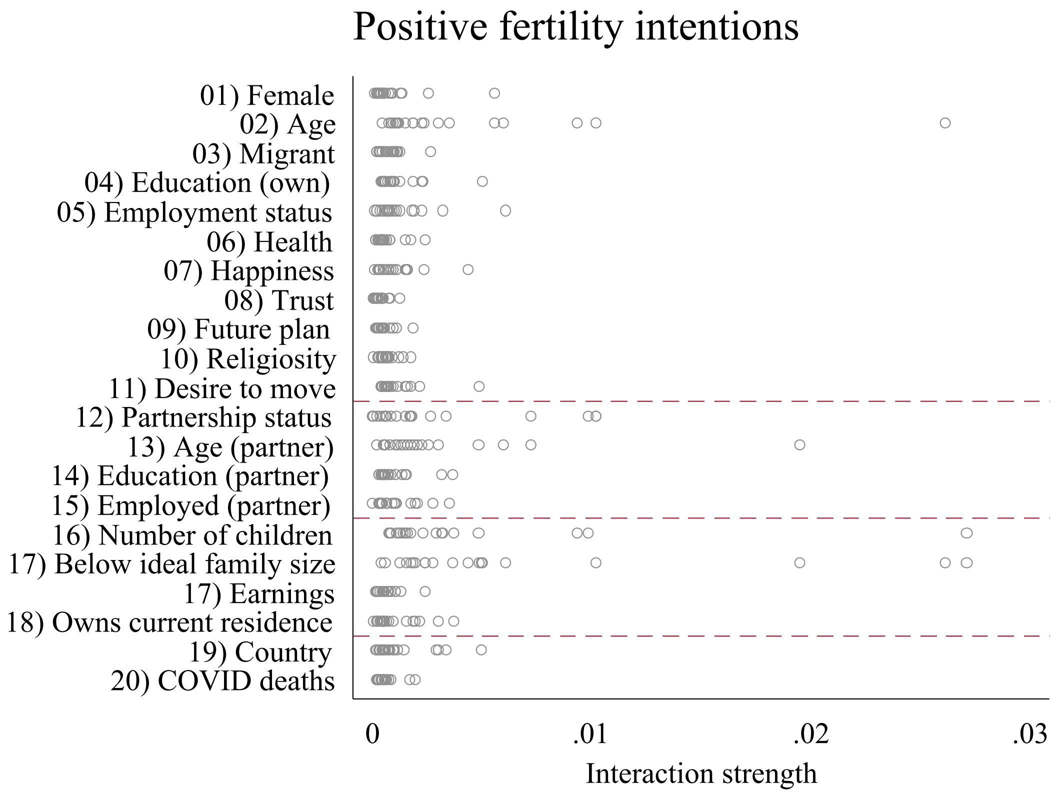
Notes: The figure shows the most important interaction in predicting uncertain fertility intentions involving the country variable and one family resource, i.e. marital status. The height of the bar displays the PDP for each combination. The dash line presents the PDP for married individuals, and the solid line the PDP for cohabiting individuals.

Figure A4: Uncertainty fertility intentions vary by intensity of pandemic and partner's age



Notes: The figure shows the most important interaction in predicting uncertain fertility intentions involving the intensity of the pandemic and one family resource, i.e. age of partner.

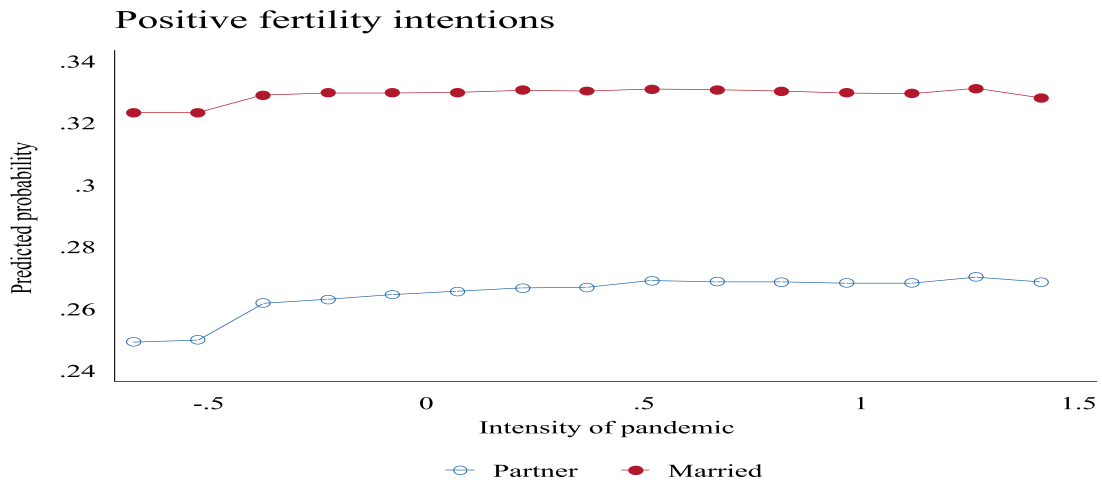
Figure A5: Interaction strength for predicting positive fertility intentions



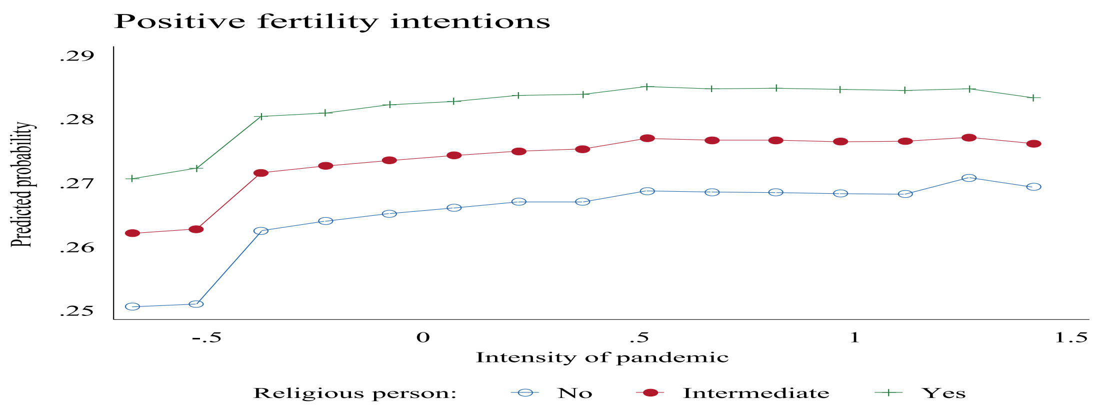
Notes: Own elaboration. The strength of interactions for predicting positive fertility intentions is computed following Greenwell et al. (2018). Each dot represents an interaction between the variable in the row and other variable in the model. Values to the right indicate stronger interactions.

Figure A6: Interaction strength for predicting negative fertility intentions

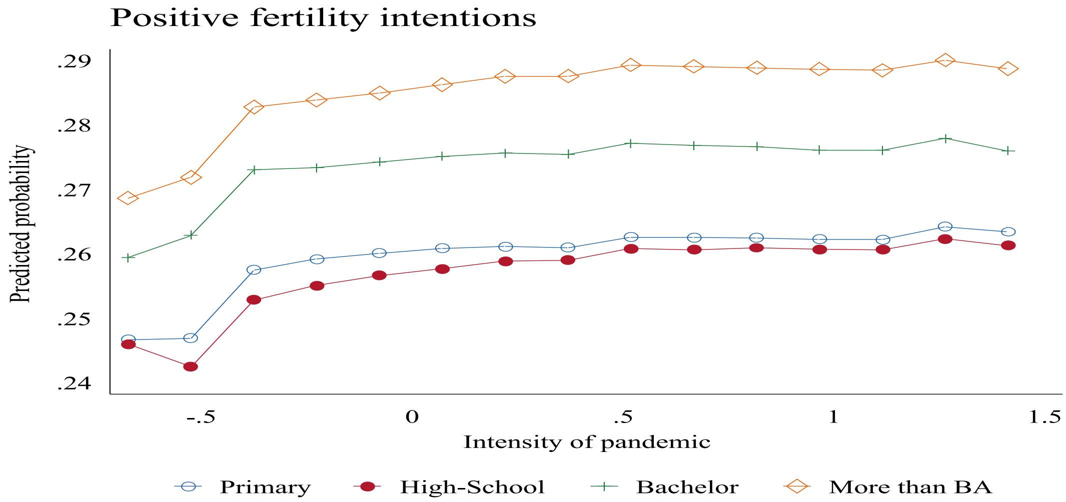
Panel (a): Marital status



Panel (b) Religiosity



Panel (c) Education level



Notes: Figure shows how the PDP of the intensity of the pandemic varies across levels of different resources. In Panel (a) we display variation across marital status, in Panel (b) variation across levels of religiosity. And in Panel (c) across levels of education.

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: Fit Statistics for the main model

Train Data

		By outcome		
	Average	No	Uncertain	Yes
Accuracy	0.899			
Precision	0.926	0.894	0.998	0.887
Recall	0.796	0.983	0.520	0.886

Test data

		By outcome		
	Average	No	Uncertain	Yes
Accuracy	0.739			
Precision	0.574	0.782	0.300	0.642
Recall	0.532	0.904	0.017	0.675

Notes: The table provides the fit statistics for the model estimated in a sample of individuals aged 20-50. We report measures for the test and the train splits. Different columns indicate the predicted intentions. Average refers to the simple average over three outcomes.

Table B2: Confusion matrices

Test data

	Predicted intention		
	No	Uncertain	Yes
Actual intention			
No	1736	9	176
Uncertain	222	6	135
Yes	263	5	557

Train data

	Predicted intention

	No	Uncertain	Yes
Actual intention			
No	16507	2	281
Uncertain	1149	1809	518
Yes	808	1	6278

Notes: The table presents the confusion matrix for the model estimated in a sample of individuals aged 20-50. Results are presented separately for the test and train splits