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RESEARCH

A Spatial Analysis of Factors Affecting Total Fertility Rates in OECD Countries: The Role of Digitalization

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Abstract
This study examines the relationship between digitalization and total fertility rates (TFR) across OECD countries over the period 2000–2021, accounting for spatial interdependence in fertility dynamics. Digitalization is conceptualized as a multidimensional process and is primarily measured using fixed broadband subscriptions per 100 people, complemented by mobile broadband penetration and ICT goods exports as robustness indicators. Employing spatial panel econometric techniques and comparing the results with non-spatial fixed-effects models, the analysis reveals a robust positive association between digitalization and realized fertility at the macro level. The preferred spatial error model indicates significant spatial dependence, suggesting that fertility outcomes are shaped by regionally correlated unobserved factors, such as shared welfare regimes, cultural proximity, and synchronized economic conditions, rather than direct spillovers of fertility levels. The results further identify an inverted U-shaped relationship between income per capita and fertility, as well as a U-shaped association between female labor-force participation and fertility, consistent with evolving work–family arrangements in advanced economies. While digitalization and female labor-force participation each display independent relationships with fertility outcomes, their interaction does not attain statistical significance. Overall, the findings underscore the importance of digitalization and spatial context in understanding contemporary fertility patterns and suggest that coordinated investments in digital infrastructures alongside family-supportive institutions may help mitigate persistently low fertility in OECD countries.

Keywords Digitalization · Broadband access · Total fertility rate · Spatial econometrics · OECD

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Introduction

Fertility rates are central to a country's demographic structure and have long been the subject of interdisciplinary research. Over the past decade, sustained declines in total fertility rates (TFR) across most advanced economies have intensified scholarly attention, particularly within the social sciences. OECD member states constitute a critical case, as fertility patterns have shifted markedly over the past century. Despite cross-country variation in the pace and magnitude of decline, total fertility rates across most OECD countries remain well below the replacement threshold of 2.1 children per woman, with countries such as Germany, Italy, Japan, and Spain experiencing sustained low-fertility regimes for more than two decades (OECD Family Database, 2023; OECD, 2024). These trends carry significant demographic and economic consequences, as shrinking cohorts accelerate population ageing and exert pressure on labor supply, public finances, productivity, and long-run growth. Despite a wide range of policy interventions, mixed evidence on their long-term effectiveness underscores the need to examine broader contextual drivers of fertility change in order to better understand contemporary demographic dynamics(Kearney & Levine, 2025; Spears & Geruso, 2025).

Explanations for fertility decline have evolved through several complementary theoretical perspectives. Classical Demographic Transition Theory (DTT) links declining fertility to modernization-related structural transformations, emphasizing rising education, mortality decline through improvements in health and food security, and rural–urban differentials (Coale & Watkins, 1986). Sociological approaches complement these structural accounts by highlighting the role of social norms embedded in kinship systems, religion, and local culture in shaping reproductive behavior (Caldwell, 1982). While differing in emphasis, these perspectives operate at distinct analytical levels and are largely complementary. From the 1980 s onward, fertility research increasingly incorporated ideational and behavioral explanations. The Second Demographic Transition (SDT) emphasizes secularization, growing individual autonomy, and post-materialist values as drivers of fertility postponement, rising cohabitation, and persistent sub-replacement fertility (Van de Kaa, 1987; Lesthaeghe, 2020). Subsequent work highlights path dependence, showing how regional legacies of earlier demographic transitions shape the timing and pace of later behavioral change, generating enduring spatial heterogeneity in fertility outcomes (Lesthaeghe & Neels, 2002; Lesthaeghe, 2025). Together, these literatures suggest that fertility dynamics emerge from interactions between ideational change and structural conditions across space and time (Kearney & Levine, 2025).

Economic theories further frame childbearing as an optimization problem, conceptualizing fertility as a trade-off between child quantity and quality under resource constraints (Becker, 1960; Becker & Barro, 1988). Rising female labor-market returns increase opportunity costs, while higher household income may reduce fertility by encouraging greater investment per child. Critics, however, emphasize that fertility choices are embedded within broader social and institutional contexts. Reflecting this shift, recent scholarship has expanded the analytical lens beyond conventional economic determinants to incorporate structural and normative transformations associated with the twenty-first century, including climate uncertainty, widening inequalities, and technological change (Doepke et al., 2023; Kearney & Levine, 2025; Baraitser, 2025). Among these emerging forces, digitalization, defined as a broad process encompassing digital infrastructure, mobile connectivity, and the integration of digital technologies into economic and social life, occupies a distinctive position because it directly reshapes everyday decision environments through changes in work organization, access to services, and exposure to alternative life courses. By facilitating remote work, expanding digital service provision, and transforming patterns of social interaction, digital technologies may alter motherhood–career trade-offs and, in turn, influence fertility decisions and outcomes (Billari et al., 2019; Proskurina et al., 2022).

The spatial dimension adds further complexity to understanding digitalization's demographic effects. Norms and behaviors diffuse across space through cross-border information flows and labor mobility, implying that the fertility effects of digitalization may generate spatial spillovers. Historical evidence shows that fertility declines often diffused unevenly, spreading more rapidly across culturally and linguistically connected regions, underscoring the importance of spatial interdependence in demographic change (Coale & Watkins, 1986; Boyle, 2003). Against this backdrop, this paper examines the relationship between digitalization and TFR across OECD countries from 2000 to 2021, with particular attention to spatial dependence and cross-country spillover effects. The research questions of this study are: *1) How does digitalization shape cross-country variation in total fertility rates across OECD countries during the period 2000–2021? 2) To what extent does TFR across OECD countries exhibit spatial interdependence*, *reflecting cross-country spillovers rather than purely country-specific dynamics?* To answer these questions, we estimate spatial panel econometric models that explicitly account for cross-country interdependence while controlling for a comprehensive set of economic, social, and institutional covariates, and compare these results with non-spatial fixed-effects estimates.

This study makes two main contributions. First, to the best of our knowledge it provides one of the first systematic analyses of the digitalization–fertility relationship in the OECD, integrating digitalization into debates on the new economics of fertility. Second, by adopting a spatial econometric framework, it demonstrates how spatial heterogeneity and interdependence across countries shape fertility outcomes, offering insights relevant for the design of place-sensitive family and labor policies. The remainder of the paper proceeds as follows. This paper begins by reviewing the discussion on factors affecting fertility rates, then describes the data and empirical strategy. Empirical results and robustness checks follow, and the paper concludes with a discussion of policy implications.

A Brief Discussion on Factors Affecting Fertility Rates

Economics of Fertility

Economic analyses have traditionally conceptualized fertility as a rational choice made by utility-maximizing households under resource constraints. Within the neo-classical framework, fertility reflects a trade-off between child quantity and quality, whereby rising income and opportunity costs-particularly those associated with women's time-increase the relative cost of childrearing and lead households to prefer fewer, more intensively invested children (Becker, 1960; Becker & Barro, 1988). This framework has been widely employed to explain long-run fertility decline in advanced economies, where rising wages and female labor-force participation have elevated the economic costs of childbearing (Blake, 1968; Cain & Weininger, 1973). Extensions incorporating relative income and social comparisons further emphasize that fertility decisions are shaped by reference groups, framing demographic transition as a response to changing economic incentives rather than purely cultural change (Easterlin, 1975).

Consistent with this perspective, empirical research on fertility determinants spans both micro-level analyses of individual and household behavior and macro-level studies of broader economic and institutional conditions. At the micro level, fertility decisions are shaped by a combination of partnership trajectories, labor-market conditions, and individual preferences, which jointly influence the timing and likelihood of childbearing. Harmonized longitudinal evidence from Europe and the United States demonstrates that union formation, relationship stability, and re-partnering patterns play a central role in structuring fertility trajectories over the life course (Kuang et al., 2025). Complementing this relational perspective, preference-based explanations emphasize persistent heterogeneity in fertility behavior, showing that women's work–family orientations generate systematically different outcomes that cannot be fully accounted for by education, income, or institutional settings alone (Hakim, 2003). Labor-market conditions constitute an additional and closely related micro-level channel. Evidence from Norway indicates that individual unemployment reduces first-birth probabilities, while adverse local labor-market conditions suppress higher-order births, highlighting the sensitivity of fertility decisions to both individual and contextual economic uncertainty (Kristensen & Lappegård, 2022). Importantly, the influence of socio-economic characteristics such as education is not uniform. Using survey data for women aged 25–34 in China, Zhang (1990) documents a non-linear (J-shaped) relationship, whereby higher education initially delays childbearing but facilitates fertility recovery once economic security improves. Beyond economic and partnership-related factors, cultural and institutional contexts further condition fertility behavior. Cross-national survey evidence reveals systematic fertility differentials by religious affiliation, underscoring the role of norms and values in shaping reproductive preferences (Heaton, 2011). Similarly, evidence from low-income settings highlights the continued relevance of age, education, occupation, and household structure in shaping fertility outcomes (Kassaw et al., 2025). Finally, policy evaluations using Norwegian register data show that universal child benefits increase second and third births, confirming that institutional interventions can meaningfully alter fertility behavior, particularly at higher parities (Andersen et al., 2018).

Complementing micro-level studies, macro-level analyses document a robust association between rising income per capita and declining fertility (Herzer et al., 2012), while macroeconomic instability and unemployment are linked to fertility postponement across European countries (Adsera, 2011; Matysiak et al., 2021). Education emerges as a central driver of demographic transition in historical and cross-national samples, operating through delayed family formation and preference change (Murtin, 2013). Recent evidence further suggests that improvements in living conditions and access to basic services facilitate fertility decline by expanding reproductive agency (Van Hoyweghen et al., 2023).

Institutional and policy-oriented studies -largely focused on OECD countries- show that family policies shape fertility both directly and indirectly. Comparative analyses highlight widespread postponement of childbearing and persistent gaps between desired and realized fertility, while emphasizing the role of childcare provision, parental leave, and tax benefits in reducing childrearing costs (D'Addio & d'Ercole, 2005); Gauthier & Hatzius, 1997). More recent panel evidence indicates that comprehensive policy packages are more effective than isolated measures (Zhang et al., 2023), that in-kind transfers such as subsidized childcare are more redistributive and fertility-supportive than cash benefits alone (Förster & Verbist, 2012), and that supportive family policies and flexible labor markets have weakened -and in some contexts reversed- the negative association between female labor-force participation and fertility (Doepke et al., 2023; Šmeringaiová, 2025).

Digitalization and Fertility

The rapid diffusion of digital technologies has introduced additional dimensions to reproductive decision-making, prompting a re-examination of the economic foundations of fertility behavior. The spread of information and communication technologies (ICTs), particularly digital infrastructure and mobile connectivity, has reshaped informational environments, social interactions, and labor-market structures, thereby creating new channels through which digitalization may influence fertility outcomes (Nie et al., 2023; Si et al., 2025). To conceptualize this relationship, the digitalization–fertility nexus is examined through three complementary analytical lenses: *(i)* cultural and ideational change, *(ii)* structural economic transformation, and *(iii)* spatial diffusion and interdependence. These mechanisms should not be interpreted as isolated pathways; rather, they reflect interconnected dimensions of a broader socio-economic transformation through which digitalization shapes fertility behavior.

Cultural and Ideational Change: Preferences, Information, and Norms

From a cultural–ideational perspective, fertility change is closely linked to shifts in values, preferences, and social norms, as emphasized by the SDT framework (Vitali et al., 2009). Rising individual autonomy, self-realization, and gender equality reshape reproductive preferences and weaken traditional pro-natalist norms. Complementing this view, Hakim's (2003) preference theory highlights persistent heterogeneity in women's work–family orientations, underscoring that fertility behavior reflects individual values alongside structural constraints. These theoretical frameworks provide the foundation for understanding how digitalization interacts with cultural and normative processes to influence fertility outcomes.

Digitalization interacts with ideational processes primarily by reducing informational frictions. Digital technologies substantially lower information search costs (Aker et al., 2012), expanding access to reproductive health knowledge, contraception information, and childrearing practices. Through social learning and exposure effects, this enhanced information access influences both the timing and quantum of childbearing by reshaping desired family size and contraceptive demand.

Beyond information provision, digital platforms facilitate normative diffusion through online social networks, which are often associated with weaker pro-natalist attitudes than offline ties (Zhao et al., 2024). Digital environments transmit narratives related to economic uncertainty, climate change, and future prospects, shaping fertility intentions and postponement decisions (Ivanova & Balbo, 2024). Increased online engagement strengthens preferences for self-development and individual autonomy, reinforcing the broader historical transformations emphasized by Hakim (2003), including the contraceptive revolution and expanded female labor-market participation (Chen et al., 2022).

Digital technologies also affect family dynamics and interpersonal relations in complex ways. While ICTs enhance communication within geographically dispersed families, they may also displace face-to-face interaction, with effects that vary by household structure and usage patterns (Tammisalo & Rotkirch, 2022). For example, in Malawi, a country with high-fertility rates, mobile phone ownership has been shown to facilitate long-distance relationships while being associated with reduced frequency of sexual intercourse and increased contraceptive use (Billari et al., 2020). Empirical research supports the relevance of these ideational channels. Broadband expansion in the United States explains a non-trivial share of the decline in teen fertility by reducing unintended and mistimed births (Guldi & Herbst, 2017), while evidence from Malawi shows that mobile phone ownership affects fertility primarily through preference change, role modeling, and information access rather than partnership formation (Billari et al., 2020). Together, these findings indicate that digitalization reshapes fertility behavior by transforming informational and normative environments.

Structural Economic Transformation: Labor Markets, Opportunity Costs, and Uncertainty

A second analytical lens emphasizes structural economic mechanisms, consistent with the structural perspective on fertility transitions (Vitali et al., 2009). Whereas the previous subsection focused on preference formation and normative diffusion, this perspective highlights how digitalization reshapes fertility incentives through labor-market structures, opportunity costs, and economic uncertainty. One pathway operates through improvements in well-being and financial inclusion. Beyond its effects on preferences and norms discussed above, the diffusion of digital financial services enhances households' ability to smooth consumption and self-insure against income shocks, potentially reducing reliance on children as a form of economic security. Billari et al. (2020) conceptualize this mechanism as a demand-side preference channel. While increased economic security may delay fertility for some groups, it also reduces uncertainty and improves planning capacity, which does not necessarily translate into lower realized fertility at the aggregate level.

Digitalization may also operate in the opposite direction. Si et al. (2025) argue that broadband expansion promotes fertility by improving service access and labor-market flexibility, thereby strengthening household resilience. A key conditioning channel operates through female labor-market participation and work–family compatibility. Digital technologies facilitate remote work, flexible schedules, and platform-based employment, potentially easing the reconciliation of paid work and childcare responsibilities -particularly in contexts where women bear a disproportionate share of domestic labor.

Empirical evidence underscores the context-dependent nature of this channel. Using German data, Billari et al. (2019) show that broadband availability increases fertility among highly educated women aged 25-45 by expanding opportunities for home-based and part-time work, suggesting that digitalization lowers the opportunity costs of childbearing primarily for women with strong labor-market attachment. Complementary evidence from policy reforms indicates that reductions in workplace rigidity, when combined with childcare support, are associated with higher fertility among working women (Guner et al., 2024; Bratsberg & Walther, 2025).

Taken together, the cultural–ideational and structural economic perspectives imply that digitalization may influence fertility through multiple, potentially offsetting mechanisms. While digital exposure can encourage fertility postponement by reshaping preferences and norms, it can simultaneously reduce uncertainty and ease work-family constraints by expanding access to services and flexible employment arrangements. At the macro level, these individual-level adjustments translate into observable differences in realized fertility across countries, motivating an empirical assessment of the net association between digitalization and fertility in OECD.

H1 *Digitalization is positively associated with realized fertility rates at the macro level.*

Moreover, the fertility implications of digitalization are unlikely to be uniform across countries. Structural economic theories emphasize that opportunity costs of childbearing depend critically on women's labor-market attachment and institutional support for work–family reconciliation. From this heterogeneity perspective, digitalization may interact with existing labor-market conditions, implying that its fertility effects differ across countries with varying levels of female labor-force participation rather than operating uniformly across contexts. At the same time, the widespread diffusion of digital technologies may induce broadly similar adjustments in work-family arrangements across advanced economies, potentially limiting observable cross-country variation in these effects. This consideration motivates an empirical test of whether the digitalization-fertility relationship varies systematically across labor-market contexts.

H2 *The association between digitalization and fertility varies across countries with different levels of female labor-force participation.*

Spatial Diffusion and Interdependence: Connectivity Beyond Borders

A third lens emphasizes the inherently spatial nature of fertility dynamics. At this stage, mechanisms such as social learning and normative diffusion operate across countries rather than within them. Fertility does not evolve in isolation within national borders but diffuses across regions through migration, social interaction, and policy learning. Early evidence of regional fertility diffusion is documented by Tolnay (1995), while more recent studies show that fertility rates in one country are influenced by those of neighboring countries through shared labor markets and social norms (Campisi et al., 2020).

Digital connectivity is likely to amplify these spatial spillovers by accelerating cross-border information flows and social learning. Online platforms facilitate exposure to alternative family models, policy regimes, and social expectations, strengthening interdependence in fertility behavior across countries. From a spatial-econometric perspective, digitalization thus affects fertility not only directly but also indirectly through intensified spatial correlation and diffusion processes. Taken together, these arguments suggest that fertility dynamics are not spatially independent, motivating the empirical examination of cross-country spatial interdependence in fertility outcomes.

H3 *Fertility outcomes exhibit positive spatial interdependence across countries.*

Data, Methodology, and Models

Data and Methodology

The objective of this research is to examine the extent to which digitalization, as a distinctive factor, contributes to variations in fertility rates across OECD countries during the period 2000-2021, and to assess whether fertility rates exhibit spatial dependence. Our dependent variable is the total fertility rate (TFR), measured as the average number of births per woman over her reproductive lifespan. As a period measure, TFR provides an accurate estimation of completed fertility levels under the assumption of stable birth timing patterns across cohorts. However, we acknowledge that shifts in the timing of childbearing -such as delayed or accelerated fertility- can influence TFR estimates, potentially creating temporal distortions in cross-sectional comparisons. Despite this limitation, TFR remains the most widely used and internationally comparable fertility indicator (Kearney & Levine, 2025), making it appropriate for our cross-national spatial analysis.

In this study, digitalization is conceptualized as a multidimensional process encompassing digital infrastructure, mobile connectivity, and the integration of digital technologies into economic activity. To operationalize this concept empirically, fixed broadband subscriptions per 100 people (*broadband*) are employed as the primary indicator of digital infrastructure, capturing long-term investment in stable, high-capacity connectivity. Mobile broadband subscriptions per 100 people (*mobile*) are included as a complementary proxy reflecting the diffusion of portable and individual-level digital access, which may operate through distinct behavioral channels. Finally, information and communication technology (ICT) goods exports as a share of total goods exports (*ict*) are used to proxy the structural embedding of digital technologies in a country's production and export composition. ICT goods exports are used to capture the production-side dimension of digitalization, reflecting the extent to which digital technologies are embedded in a country's industrial and export structure, with potential implications for fertility through changes in labor demand, skill intensity, and work-family trade-offs. In addition, a set of control variables is incorporated, as reported in Table 1. All variables are expressed in natural logarithms.

We employ a spatial data analysis approach that explicitly accounts for spatial effects in demographic patterns. Recent research highlights the advantages of spatial methodologies in explaining fertility and other demographic variations across regions and countries (Bryan & Jenkins, 2015; Campisi et al., 2020). Spatial effects consist of two main components: spatial dependence and spatial heterogeneity (LeSage & Pace, 2009: 17; Anselin, 1988: 11). Spatial dependence, often referred to as spatial autocorrelation, arises when outcomes observed in one location are systematically related to those in neighboring locations. In this context, the value of a demographic indicator in a given region is shaped not only by local conditions but also by the corresponding values in surrounding regions (Frexedas & Vayá, 2005: 154). Positive spatial spillovers imply that unobserved factors -or "shocks"- affecting fertility propagate across borders, leading to correlated demographic dynamics among neighboring countries. This clustering may appear as synchronized fertility increases or declines, reflecting the diffusion of social norms, exposure to common economic conditions, or the regional transmission of policy interventions and their effects. Recognizing these spatial interdependencies provides strong justification for the application of spatial econometric models in the study of fertility. This econometric approach systematically explains in the following steps.

The value of variable X in region i is subject to the conditional probability of its value in the neighbor location j. This can be stated as follows:

Table 1 Definitions of the variables

Variables	Explanation	Data Source
Dependent Variable		
TFR	Fertility rate, total (births per woman)	OECD (2023b)
Independent Variables		
broadband	Fixed broadband subscriptions (per 100 people)	OECD (2023a)
gdppc	GDP per capita, (constant 2015 US$)	World Bank (2023)
gdppc_sq	Square of GDP per capita, (constant 2015 US$)	Own calculation
inequality	Pre-tax national income (top 10% share)	World Inequality Database (2023)
laborforce	Labor force participation rate of females (%)	World Bank (2023)
laborforce_sq	Square of labor force participation rate of females (%)	
ur	Unemployment rate, female (% of female labor force)	World Bank (2023)
gpi	Gender parity index, School enrollment, primary (gross),	World Bank (2023)
inf	Inflation, GDP deflator (annual %)	World Bank (2023)
health	Current health expenditure per capita, PPP (current international $)	World Bank (2023)
trade	Trade (% of GDP)	World Bank (2023)
urban	Urban population growth (annual %)	World Bank (2023)
cash	Public expenditure on cash benefits to households (% of GDP)	OECD Familiy Database (2023)
inkind	Public expenditure on in-kind benefits to households (% of GDP)	OECD Familiy Database (2023)
laborforce*broadband	Interaction term	Own calculation
Independent Variables for Robutness Check		
mobil	Mobil broadband subscriptions (per 100 people)	OECD (2025)
ict	Information and communication technology goods exports (% of total goods exports)	World Bank (2023)

Source: Compiled by authors

$$P\left[x_i/x\right] = P\left[x_i/x_j\right] \tag{1}$$

$$Cov\left(x_i, x_j\right) = E\left(x_i, x_j\right) - E\left(x_i\right)E\left(x_j\right) \neq 0 \tag{2}$$

$$\forall\, i \neq j \in J$$

First, the spatial weight matrix is constructed based on the geographic neighborhood to incorporate spatial effects into the model. This matrix is positive and symmetrical and has an $n\ x\ n$ dimension. Its properties are demonstrated by W.

$$W = \begin{bmatrix} w_{11} & \cdots & w_{1n} \\ w_{21} & \cdots & w_{2n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{bmatrix}$$

The weight matrix, of which rows are normalized so that the sum of them is 1, allows all weights to be between 0 and 1. This normalized matrix shows the average value of neighboring locations (Anselin & Bera, 1998: 258).

Second, as a robustness check, we construct another weight matrix, namely Euclidean inverse distance matrix, to capture the spatial decay of influence with geographic separation. This matrix is calculated based on distances between national capital cities, which serve as proxies for country centroids. The inverse distance weighting scheme allows us to examine spatial relationships that diminish with geographic distance, moving beyond the binary nature of contiguity-based approaches. This methodological framework enables us to quantify how geographic proximity mediates cross-national interactions and spillover effects, thereby providing deeper insights into the spatial transmission mechanisms that drive demographic convergence and divergence patterns across countries (Balash et al., 2020).

A spatial lagged dependent variable or spatial autoregressive process in the error term may be inserted in the model if there is spatial autocorrelation in observations. These models are called the spatial lag model (SLM) and spatial error model (SEM), respectively. If spatial exogenous variables are attached to the model in addition to spatial lagged endogenous variables, the model is called the spatial Durbin model (SDM). These models are stated as follows (Elhorst, 2003: 245–249):

SLM:

$$\begin{gathered} Y_t = pWY_t + X_t\beta + \mu + \\ \epsilon_t,\ E(\epsilon_t) = 0,\ E\left(\epsilon_t \epsilon_t^{'}\right) = \sigma^2 I_N \end{gathered} \tag{3}$$

SEM:

$$Y_t = X_t\beta + \mu + \theta_t \tag{4}$$

$$\theta_t = \delta W\theta_t + \epsilon_t,\ E(\epsilon_t) = 0,\ E\left(\epsilon_t \epsilon_t^{'}\right) = \sigma^2 I_N$$

SDM:

$$\begin{gathered} Y_t = pWY_t + X_t\beta + \phi WX_t + \\ \epsilon_t,\ E(\epsilon_t) = 0,\ E\left(\epsilon_t \epsilon_t^{'}\right) = \sigma^2 I_N \end{gathered} \tag{5}$$

In the above models, W, δ , ϕ , p indicate the weight matrix, spatial autocorrelation coefficient, spatial cross-regressive parameter, and spatial autoregressive parameter, respectively. ε_{it} is assumed to be normally distributed independently of exogenous variable with zero mean and a constant variance.

The Spatial Dependence of the Fertility Model

Our research question points out the degree to which the digitalization drives the fertility rate. Therefore, we suggest an empirical model representing the socio-economic and macroeconomic drivers of fertility rates at a national level. The model for the fertility rate is as follows:

$$TFR_{it} = \alpha_0 + \sum{}_{i=1}^{q} \alpha_i X_{it} + \omega_1 DIGITALIZATION_{it} + \epsilon_{it} \tag{6}$$

$$X_{it} : \left\{ \begin{array}{c} gdppc_{it}, \ health_{it}, \ urban_{it}, laborforce_{it}, inf_{it}, ur_{it}, \\ gpi_{it}, \ trade_{it}, \ inequality_{it}, \ cash_{it}, \ inkind_{it}, \end{array} \right\}$$

$$DIGITALIZATION_{it} : \{ broadband_{it} , \ mobile_{it} , \ ict_{it} \}$$

TFR reflects the fertility rate of births per woman. X_{it} indicates the exogenous variables, including each individual independent variable. Digitalization is measured using *broadband*, as the primary indicator. To ensure robustness of our findings, we employ two alternative digitalization measures: *mobile* and *ict*. These alternative specifications serve as robustness checks to validate the consistency of our main results across different dimensions of digitalization. In addition, these specifications are extended to include the squared terms of GDP per capita and female labor-force participation, as well as an interaction term between *broadband* and *laborforce*. To ascertain the impact of spatial interactions across countries on the TFR, a spatial error panel data model is employed (Anselin, 1988: 14–15):

$$TFR_{it} = \vartheta_0 + \sum{}_{i=1}^{q} \vartheta_i X_{it} + \omega_1 DIGITALIZATION_{it} + u_{it} \tag{7}$$

$$u_{it} = \delta W u_{it} + e_{it}$$

In the above model, X_{it} indicates the exogenous independent variables, W is the weight matrix while δ indicates the spatial autocorrelation coefficient. ε_{it} is assumed to be normally distributed independently of exogenous variable with zero mean and a constant variance. In the case of spatial effects, the least square method estimates biased coefficients. For this reason, the maximum likelihood method is used to estimate the spatial panel data models.

Investigating Spatial Dependence

To account for spatial dependence on the model, the lag operator is utilized. This calculates a weighted average of the random variables in neighboring regions. If there is a spatial clustering of similar values in relation to a variable, this is known as positive spatial autocorrelation. Conversely, when dissimilar values cluster together in a region, it is known as negative spatial autocorrelation. Positive spatial autocorrelation results in regional clusters, while negative spatial autocorrelation creates regional outliers.

Accordingly, we apply Moran's I statistics to test for global spatial autocorrelation in fertility rates across our sample countries. The test statistics are calculated as follows:

$$I = \left(\frac{n}{s_0} \right) \frac{\sum{}_i^n \sum{}_j^n w_{ij} x_i x_j}{\sum{}_{i=1}^n x_i^2} \tag{8}$$

where w_{ij} is the standardized weight matrix, n is the number of countries. The value of this statistic is positive if neighboring countries have similar values (LeSage & Pace, 2009).

Appendix Table 4 presents the results of Moran's I statistics for fertility during the period 2000–2021. The statistics are positive and statistically significant across all years, indicating positive spatial dependence among neighboring countries. These findings reveal the presence of spatial clustering, whereby countries with low fertility rates tend to be geographically adjacent to other countries with similarly low fertility rates. Thus, fertility rates among OECD countries exhibit significant spatial autocorrelation.

Empirical Results

As the main estimation strategy, eight spatial panel models are estimated to use *broadband* as the primary proxy for digitalization. To address potential endogeneity and to assess robustness across specifications, a stepwise modeling approach is adopted, with each specification reported in successive columns of Table 2.[1]

Spatial dependence diagnostics strongly support the presence of spatial autocorrelation. The LM-Lag, LM-Error, and their robust counterparts are statistically significant at the 1% level, with the sole exception of the robust LM-Lag statistic, which is insignificant. This pattern indicates that spatial dependence operates primarily through the error term rather than through the dependent variable itself, pointing to the SEM as the most appropriate specification. Unlike the SLM, which assumes that fertility in one country directly depends on observed fertility levels in neighboring countries, the SEM captures spatial dependence arising from unobserved factors that are correlated across space. In this context, the results suggest that fertility shocks in one country are associated with unobserved shocks in neighboring countries-such as regional economic conditions, policy environments, or cultural and environmental

[1] For preliminary analysis, first we test the cross-sectional dependence of the variables. Neglecting cross-sectional dependence can lead to consequences such as estimator efficiency loss and invalid test statistics. There are different tests to examine cross-sectional dependence. Breusch & Pagan's (1980) Lagrange Multiplier shows the asymptotic χ^2 distribution for N fixed as $T_{ij} \rightarrow \infty$ for all (i, j). Pesaran's (2004) scaled LM test is an asymptotically standard normal distribution $T_{ij} \rightarrow \infty$ and then $N \rightarrow \infty$. However, Pesaran (2004) developed an alternative test statistic depending on the mean of the pairwise correlation coefficients to overcome size distortion. This test has an asymptotically standard normal for $T_{ij} \rightarrow \infty$ and then $N \rightarrow \infty$ in any order. The bias-corrected scaled LM test proposed by Baltagi et al. (2012) can be applied to a fixed effects homogeneous panel data model with $T_{ij} \rightarrow \infty$, $N \rightarrow \infty$, and $N/T_{ij} \rightarrow c_{ij} \varepsilon (0, \infty)$. Appendix Table 5 presents the results of cross-sectional dependence tests, in which provide evidence of the presence of cross-sectional dependence for all variables. We test stationarity of variables by using Pesaran's (2007) panel unit root test. Pesaran (2007) developed CIPS statistics allowing for cross-sectional dependence. This test is the extended form of the standard ADF regressions with the lagged cross-sectional averages. CIPS statistics are obtained from the average of t statistics of the lagged variables (CADFi). Appendix Table 6 shows the results of the Pesaran CADF unit root test. The findings indicate all variables except $broadband$, ict, $mobil$, and inf are stationary at the first difference at 1% significance level. We follow the non-spatial fixed effect OLS strategy and all results presented in Table 7 in Appendix. Fixed effect OLS estimation results show us, increase in broadband access positively contributes to TFR. Not only broadband access, other two digitalization proxies, mobile and ict, are also positively affect TFR.

factors not explicitly included in the model-rather than with neighboring countries' observed fertility outcomes. Accordingly, fertility dynamics appear to be shaped by shared regional influences rather than direct cross-country spillovers in fertility levels. By accounting for spatial correlation in the error structure, the SEM yields unbiased and more reliable estimates of the effects of observed covariates, including education, female labor-force participation, and income inequality. This finding also highlights the relevance of regional context and coordination in fertility-related policy design, as countries may be exposed to common underlying drivers of demographic change.

Turning to model specifications, Models 1 and 2 serve as baseline estimates and exclude broadband access, thereby omitting the digitalization channel. Models 3 and 4 extend the baseline by incorporating social benefits to households, distinguishing between cash transfers and in-kind benefits. Models 5 and 6 further enrich the specification by allowing for potential nonlinear effects of GDP per capita and female labor-force participation, consistent with the theoretical arguments advanced by Doepke et al. (2023). The final specifications, Models 7 and 8, additionally include an interaction term between broadband access and female labor-force participation to test for heterogeneous effects across labor-market contexts. Comparisons across spatial specifications, as well as between the spatial models and the fixed-effects non-spatial estimates reported in Appendix Table 7, reveal a high degree of consistency in coefficient signs and magnitudes. However, the interaction term between broadband access and female labor-force participation is statistically insignificant in Models 7 and 8. Consequently, Models 5 and 6-featuring nonlinear income and labor-force participation effects without the interaction term-are retained as the preferred specifications for inference.

Across all estimation scenarios, digital infrastructure, proxied by fixed broadband access, exerts a positive and statistically significant effect on TFR in OECD countries, supporting Hypothesis 1. This finding aligns with Billari et al. (2019) and Viollaz and Winkler (2022), who emphasize the role of digital infrastructure in facilitating work–family reconciliation, but contrasts with the fertility-reducing effects reported by Liu et al. (2021) and Guldi and Herbst (2017) in different institutional contexts. Taken together, the results suggest that, in advanced economies, digital infrastructure primarily reduces time constraints and uncertainty surrounding childbearing rather than discouraging fertility through preference shifts.

Turning to female labor-force participation, the estimates reveal a non-linear relationship with TFR. The linear term indicates that higher female labor-force participation initially reduces fertility, consistent with the opportunity-cost framework advanced by Mincer (1962) and Becker (1965). However, the positive and statistically significant quadratic term implies that fertility increases at higher levels of female employment, yielding a U-shaped relationship in line with Doepke et al. (2023). This pattern reconciles competing strands of the literature, including evidence of positive fertility–employment linkages in OECD countries under conditions of labor-market frictions and supportive institutions (Da Rocha & Fuster, 2006).

When introducing the interaction between digital infrastructure and female labor-force participation, the estimates reveal no statistically significant effect. Accordingly, Hypothesis 2 is not supported. The absence of an interaction effect is consistent with the non-linear nature of the fertility–employment relationship and suggests that digital infrastructure does not systematically amplify fertility through

Table 2 The results for the Spatial Error Model (Estimations with *broadband*)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
broadband			0.0055***	0.0054***	0.0058***	0.0055***	0.0105***	0.0081**
			(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0034)	(0.0034)
gdppc	−0.3102**	−0.1082	0.0295	0.2703*	3.2334***	3.0104**	3.0046**	2.861**
	(0.1495)	(0.1492)	(0.1545)	(0.1568)	(1.2411)	(1.2419)	(1.2459)	(1.2527)
gdppc_sq					−0.3708**	−0.3103**	−0.3396**	−0.2883**
					(0.1452)	(0.144)	(0.1463)	(0.1463)
inequality	−1.0338***	−0.9471***	−0.947***	−0.8487***	−0.9113***	−0.7622***	−0.9728***	−0.7864***
	(0.2125)	(0.2146)	(0.2064)	(0.2096)	(0.21)	(0.2114)	(0.2148)	(0.2139)
laborforce	−0.0054***	−0.0036*	−0.0048**	−0.0029	−0.0248**	−0.0359***	−0.031***	−0.040***
	(0.0021)	(0.002)	(0.002)	(0.002)	(0.011)	(0.0109)	(0.0118)	(0.0121)
laborforce_sq					0.0002*	0.0003***	0.0003**	0.0004***
					(0.0001)	(0.0001)	(0.0001)	(0.0001)
ur	−0.0074***	−0.009***	−0.0074***	−0.0093***	−0.0064***	−0.0082***	−0.0058***	−0.008***
	(0.0019)	(0.0019)	(0.0019)	(0.0018)	(0.0019)	(0.0018)	(0.002)	(0.0019)
trade	0.0002	0.0004	−0.0005	−0.0002	−0.0004	−0.0002	−0.0004	−0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
inf	0.0066***	0.0068***	0.0057***	0.006***	0.0065***	0.0069***	0.0067***	0.007***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0013)
gpi	0.3478	0.5408	0.2413	0.4716	0.255	0.5356	0.2122	0.5281
	(0.3934)	(0.3967)	(0.3818)	(0.3866)	(0.3847)	(0.3869)	(0.3865)	(0.3878)
health	0.0655**	0.0013	−0.1008**	−0.1782***	−0.1216***	−0.2045***	−0.1214***	−0.2093***
	(0.0324)	(0.0338)	(0.0405)	(0.043)	(0.041)	(0.044)	(0.0409)	(0.0445)
urban	0.0379***	0.0434***	0.0397***	0.046***	0.0416***	0.0457***	0.0431***	0.0467***
	(0.0085)	(0.0085)	(0.0082)	(0.0083)	(0.0085)	(0.0086)	(0.0085)	(0.0087)
cash	−0.0124***		−0.0143***		−0.0141***		−0.0157***	
	(0.0042)		(0.0041)		(0.0044)		(0.0045)	
inkind		0.0054		0.0071		0.0101*		0.0106*
		(0.0056)		(0.0054)		(0.0055)		(0.0056)

Table 2 (continued)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
laborforce*broadband							−0.0001	0
							(0.0001)	(0.0001)
Spatial Effect								
Spatial lag (p)	0.6063***	0.587***	0.6095***	0.5836***	0.5954***	0.5733***	0.5897***	0.5684***
	(0.0241)	(0.025)	(0.0254)	(0.0268)	(0.0264)	(0.028)	(0.0269)	(0.0289)
LM Lag	355.2730***	337.6622***	402.3097***	386.6204***	55.2463***	40.6337***	23.5039***	23.2733***
LM Error	439.3778***	431.6606***	463.3019***	455.9059***	397.2006***	400.4924***	312.3603***	321.5974***
Robust LM Lag	1.0360	0.6953	0.9720	0.7097	0.5744	0.3645	0.003	0.0035
Robust LM Error	85.1408***	94.6938***	61.9641***	69.9952***	342.5286***	360.2232***	288.8567***	298.3277***
Variance: sigma2_e	0.0055***	0.0057***	0.0051***	0.0054***	0.0052***	0.0054***	0.0052***	0.0055***
	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Observations	836	836	836	836	836	836	836	836
R-squared	0.0001	0.008	0.0354	0.0068	0.0315	0.0244	0.0341	0.0233

*Standard errors are in parentheses. *** $p<.01$, ** $p<.05$, * $p<.1$. Note: We also incorporated an interaction term between broadband and laborforce_sq, which was statistically insignificant* women's employment alone. Instead, digital infrastructure may influence fertility through broader mechanisms-such as improved work-life balance, flexible work arrangements, and reduced coordination costs-that operate across labor-market contexts rather than varying with aggregate female employment levels. As emphasized by Billari et al. (2019), broadband-enabled flexibility can ease the reconciliation of paid work and motherhood, while evidence from Eurofound (2020) indicates that digital work arrangements improve perceived work-life balance. These effects may accrue to women regardless of their labor-force participation status or may operate uniformly across different employment regimes, providing a plausible explanation for the absence of a statistically significant interaction term.

As expected, higher female unemployment rates exert a negative effect on TFR. This finding is consistent with Currie and Schwandt (2014), who show that women tend to postpone childbearing during periods of elevated unemployment, with adverse fertility effects intensifying over time, particularly among younger cohorts. Broader evidence further indicates that unemployment affects fertility beyond women alone: both female and male unemployment reduce fertility across different country groups, reflecting heightened economic uncertainty and delayed family formation (Cazzola et al., 2016; Da Rocha & Fuster, 2006; Matysiak et al., 2021).

GDP per capita is a central determinant of cross-country fertility differences. Doepke et al. (2023) show that while a persistent negative income–fertility relationship remains prevalent in low-income countries, it has largely weakened within and across high-income economies. In OECD countries, the relationship shifted from clearly negative in 1980 to positive by 2000, implying a U-shaped pattern over the 1980–2000 period. Consistent with this evidence, our results indicate a positive effect of income per capita on fertility, alongside a negative and smaller quadratic term, pointing to an inverted-U-shaped relationship within the OECD. This pattern suggests cyclical fertility responses to income changes among high-income countries, warranting further attention.

Income inequality, by contrast, reduces TFR, consistent with Deaton and Paxson (1997), despite mixed theoretical predictions (De La Croix & Doepke, 2003). Given that the study period encompasses the prolonged post-2008 crisis, marked by rising inequality, slower income growth, and elevated unemployment, particularly among women, these findings support the view that economic insecurity discourages childbearing.

Education plays a central role in explaining fertility differences across countries. Using the gender parity index in primary education (girls-to-boys ratio) as a proxy for educational equality, we find a positive effect on TFR in several specifications (Models 2, 9, 10, 11, and 12). This result indicates that, over the 2000-2021 period, greater educational parity at the primary level is associated with higher fertility in OECD countries. Kolk (2019) shows that fertility tends to decline at low levels of gender equality but stabilizes or recovers once equality surpasses a critical threshold, implying a non-linear relationship. Given that most OECD countries have largely overcome basic educational inequalities in the twenty-first century, the positive effect observed here is consistent with the idea that reductions in early-stage gender disparities support fertility recovery in advanced economies.

Inflation and both cash and in-kind social benefits are included to account for cost-of-living pressures and indirect public support for childbearing. The literature on cash transfers and fertility reports mixed evidence, with several studies finding weak or even negative effects (Thévenon & Gauthier, 2011), although both cash and in-kind transfers are often viewed as potentially fertility-supportive. In principle, additional income from cash transfers may ease constraints on reproductive autonomy by improving access to healthcare, contraception, or fertility treatments (Cowan & Douds, 2022; Zhang et al., 2023; Gauthier & Hatzius, 1997). Even when not explicitly designed as fertility policies, such transfers may create conditions conducive to childbearing and female labor-force participation. The empirical results, however, reveal markedly different effects by transfer type. Inflation exerts only a small positive effect on TFR, whereas cash and in-kind benefits influence fertility in opposite directions. Cash transfers consistently reduce TFR, while in-kind benefits, such as childcare services and family support programs, raise fertility, although the latter effect is not fully robust across specifications. This contrast highlights the importance of policy composition rather than aggregate family spending. Cross-country variation in the structure of family benefits provides further insight. In most OECD countries, cash benefits dominate family support, whereas in countries such as Chile, Colombia, Denmark, Finland, Iceland, Japan, Korea, Mexico, Norway, Sweden, Turkey, and the United States, in-kind services account for more than half of total family benefits (Fluchtmann et al., 2023). Notably, these countries tend to exhibit fertility rates above the OECD average, lending plausibility to the fertility-enhancing role of service-based support. By contrast, the robust negative effect of cash transfers on total fertility rates suggests that income support alone may be insufficient to offset the opportunity costs and coordination challenges of childbearing. This finding aligns with evidence from Bokun (2024), who reports mixed and short-lived fertility responses to cash transfers in Poland. While not establishing causality, the results carry important policy implications in the context of expanding family expenditures amid persistently low fertility. They suggest that cash transfers may be less effective than in-kind support in addressing structural barriers to fertility, and that the responsiveness to income-based policies varies across demographic groups, reflecting unequal economic and social constraints on childbearing.

Following Gries and Grundmann (2014), we include trade openness, measured as the share of trade in GDP, to capture the potential fertility effects of human capital-biased trade patterns. In developed economies, increased exposure to international trade may raise demand for skilled labor and intensify human capital investment, thereby discouraging fertility, whereas the opposite mechanism may operate in developing countries. Consistent with this reasoning, Galor and Mountford (2008) document a negative effect of trade openness on fertility in OECD countries during earlier periods, reflecting their specialization in human capital–intensive goods. In our analysis, however, trade openness does not exert a robust effect on TFR across specifications, suggesting that the fertility–trade linkage may have weakened or become context-specific in contemporary OECD economies.

Urban population share and health expenditure are included to capture cross-country differences in socio-economic development. Urbanization is commonly viewed as a marker of modernization, and prior evidence-largely from developing-country samples-suggests a negative effect on fertility, although results are sensitive to specification and potential omitted variables (Gries & Grundmann, 2018). Alternative perspectives argue that urbanization may raise fertility by weakening traditional birth-spacing norms and expanding access to education and economic opportunities (Cleland & Wilson, 1987; Martine et al., 2013). Consistent with this latter view, our results show that a higher share of the urban population increases fertility in OECD countries. By contrast, higher health expenditure, reflecting more advanced stages of development, reduces fertility.

Finally, all spatial specifications reveal a positive and statistically significant spatial error coefficient, confirming Hypothesis 3. This result indicates that fertility dynamics are shaped by spatially correlated unobserved shocks rather than by direct spillovers in observed fertility levels. Such shocks likely reflect similarities in welfare regimes, cross-border policy diffusion, cultural and linguistic proximity, and synchronized economic cycles within the OECD. Countries embedded in comparable institutional and economic environments tend to experience parallel fertility responses to common shocks -such as recessions, policy reforms, or shifts in gender norms- even in the absence of direct demographic contagion. These findings underscore the importance of regional context and institutional clustering in shaping fertility dynamics, lending substantive meaning to the observed spatial dependence beyond its statistical manifestation.

Robustness Checks

To assess the robustness of the empirical results, we perform two complementary checks. First, we examine the sensitivity of the spatial estimates to the specification of the spatial weight matrix by re-estimating the model using an inverse Euclidean distance matrix based on capital-city distances. This alternative matrix places greater weight on geographically closer countries and allows us to test whether the findings depend on the definition of spatial proximity. Second, we evaluate robustness with respect to the measurement of digitalization by replacing fixed broadband access with two alternative indicators: mobile broadband subscriptions per 100 persons, capturing individual level mobile connectivity, and ICT goods exports as a share of total exports, reflecting the structural integration of digital technologies into economic activity.

Table 3 reports the results from these alternative specifications. Models 1–6 employ the standard contiguity-based weight matrix with the three digitalization measures, while Models 7–12 use the inverse-distance matrix. Across all specifications, digitalization continues to exert a positive and statistically significant effect on TFR, and the spatial error coefficient remains stable in sign and significance. These results confirm that the main findings are not driven by the choice of digitalization proxy or spatial weighting scheme and provide further support for the presence of spatially correlated fertility dynamics within the OECD.

Table 3 The results for the Spatial Error Model for robustness check

	Estimations with Contiguity Matrix						Estimation with Euclidean inverse matrix					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
broadband					0.0058***	0.0055***					0.0038***	0.0039***
					(0.0008)	(0.0008)					(0.001)	(0.0009)
ict			0.0361***	0.0377***					0.0378***	0.037***		
			(0.0095)	(0.0095)					(0.0094)	(0.0094)		
mobil	0.0273**	0.0318**					0.023*	0.0245*				
	(0.0125)	(0.013)					(0.0139)	(0.0145)				
gdppc	5.1258**	0.5162	0.1871	0.1045	3.2334***	3.0104**	6.6686***	2.5238	1.0132	1.7152	3.6345***	4.3216***
	(1.9935)	(2.073)	(1.2108)	(1.2077)	(1.2411)	(1.2419)	(1.9067)	(1.9533)	(1.1264)	(1.1275)	(1.1918)	(1.1801)
gdppc_sq	−0.6584***	−0.1152	−0.0501	−0.0172	−0.3708**	−0.3103**	−0.8438***	−0.3536	−0.0689	−0.1361	−0.3589**	−0.4175***
	(0.2284)	(0.2386)	(0.1429)	(0.1414)	(0.1452)	(0.144)	(0.2204)	(0.2266)	(0.1358)	(0.1335)	(0.1427)	(0.1387)
inequality	−1.6672***	−1.2731***	−0.8954***	−0.7999***	−0.9113***	−0.7622***	−1.1749***	−0.6503*	−0.6022**	−0.5873**	−0.6179**	−0.5588**
	(0.2829)	(0.3017)	(0.2132)	(0.2124)	(0.21)	(0.2114)	(0.3206)	(0.3362)	(0.2399)	(0.2336)	(0.2419)	(0.2356)
laborforce	0.033*	0.0437**	−0.0285**	−0.0349***	−0.0248**	−0.0359***	0.0281	0.0347*	−0.0464***	−0.0501***	−0.0504***	−0.0558***
	(0.018)	(0.0187)	(0.0112)	(0.0112)	(0.011)	(0.0109)	(0.0184)	(0.019)	(0.0117)	(0.0116)	(0.0117)	(0.0116)
laborforce_sq	−0.0004**	−0.0004**	0.0003**	0.0003***	0.0002*	0.0003***	−0.0003*	−0.0003*	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ur	−0.0103***	−0.017***	−0.0069***	−0.0078***	−0.0064***	−0.0082***	−0.0133***	−0.0195***	−0.0049**	−0.0037*	−0.0066***	−0.0057***
	(0.0025)	(0.0024)	(0.002)	(0.0019)	(0.0019)	(0.0018)	(0.0026)	(0.0025)	(0.0021)	(0.002)	(0.0021)	(0.002)
trade	−0.0012***	−0.0008**	0.0001	0.0002	−0.0004	−0.0002	−0.0018***	−0.0014***	−0.0003	−0.0001	−0.0002	0.0001
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
inf	−0.001	0.0002	0.0075***	0.0077***	0.0065***	0.0069***	−0.0008	0.0003	0.0075***	0.0073***	0.007***	0.0069***
	(0.0018)	(0.0018)	(0.0013)	(0.0013)	(0.0012)	(0.0012)	(0.0019)	(0.002)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
gpi	0.3234	0.9217**	0.4034	0.5784	0.255	0.5356	0.1177	0.5172	0.9807**	1.1934***	0.8479*	1.0985**
	(0.4466)	(0.4564)	(0.3896)	(0.3886)	(0.3847)	(0.3869)	(0.4913)	(0.5156)	(0.4364)	(0.4427)	(0.441)	(0.4465)
health	0***	0***	0.0614*	0.0022	−0.1216***	−0.2045***	−0.0001***	−0.0001***	−0.2043***	−0.2549***	−0.309***	−0.3795***
	(0)	(0)	(0.0332)	(0.0343)	(0.041)	(0.044)	(0)	(0)	(0.0356)	(0.0398)	(0.0413)	(0.0464)
urban	0.0188**	0.0199**	0.0325***	0.0348***	0.0416***	0.0457***	0.0117	0.0183*	0.0306***	0.0304***	0.0448***	0.0461***
	(0.0095)	(0.0098)	(0.0086)	(0.0086)	(0.0085)	(0.0086)	(0.0104)	(0.0108)	(0.0099)	(0.0097)	(0.0098)	(0.0097)
cash	−0.0377***		−0.0079*		−0.0141***		−0.0351***		0.0049		0.002	
	(0.0056)		(0.0044)		(0.0044)		(0.0056)		(0.0048)		(0.0049)	

Table 3 (continued)

	Estimations with Contiguity Matrix						Estimation with Euclidean inverse matrix					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
inkind		0.0012		0.0088		0.0101*		−0.0018		0.0172***		0.019***
		(0.0091)		(0.0055)		(0.0055)		(0.0089)		(0.0063)		(0.0063)
Spatial effect												
Spatial: lambda	0.4968***	0.4958***	0.6081***	0.5985***	0.5954***	0.5733***	0.2003***	0.2042***	0.2699***	0.2698***	0.2465***	0.2439***
	(0.0433)	(0.0454)	(0.024)	(0.0245)	(0.0264)	(0.028)	(0.0306)	(0.0304)	(0.0128)	(0.0127)	(0.0174)	(0.0179)
LM Lag	4.0966**	4.6884**	186.5679***	121.8321***	55.2463***	40.6337***	0.0909	0.1753	0.0501	0.0416	0.0043	0.0020
LM Error	211.2335***	207.6853***	422.4081***	420.6337***	397.2006***	400.4924***	4.9251**	6.6115**	13.9894***	46.7235***	3.3128*	9.0032***
Robust LM Lag	0.0003	0.0004	0.3541	0.1487	0.5744	0.3645	0.0128	0.0029	0.0041	0.0002	0.002	0.003
Robust LM Error	207.1372***	203.9973***	236.1943***	298.9503***	342.5286***	360.2232***	4.8471**	6.4391**	13.9435***	46.6820***	3.3087*	9.0014***
Variance: sigma2_e	0.0033***	0.0035***	0.0053***	0.0054***	0.0052***	0.0054***	0.0062***	0.0067***	0.0116***	0.0115***	0.0117***	0.0116***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Observations	494	494	836	836	836	836	494	494	836	836	836	836
R-squared	0.0032	0.0036	0.0022	0.0025	0.0315	0.0244	0.01	0.0039	0.0305	0.0527	0.0564	0.0733

Standard errors are in parentheses. *** $p<.01$, ** $p<.05$, * $p<.1$

*Mobile broadband subscription data are available for the period 2009–2021; therefore, estimations including mobile broadband are conducted over this period. We also incorporated interaction terms between mobile*laborforce, ict*laborforce, and laborforce_sq, all of which were statistically insignificant across all specifications.*

Discussion and Policy Implications

This study examines the role of digitalization in shaping TFR across OECD countries over the period 2000–2021 using a spatial panel data framework. Two questions guide the analysis: first, how digitalization contributes to fertility outcomes; and second, whether fertility dynamics exhibit spatial dependence, reflecting interconnections among neighboring countries rather than purely country-specific processes. By distinguishing between digital infrastructure, mobile connectivity, and the broader integration of digital technologies, and by explicitly accounting for spatial heterogeneity, the findings provide new insights into the structural and spatial drivers of fertility trends in OECD countries.

The theoretical framework emphasized two broad channels through which digitalization may affect fertility: informational and social-learning mechanisms, and labor-market–related mechanisms linked to work–family reconciliation. The empirical results provide clear support for the first hypothesis. Across all specifications, digitalization-captured through digital infrastructure, mobile connectivity, and the broader integration of digital technologies—is positively associated with TFR in OECD countries. This pattern suggests that digitalization may alleviate constraints on childbearing by facilitating flexible work arrangements, expanding access to family-related services, and reducing coordination costs associated with parenting in high-income contexts.

By contrast, the second hypothesis -predicting heterogeneity in the digitalization–fertility relationship across different levels of female labor-force participation- is not supported. The interaction term between digital infrastructure and female labor-force participation is statistically insignificant, and marginal effects indicate that the fertility impact of digital infrastructure does not vary systematically across labor-market contexts. Rather than undermining the conceptual framework, this finding suggests that in OECD economies the fertility-enhancing effects of digital infrastructure operate largely independently of women's employment participation. One plausible interpretation is that digital technologies have become sufficiently pervasive to generate broadly similar work–family adjustments across advanced economies, thereby attenuating observable moderation effects. Alternatively, heterogeneity may emerge only in specific institutional settings or with longer adjustment lags than those captured in the baseline specification.

The remaining covariates further contextualize the main findings. The estimated non-linear relationship between income and fertility is consistent with opportunity-cost and institutional mechanisms emphasized in the demographic and labor-economics literature. In particular, the inverted U-shaped income effect indicates that, beyond a certain threshold, rising income levels in highly developed economies are associated with declining fertility. Income inequality is found to exert a negative effect on the total fertility rate, suggesting that unequal economic conditions may amplify constraints on childbearing. Female labor-force participation also exhibits a negative association with fertility, reflectnullking the continued relevance of work-family trade-offs in advanced economies. Importantly, the results point to differentiated role of familiy policies. Monetary intencives for parenthood, such as cash benefits, appear ineffective or even counterproductive, whereas in-kind support has an positive impact on TFR. These findings underscore the importance of policy composition rather than the overall level of familiy-related expenditures.

Taken together, these findings suggest that digitalization alone is insufficient to reverse fertility decline but may reinforce fertility when embedded within supportive institutional environments. Policies that facilitate work–family balance, such as flexible work arrangements enabled by digital technologies, accessible childcare services, and parental leave schemes, appear more closely aligned with fertility-supportive outcomes than purely financial transfers. Moreover, investments in broadband infrastructure and digital literacy may enhance the effectiveness of such policies by improving access to services and expanding feasible employment arrangements, particularly in regions facing persistent digital divides.

A central contribution of the analysis lies in the identification of positive and statistically significant spatial error dependence in all model specifications. This indicates that fertility dynamics across OECD countries are influenced by spatially correlated unobserved factors, rather than by direct spillovers in observed fertility levels. In substantive terms, fertility responses appear to be shaped by common shocks and shared structural environments, such as similarities in welfare regimes, institutional arrangements, gender norms, and synchronized macroeconomic cycles, rather than by demographic contagion per se. Countries embedded in comparable institutional and economic contexts tend to experience parallel fertility responses to events such as economic downturns, policy reforms, or shifts in social norms, even in the absence of direct cross-border imitation in fertility behavior.

The presence of spatial dependency implies that fertility policies, and the role of digitalization within them, cannot be assessed in isolation at the national level. The effectiveness of digital infrastructure investments depends not only on domestic policy design, but also on shared institutional environments and common shocks across countries embedded in similar welfare and labor-market regimes. In this context, digitalization should be understood as a regionally embedded process rather than a purely national technological input, interacting with childcare systems, work–family reconciliation policies, and gender norms that often cluster spatially within the OECD. Consequently, coordinated investments in broadband infrastructure and complementary family policies may generate more consistent and mutually reinforcing fertility outcomes than fragmented national approaches. These findings reinforce the conclusion that while digitalization can support fertility, primarily by easing work-family constraints, its demographic impact ultimately hinges on the institutional and spatial context in which digital technologies are adopted.

From a policy perspective, these findings highlight the absence of a one-size-fits-all approach within the OECD. Although the empirical analysis identifies a positive association between digital infrastructure and fertility at the aggregate level, descriptive evidence reveals substantial cross-country heterogeneity in fertility outcomes at similar levels of digitalization. In 2021, countries with comparable digital infrastructure exhibit TFR ranging from very low levels in Spain (1.19) and Japan (1.30) to substantially higher levels in Czechia (1.83) and Iceland (1.82). Even among highly digitalized countries, fertility outcomes diverge sharply: France combines advanced digital infrastructure with relatively high fertility (1.83), whereas Korea displays extremely low fertility (0.81) despite similar digital infrastructure levels. These contrasts suggest that digital infrastructure alone does not generate uniform fertility responses. Instead, its demographic implications are conditioned by institutional and socio-economic contexts, including welfare regimes, family policy arrangements, labor-market structures, and prevailing gender norms. Regional clustering reinforces this interpretation: Nordic countries especially Sweden, Denmark and Finland tend to combine high digital infrastructure and mobile connectivity with comparatively higher fertility, Southern European countries exhibit persistently low fertility despite similar digital infrastructure and mobile connectivity, and East Asian OECD countries (Japan and South Korea) display very low fertility outcomes even under advanced digitalization. These patterns are consistent with the spatial error results, indicating that fertility dynamics are shaped by shared institutional environments and demographic trajectories rather than by digitalization acting as an isolated technological input.

Finally, this study is subject to several limitations. The use of aggregate TFR data constrains the ability to capture individual-level heterogeneity in fertility decisions and digitalization. Moreover, the analysis does not directly observe individual internet use, household-level work–family dynamics, or socio-economic characteristics that may mediate the relationship between digitalization and fertility. Future research could integrate micro-level or survey-based data, or employ longitudinal and cohort-based approaches, to explore how different demographic groups utilize digital technologies and how these interactions shape fertility behavior over the life course.

Appendix

Table 4 Spatial autocorrelation of fertility rate (2000–2021)

year	I	E(I)	Sd(I)	Z	*P*-value
2000	0.7587	−0.027	0.1366	5.7538	0.0000
2001	0.764	−0.027	0.1367	5.788	0.0000
2002	0.7863	−0.027	0.1363	5.9652	0.0000
2003	0.805	−0.027	0.1359	6.1246	0.0000
2004	0.8027	−0.027	0.1362	6.0923	0.0000
2005	0.8003	−0.027	0.1365	6.0633	0.0000
2006	0.8068	−0.027	0.1364	6.1114	0.0000
2007	0.8191	−0.027	0.1362	6.2103	0.0000
2008	0.8241	−0.027	0.1351	6.3011	0.0000
2009	0.818	−0.027	0.1348	6.2667	0.0000
2010	0.8035	−0.027	0.1333	6.2312	0.0000
2011	0.7902	−0.027	0.1326	6.1619	0.0000
2012	0.7963	−0.027	0.1306	6.3061	0.0000
2013	0.7799	−0.027	0.1294	6.2361	0.0000
2014	0.7715	−0.027	0.126	6.3396	0.0000
2015	0.7758	−0.027	0.1224	6.5604	0.0000
2016	0.7843	−0.027	0.1176	6.9015	0.0000
2017	0.7843	−0.027	0.115	7.0537	0.0000
2018	0.7787	−0.027	0.1138	7.08	0.0000
2019	0.7683	−0.027	0.1148	6.9286	0.0000
2020	0.764	−0.027	0.1161	6.8147	0.0000
2021	0.7745	−0.027	0.1163	6.8905	0.0000

Source: Authors' calculation

Table 5 The results of cross-sectional dependence tests

Variables	Breusch-Pagan LM	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD
TFR	5435.791***	126.2190***	125.3142***	19.97605***
broadband	1420.11***	355.1811***	354.2764***	118.2585***
ict	2529.95***	48.72***	47.13***	18.74***
mobil	7041.54***	169.04***	167.45***	77.38***
inequality	2706.695***	53.4366***	52.5318***	5.3517***
gdppc	11080.22***	276.7505***	275.8457***	92.7142***
laborforce	6617.085***	157.7230***	156.8182***	40.2823***
ur	3077.036***	63.3132***	62.4085***	16.8769***
health	13951.80***	353.3328***	352.4280***	117.6167***
urban	2703.805***	53.3595***	52.4547***	4.5496***
inf	1973.714***	33.8887***	32.9839***	25.0953***
gpi	3314.382***	69.6430***	68.7382***	13.2250***
trade	6685.296***	159.5421***	158.6373***	49.4160***
cash	3847.977***	83.8735***	82.9687***	28.4881***
inkind	6629.110***	158.0437***	157.1389***	49.5903***

Note: *** *p<.01*, ** *p<.05*, * *p<.1*

Table 6 The results of the CADF unit root test

Variables	Level	First Difference
TFR	−1.935(1)	−3.487(0)***
broadband	−2.930(0)***	-
ict	−2.118(2)**	-
mobil	−2.316(1)***	-
inequality	−2.328(1)	−3.584(1)***
ur	−1.944(1)	−3.914(0)***
gdppc	−1.632(1)	−3.188(0)***
laborforce	−2.003(1)	−3.905(0)***
urban	−2.064(0)	−3.563(0)***
inf	−3.930(0) ***	-
health	−1.631(1)	−2.779(1)***
gpi	−2.425(1)	−4.216(0)***
trade	−1.769(0)	−3.475(0)***
cash	−1.180(1)	−3.297(0)***
inkind	−1.468(1)	−2.599(0)***

*Note: *** p<.01, ** p<.05, * p<.1*

The critical values of CIPS statistics at %1, %5, and %10 are − 2.730, −2.610, and − 2.540, respectively. The values in the parentheses indicate the lag level

Table 7 Results for the non-spatial model (fixed effect OLS)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
broadband	0.0075***	0.0078***				
	(0.0009)	(0.0009)				
ict			0.0025*	0.0025*		
			(0.0014)	(0.0014)		
mobile					0.0326**	0.0351**
					(0.0155)	(0.0161)
gdppc	5.8199***	6.6289***	1.6756	2.4613*	8.2313***	4.046**
	(1.2618)	(1.237)	(1.2695)	(1.2571)	(1.9941)	(2.0501)
gdppc_sq	−0.6221***	−0.6898***	−0.1795	−0.2601*	−1.0347***	−0.5407**
	(0.1517)	(0.1462)	(0.1545)	(0.1507)	(0.2307)	(0.2379)
inequality	−0.6434**	−0.5764**	−0.6756**	−0.7015***	−1.3392***	−0.8504**
	(0.2677)	(0.258)	(0.2794)	(0.2701)	(0.3548)	(0.372)
laborforce	−0.0445***	−0.0498***	−0.0419***	−0.0436***	0.0414**	0.0487**
	(0.0129)	(0.0127)	(0.0135)	(0.0134)	(0.0199)	(0.0206)
laborforce_sq	0.0004***	0.0005***	0.0004***	0.0004***	−0.0004**	−0.0005**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
ur	−0.0078***	−0.0068***	−0.0068***	−0.005**	−0.014***	−0.0208***
	(0.0022)	(0.0021)	(0.0024)	(0.0022)	(0.0027)	(0.0026)
trade	0.0007*	0.001***	0.0017***	0.0021***	−0.0008*	−0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
inf	0.0058***	0.0056***	0.0063***	0.0059***	−0.0012	0
	(0.0014)	(0.0014)	(0.0015)	(0.0015)	(0.0021)	(0.0021)
gpi	0.4924	0.8507*	0.7034	0.9868*	0.1016	0.5061
	(0.484)	(0.4885)	(0.5046)	(0.512)	(0.5404)	(0.5658)
health	−0.3355***	−0.432***	−0.0881**	−0.1394***	−0.0001***	−0.0001***
	(0.043)	(0.0483)	(0.0351)	(0.0392)	(0)	(0)
urban	0.0683***	0.0688***	0.0648***	0.0634***	0.0109	0.0176
	(0.0103)	(0.0101)	(0.011)	(0.0109)	(0.0114)	(0.0119)
cash	0.004		0.0094*		−0.037***	
	(0.0053)		(0.0055)		(0.0062)	
inkind		0.0273***		0.0233***		−0.0026
		(0.007)		(0.0073)		(0.0096)
constant	−8.549***	−10.5306***	−1.2226	−3.0656	−14.1576***	−6.5921
	(2.5641)	(2.5428)	(2.6052)	(2.6043)	(4.0981)	(4.2022)
Observations	836	836	836	836	494	494
R-squared	0.2375	0.2515	0.1702	0.1777	0.4232	0.3772

Standard errors are in parentheses. *** $p<.01$, ** $p<.05$, * $p<.1$

Mobile broadband subscription data are available for the period 2009–2021; therefore, estimations including mobile broadband are conducted over this period

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Declarations

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