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Agenda item 4: Fertility

PROJECTIONS OF AGE-SPECIFIC FERTILITY RATES THROUGH AN AGENT-BASED MODEL OF SOCIAL INTERACTION

Invited Paper

Submitted by Austria and Germany[1]

Abstract

1. Empirical studies indicate that the transition to parenthood is influenced by an individual's peer group. To study the mechanisms that create interdependencies across individuals' transition to parenthood and its timing we apply an agent-based simulation model. We build a one-sex model and provide agents with four different characteristics. Based on theses characteristics agents endogenously form their network. Network members then may influence the agents' transition to higher parity levels. Our numerical simulations indicate that accounting for social interactions can explain the shift of fertility rates in Austria over the period 1991 to 2001. We apply our model to forecast age-specific fertility rates up to 2021.

1. Introduction

2. Human behaviour, including childbearing behaviour, is performed by socialized actors deeply rooted in a web of social relationships like those created by kinship, love, power, friendship, competition, or interest. Within one's social circle of relationships individuals may exchange information about possibilities and consequences of specific childbearing choices, learn about other persons' preferences, form expectations on their future choices, feel induced to conform to others' norms about family-related behaviour, and modify their interpretation of a specific behaviour.

3. Interpersonal interactions among these relatively small groups of individuals produce social effects observable in macro patterns of behaviour and demographic research on union and

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family formation has concentrated on the latter. Empirical evidence increasingly suggests social interaction as an important determinant of demographic behaviour. Diffusion processes are currently an integral part of the literature on fertility decline (Knodel and van de Walle 1979, Watkins 1987, Cleland and Wilson 1987, Mason 1992, Pollak and Watkins 1993, Palloni 1998). While most research is carried out in developing countries some contagion models have been applied to union behaviour in the European context (Nazio and Blossfeld 2003). Diffusion approaches build on the idea that social networks of kin, peers and institutions, as markets and legal and the administrative system, are potential communication channels for ideas and behaviour (Granovetter 1985, Rogers 1995).

4. In fertility explanations social interaction are relevant both at the micro and at the macro level. Individual and population fertility are interdependent because the aggregation of individual fertility behaviour produces externalities (like the erosion of norms, pressure to conform, path dependency of the information exchange). Kohler (2001) efficiently summarizes the features of this micro-macro link: a) social interaction can alter the distribution of knowledge in the population and affect reproductive decisions under uncertainty by conveying information on the consequences of low fertility or on the dynamics of social change, b) it may establish a collective behaviour among community members and initiate a fertility change when other factors would instead inhibit it, c) it may induce an endogenous transformation of social institutions and social norms.

5. Montgomery and Casterline (1996, 1998) separate the concept of diffusion into the two components social learning and social influence. Social learning takes place interpersonally when other individuals provide information that shape a persons' subjective beliefs while social influence denominates the effects of interpersonal interactions that are intrinsically "social" such as to avoid conflict within social groups. The latter are expressed in an individuals' preferences and in her information sets as well. Kohler et al. (2000) empirically investigate the impact of family planning programs taking into consideration the influence of social interactions on the diffusion of knowledge, attitudes, and behaviours related to family planning. They distinguish between the direct and indirect effect of family planning programs on an individuals' probability to apply family planning. According to their estimates the contribution of social interactions amounts to 43% of the total program effects. Moreover, intensified social interactions may either increase or decrease the total effect.

6. The analysis of social mechanisms like social learning and social influence plays an increasingly relevant role in demographic explanations of observed family formation patterns also in contemporary Europe, like in the hypothesis formulated by Kohler et al. (2002) on the emergence of lowest-low fertility. However, the increasing inclusion of social interaction in the demographic theoretical framework matches with a relatively unrealistic model of social learning and social influence mechanisms (Chattoe 2003).

7. This lack of precision seems to constitute a general problem in the development of demographic behaviour theory. Specifically, there is a certain agreement that demography suffers from a poor level of precision in the theoretical construction, a statistical modeling that is not or insufficiently theory-driven, and the non – or hard – observability of important concepts and indicators involved in the theory (Burch 1996, de Brujin 1999). Partially this is due to the inadequateness of the demographers' methodological toolbox to answer demographic relevant questions. The very recent inclusion of agent-based simulations and systematic and comparative in-depth investigations offer new possibilities to develop cognitive valid behavioural theories

and to speculate on the consequences of alterative micro-macro feedbacks in order to explain demographic patterns (Billari and Prskawetz, 2003, Billari et al. 2003, Billari et al., 2006).

8. Modelling individual fertility decisions requires to include the decision mechanism at the microlevel, the society at the macrolevel, the interactions between the micro- and the macro-level, and the interactions among individuals within their peer groups. We need a sound microfoundation of individual behaviour and a mechanism taking into account social interaction between individuals and describing the interaction between the individuals and the environment in terms of socioeconomic conditions. Agent based models, and to some extent also microsimulations, have the potential to include these three attributes.

9. Agent-based models allow for a straightforward modeling of social interactions among agents and of interactions between the micro and macro level. Agent-based models enable us not only to consider past developments but also to build scenarios for alternative structural frameworks. Unlike the socially isolated actors in a typical microsimulation model, the agents in an ABM interact independently. The key features characterising ABMs are that agents are autonomous, interdependent, follow simple rules, and they are adaptive and backward-looking (Macy and Willer, 2002). Consequently, ABMs allow for a higher degree of complexity than for instance microsimulations. While the focus is on the aggregate level (age-specific fertility in Austria), our model is based on the micro level and explains how aggregate level properties emerge from the behaviour of the agents on the micro level. Thus, aggregate outcomes are rooted in the interaction of agents.

10. In this paper we introduce an agent-based model to study social interaction and in particular endogenous network formation and its implication for the transition to parenthood. In the first place such a model allows us to test whether transitions in age-specific fertility experienced in the past can be explained by social interactions. Secondly, and the focus of the current paper, we can use this model to project age-specific fertility rates. Section 2 is devoted to the implementation of the model. The data we use to calibrate our model are discussed in section 3. Simulation results and fertility projections based on these simulation results are presented in section 4. Finally, section 5 concludes our findings.

2. Model Implementation[2]

11. We set up a one-sex model that allows us to simulate the different life cycle stages of females. Each individual agent has an identity number *id*, four characteristics, and a social network that includes friends, siblings and the agent's mother[3]. The agent's characteristics are age x, education e, intended education ie, and parity p. We set the lower and upper age of reproduction to be equal at 15 and 49 years respectively and the maximum age of our agents as 95 years. Though agents older than 49 cannot give birth in our model, they still may influence other agents. Education is an influential factor for social network formation and size (Moore, 1990) and thus becomes our second characteristic. We distinguish three stages of education: primary and lower secondary, upper secondary, and tertiary. Since education does not effect an agent's network on the day of graduation but already during training, we further include the intended education as an important characteristic of the agent[4]. Based on these three characteristics – age, education and intended education – an adult agent chooses on average s

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[2] See Aparicio Diaz et al. 2007 for further details.
[3] The agent's mother and siblings are not known for the initial population.
[4] The argument to include intended education in addition to attained education is based on the anticipatory analysis in life-course research discussed in Hoem and Kreyenfeld (2006).

members for her social network. These members influence the agent's decision of childbearing, i.e. her parity, that constitutes the fourth characteristic of the agent. The agent's desire to give birth, that is to increase parity, is weakened or intensified by the influence of the social network *snw*.

Initial population

12. We initialize the simulation with *N* individuals and base our simulations on Austrian data, as defined in section 3. The Austrian age distribution for females constitutes the initial age distribution. The level of education of individuals aged 15 or older is assigned according to the Austrian age-specific educational distribution for females. On the basis of the assigned age and educational level, each agent is assigned her parity according to the Austrian age- and education-specific parity distribution of females.

13. Since most people finish their education before they turn 30, we assume that the educational distribution at age 30 in the base year determines the intended education at earlier ages[5].

14. We do not allow an intended education *ie* lower than the already achieved education e. Therefore, agents with $e = 2$ are assigned intended education $ie = 2$ or 3 and agents with $e = 3$ are assigned $ie = 3$. Agents younger than 15 are not assigned an intended education and for all individuals above the age of 28 the intended education ie is set equal to the actual education[6]. Moreover, individuals at the educational level 1 and older than 20 are also assigned their actual education 1 as their intended education since transition between level 1 and 2 practically happens solely until the age of 20. For agents with parity greater or equal to one an age at first birth a is assigned according to the education-specific distribution of age at first births (cf. section 3). Since the behaviour of women in training for education level *e* is more comparable with the behaviour of those who already achieved the level *e*, we assign the age at first birth a according to the agents' intended education *ie*. Once all initial agents have got assigned their individual characteristics, adult agents create their social network by choosing relevant others based on the three characteristics: age, education, and intended education.

Simulation steps

15. During each simulation step, each agent ages by one year and dies off at the age of 95. Individuals younger than 15 are considered as children without education. At age 15 an individual becomes an adult with education level one and an intended education assigned on the basis of the education distribution of the population aged 30. Further she builds her own social network which includes friends chosen according to the procedure described below. Agents born during the simulation already have a social network consisting of their mother and siblings[7]. Though children do not exhibit their own social network of friends, they can nevertheless be part

[5] Of course, some individuals finish secondary or tertiary education later than age 30. Therefore, it seems to be desirable to look at the educational distribution, for instance, at the age of 40 or 50 to be sure not to loose any individual obtaining a higher level of education during her life course. However, applying the educational distribution of older cohorts would result in a bias toward lower levels of education since higher education was not that common for older cohorts this holds in particular for females.
[6] Although there are some cases of individuals who advance to higher levels of education above that age limit, the period data on which we base the empirical estimations do not lead to strictly positive transition rates for that age group.
[7] Through the inclusion of the mother as a peer, we attain the effect that the number of siblings influences the agent's fertility, in addition to the parity of the siblings themselves.

of one. When an agent turns 50, we assume that childbearing ceases. However agents older than 50 may still influence other adults of childbearing age.

16. In the course of the simulation an adult agent may change her educational level. The age-specific educational transition rate is based on empirically observed transition rates *etra* for Austria (see section 3). From empirical data we know that agents with a higher intended education are more likely to increase their level of education, likewise are non-mothers. To achieve this we scale the empirical education transmission rate *etra* by *a* multiplier $w(c)$ where c is a vector of characteristics $c = (x,e,ie,p)$. We assume that every agent may increase her educational level but postulate that those who have not yet attained their intended education are subject to a higher transition rate and consider that women with a higher parity have a lower transition rate to higher education – in particular there is a pronounced difference between mothers and non-mothers.

Endogenous social network

17. We apply a model of endogenous social network formation. Regarding Granovetter (1973, 1983) the network ties shape an individual's opportunities as well as her norms and values. A vast bunch of literature studying the topology of social networks has emerged recently (Watts and Strogatz, 1998, Barabasi, 1999, Newman, 2003). However, these models do not provide any theory explaining how such complex network structures may emerge (Flache and Macy, 2006). Therefore, we use a searchable network topology originating from Watts et al. (2002) who introduced a network structure taking into account the fact that individuals partition the social world in more than one way. They applied this network to explain the process of delivering messages to a target person. In the sequel we will use a similar network structure for the diffusion of childbearing behaviour. As mentioned in the introduction, our model should take into consideration that links in a social network may be based on any individual characteristic like age, kinship, love, power, friendship, professional occupation, geography, and so on. Thus, we have agents living in a multidimensional space, where each dimension represents one characteristic.

18. The agents within such a searchable network exhibit network ties and individual characteristics. For our purpose we consider the characteristics age, education, and intended education to create a social network *snw*. Watts' approach envisions that individuals organize the society hierarchically into a series of layers, where the top layer represents the whole population which is split according to the agents' characteristics into smaller subsets of individuals which are likewise split into more specific subgroups. The social groups that are formed through this hierarchic division depend on the branching ratio b and the group size g of the lowest hierarchic level.

19. The similarity among any two individuals, d_{ij}, is given by the height of their lowest common ancestor level in this hierarchy. If two individuals i and j belong to the same group we define their similarity d_{ij} equal to one, if they belong to different groups which are directly connected, their similarity becomes $d_{ij} = 2$ and so on. The probability of acquaintance (i.e. the probability of a link) between two individuals with a distance d is given by

$$pr(d) = c \exp(-\alpha d), \tag{1}$$

with α being an adjustable parameter and c being a constant required for normalization. Thus, even two individuals belonging to the same group are not necessarily connected. However, if the parameter α, determining the agent's level of homophily, is assigned high values, the chance of a connection between individuals in the same group becomes high. To build up the social network an agent chooses a distance *d* according to the above probability distribution (1) and then picks a friend uniformly among all individuals with distance *d* [8]. This procedure is repeated until an average number of friends, *s*, is found. The mean network size is an exogenous parameter. The actual number of friends for an agent is log-normally distributed.

20. Since individuals belong to three groups (by age, education, and intended education) the procedure described in the previous paragraph is repeated for each of these characteristics. Since we postulate that the characteristics are independent people belonging to the same group in one dimension may be far away from each other in another dimension. However, if there is a link established in one dimension due to the random process described above, the agent considers the chosen agent to be a member of her peer group. Since networks are known to be unstable over time (Wellman 1997), we assume that each adult may exchange one or more members of her social network.

Social influence and parity transition

21. An adult agent (aged between 15 and 49) may give birth to a child. The decision to change her parity status is influenced by her social network (see for instance Bernardi 2003, 2007). The propensity to have a first child increases with the share of parents within the agent's social network. Similarly the propensity to higher order births increases with the share of parents of higher order parity. To ensure that the social influence modeled at the individual level is "anchored" at the social influence we observe at the macro level, we postulate that the social influence vanishes if the parity distribution of an agent's network coincides with the parity distribution at the macro-level. Formally, the social influence *si* for an agent of parity *p* is modeled as a function of the difference between the share of mothers at parity $\tilde{p} > p$ within the social network, *rop*, and in the whole population, *ROP*. The social influence positively affects the age- and parity-specific birth probabilities *bpr* of Austria (see section 3).

22. To determine the social influence *si*, we first define the relevant share of network members *rop(p)* whose parity exceeds the agent's parity *p*.

$$rop(p) = \frac{\#\{j : p_j > p \ AND \ j \in snw\}}{\#\{j : p_j \geq p \ AND \ j \in snw\}}, \tag{2}$$

where p_j denotes the current parity of agent *j* who is a member of agent *i* 's social network *snw* and $\#\{j : p_j > p \ AND\ j \in snw\}$ denotes the number of network members with parity greater *p*. Note, that for higher order births we ignore (in the numerator of equation (2)) those agents within the peer network who are at parity $\tilde{p} < p$ [9].

23. Likewise, we compute the share of adult agents with parity greater *p*, *ROP(p)*, on the aggregate level,

$$ROP(p) = \frac{\#\{j : p_j > p\}}{\#\{j : p_j \geq p\}}.$$

[8] Technically this procedure is implemented in the way that the agent draws a random number in the interval (0,1) and the random number then determines the specific value of *d* as determined by the probability distribution (1).
[9] Bernardi et al. 2007 found that women who already have children do not refer to childless peers concerning former fertility decisions.

24. The difference between *ROP* on the aggregate level and *rop* on the individual level determines the social influence on an agents age- and parity-specific birth probability *bpr*(*x,p*). We model social influence as an s-shaped function with slope β,

$$si(p) = 0.1 * \frac{\exp(\beta * (rop(p) - ROP(p)))}{1 + \exp(\beta * (rop(p) - ROP(p)))} + 0.95\,. \qquad (3)$$

25. The parameter β gives the intensity of the social influence when the share of network members of a specific parity diverges from the one on the aggregate level. Choosing $\beta = 0$ results in a social influence of 1 in any case, which means that the influence of the social network is completely ignored. Lyngstad and Prskawetz (2006) point to a weaker influence for second birth, thus we reduce the social influence for higher order births *si (p>0)* by decreasing β to a fifth of its original value.

26. The value *si* is multiplied with the empirical age- and parity-specific birth probability at time *t*, $\overline{bpt}_t(x, p)$, to take the social influence into account. Thus, an agent *i* at age *x* is assigned a probability of birth,

$$bpt_i(x, p) = \overline{bpr}_t(x, p) si(p). \qquad (4)$$

27. The multiplier given in (3) ensures that the birth probability *bpr*(*x,p*) of an agent *i* facing a value of *rop* within her social network which is equal to *ROP* on the aggregate level is not being distorted. Put differently, when the social influence at the individual/micro level is equal to the social influence at the macro level we assume that the social influence vanishes (i.e. it is equal to one). In case that the micro level share *rop(p)* differs from the macro level share *ROP(p)*, the social influence is assigned a value in the range (0.95, 1.05) assuming that positive and negative deviations are symmetric. To also allow for an asymmetric social influence, but retaining the condition of s*i* = 1 if *ROP(p) = rop(p)*, we introduce the asymmetry through the slope β. We postulate an asymmetry that strengthens the positive and weakens the negative social influence. More precisely, a social influence function with slope $\beta = 6$ and an asymmetry of +30%, as shown in Figure 1, actually leads to an influence function with slope $\beta = 6 - 1.8 = 4.2$ for negative influence, thus for agents with a lower *rop(p)* at the individual level than *ROP(p)* at the macro level, and a slope $\beta = 6 + 1.8 = 7.8$ for positive influence. In this way we achieve that the asymmetric social influence modeled at the individual level is again “anchored” at the social influence we observe at the macro level.

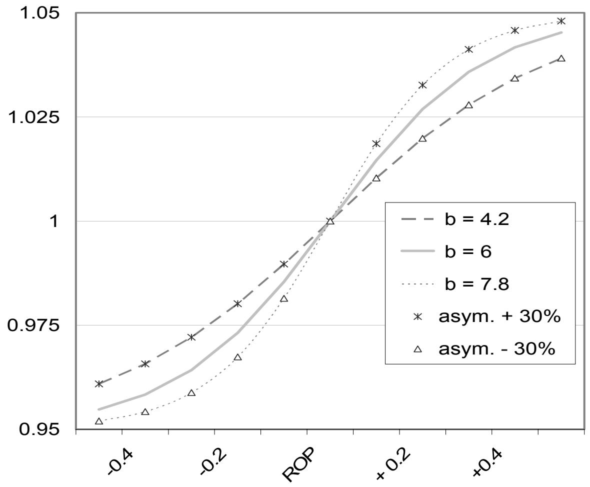

Figure 1: Symmetric and asymetric social influence function

28. Interacting macrolevel data on age- and education-specific fertility rates with microlevel data on socio-economic characteristics and social influence within the agents' peer groups allows us to model the agents individual propensity of childbearing. The structure of our modelling approach captures an individual's situation and her exposure to social norms and social pressure. Individual changes on the micro level result in a modified probability to give birth at the macro level. Thus, the birth probabilities at t+1 become

$$\overline{bpr}_{t+1}(x,p) = \overline{bpr}_{t}(x,p)\overline{si}_{t}(x,p) \qquad (5)$$

where $\overline{si}\,(x,p)$ is the average of the social influence values *si* of all agents at age *x* and parity *p*. These updated probabilities to give birth enter equation (4) for the next time step.

29. *Transition to parenthood:* After transition to parenthood an agent increases her parity by one. Since we work with a one-sex model we refer to the Austrian sex ratio at birth *srb* (see section 3) as a multiplier for the number of new agents. Hence only the female babies are created as new agents. Then they age each simulation step until arriving at adulthood (at age 15) when they choose their friends for the social network. During childhood an agent's network only consists of the agent's mother and siblings, to whom the new agent is also added as a network member.

3. Data

30. **Age Distribution:** For the initial population we alternatively use the age-distribution of Austrian females in 1991 or 2001[10].

31. **Distribution by Age and Education:** We assign the level of education according to the agents' age. Agents younger than 15 receive education 0, while all other agents may get a primary/lower secondary, upper secondary, or tertiary education according to the age-specific educational distribution of Austrian females in 1991 or 2001[11]. We distinguish (for adult agents) three stages of education, whereas the Austrian data we use as input distinguish 6 to 8 stages.

[10] Source: Statistik Austria (2005a), Table 8.7.
[11] Sources: Statistik Austria (1994), Table 14, Statistik Austria (2004), Table 15.

We therefore merged these groups as follows: (i) primary/lower secondary education encompasses basic schooling (up to 9 years) and lower secondary education (including apprenticeships and normally between 10 and 12 years of schooling), (ii) upper secondary education which encompasses the Austrian gymnasium and its equivalents, such as corresponding non-academic vocational training at a similar level and (iii) tertiary education (including postgraduate studies, the training of primary school and gymnasium teachers, art academies, and so on).

32. **Distribution by Age, Education, and Parity:** Based on the Austrian distribution by age, education and parity of 1991 or 2001[12], we assign a corresponding parity for the initial agents.

33. **Parity-specific Birth Probability by Age:** The birth probabilities we apply in our simulations derive from computations by Tomas Sobotka on the basis of data provided by Statistik Austria. We apply the corresponding data from 1991 and 2001.

34. **Educational Transition Rate by Age:** The age-specific transition rates for educational groups are based on period measures. We alternatively start from the age and educational structure of the population in 1991, or 2001 and denote $F(x,e)$ the number of agents at age x and with educational level e. For each age group we build the share of females having primary or lower secondary, upper secondary and tertiary education:

$$f(x,e) = \frac{F(x,e)}{\sum_e F(x,e)}.$$

35. By working with shares instead of absolute values we control for different cohort size. We then presume that the age and educational structure of the population stays constant over time and build the age-specific transition rates as follows:

$$t(x,e) = \frac{f(x+1,e+1) - f(x,e+1)}{f(x,e)},$$

where $t(x,e)$ indicates the transition rate at age x from the educational level e to level $e+1$ in the next time step.

36. **Age at First Birth by Education:** We use data on age at first birth taking into account the mothers' level of education from the census 1991 or 2001. Since these data are only provided for five year age groups we interpolate the data with piecewise cubic hermite polynomials.

37. **Sex Ratio at Birth:** Since we do not include male agents to our model, we need the sex ratio at birth to calculate the number of new agents per simulation step. We again use Austrian data[13] of the particular base year for this purpose.

4. Simulation results

38. In this section we discuss the results from simulations of the agent-based model introduced in the previous sections. We set the population size equal to $N = 6000$ and present the average over 200 simulation runs. In a first experiment we initialize the model with Austrian data from 1991 and run our simulation for 20 years up to 2011. A thorough sensitivity analysis indicates, that we obtain the best fit to actual data by postulating an asymmetry in the functional

[12] Sources: Statistik Austria (1996), Table 48, Statistik Austria (2005c), Table 47
Analogous as for the distribution by age and education we pool the eight educational groups to 3 groups.
[13] Statistik Austria (2005b), Table 2.26.

form of the social influence for the 1990s. Thus we add an asymmetry of 30% (see Figure 1) during this decade and an asymmetry of 60% from 2000 onwards. The social influence on fertility behaviour is therefore amplified if *rop*>*ROP* and dampened for *rop*<*ROP*. Model parameters are assigned the following values: We set the group size of the hierarchy equal to 5 individuals (*g* = 5), the branching ratio *b* equal to 2 and postulate an average size of the network of 10 peers (*s* = 10, Fliegenschnee, personal communication, 2006). Results for this experiment – both historical developments (from 1991 to 2001) and some first projections (to 2011) – are summarized in Figure 2. The mean age at first birth (Figure 2a) depicts an increasing trend and validates the promising performance of our proposed model though the empirically observed line is slightly above the simulated one as caused by a bend in the early nineties which is not replicated by our model.

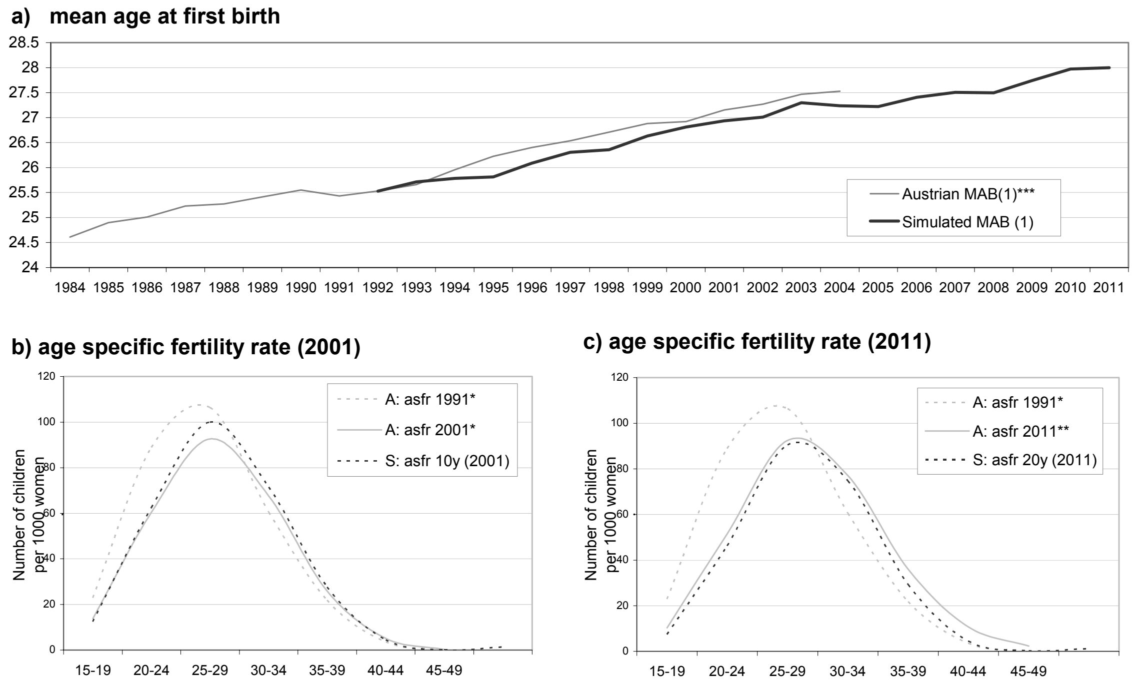

Figure 2: Simulation results for simulating 20 years starting from 1991.

39. After the first 10 years of the simulations, the probability of first birth comes close to the empirically observed curve in 2001 (Figure 2b). Further simulations for another 10 years yields the first birth probabilities in 2011 (Figure 2c). Since similar data are not available from Statistik Austria we compare the 2011 time series of first birth probabilities with the corresponding (last obtainable) empirical data from 2005. The evolution of age-specific fertility rates (empirically observed and projected ones by Statistik Austria for 2011 as well as simulated ones) is presented in Figure 2a and Figure 2b. Simulated fertility rates for 2001 (Figure 2a) overestimate the empirically observed rates (particularly for ages between 25 to 29). This difference can be explained by the extremely low fertility rate in Austria during 2001 as caused by a change in family policies (introduction of new child benefits in the following year). In 2001 the total fertility rate reached a low of 1.33 as compared to 1.36 in 2000 and 1.39 in 2002. The latter Figures are closer to the simulated fertility rate of 1.39 for the year 2001.

40. So far we have demonstrated that our model is capable to reproduce changes in the timing of fertility that occurred during the last decades. Next we apply our model to project future trends of fertility and compare our projections to the age-specific fertility assumptions applied by Statistik Austria for their recent population projection (Hanika, 2006). While

population forecasts are usually based on time series extrapolation of recent fertility trends combined with some expert knowledge, our approach has a theoretical foundation. We use a causal model to explain trends in timing of fertility rather than continuing existing trends. Sanderson (1998) argues that combining forecasts from such models with standard forecasts results in more accurate predictions if the forecast errors of the two different approaches are not highly correlated.

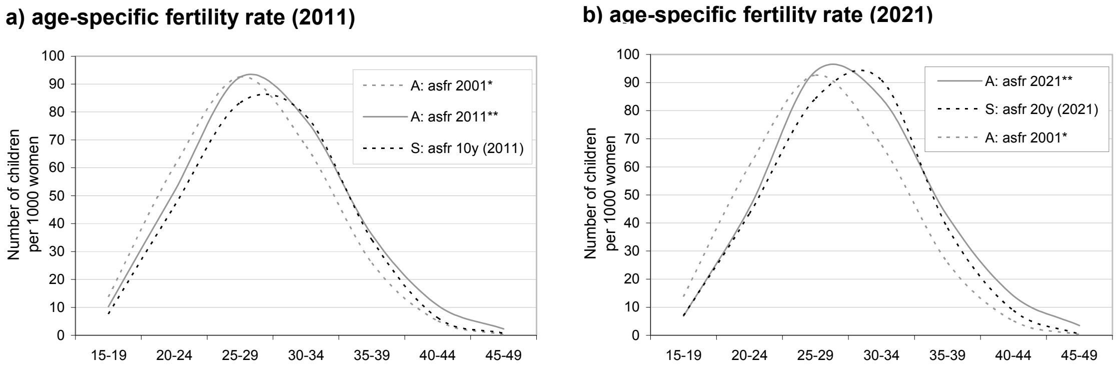

Figure 3: Simulation results for simulating 20 years starting from 2001

41. Starting from the year 2001, we forecast fertility rates to 2021. We retain the model parameters as in previous simulations and postulate an increase in the asymmetry of the social influence from 30% prior to 2010 to 90% from 2010 onwards. Figure 3 compares simulated age-specific fertility rates and those assumed by Statistic Austria for 2011 and 2021 respectively. The simulated rates for 2011 (Figure 3a) are considerably lower compared to the assumptions by Statistic Austria. This underestimation of fertility rates in our simulations is mainly caused by the exceptionally low fertility rates in Austria in 2001, which is the base year of this simulation. The relatively low birth probabilities of 2001, especially for the age group 25 to 29, are passed on through the whole simulation implying also the quite low fertility rate in 2021 (see Figure 3b).

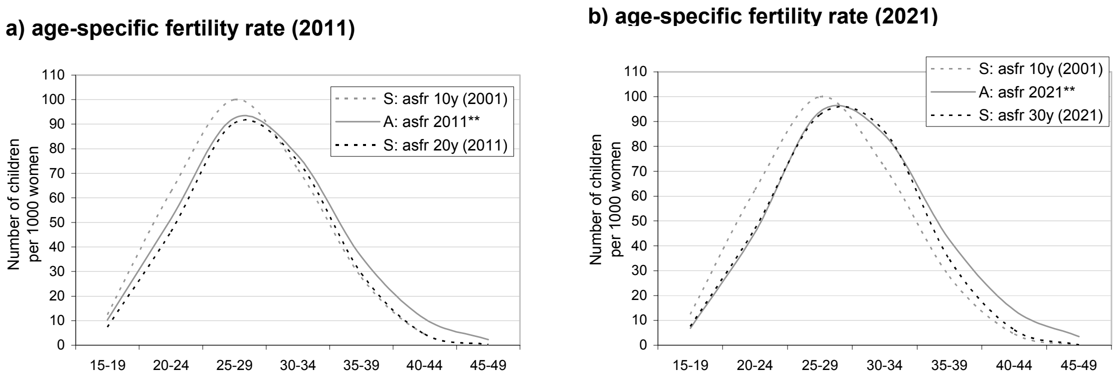

Figure 4: Simulation results for 30 years starting from 1991.

42. As we consider the year 2001 not to be an appropriate base year – due to its exceptionally low fertility rates – we project fertility rates for the years 2011 and 2021 again using 1991 instead of 2001 as the base year. The results are depicted in Figure 4. The shape of the age-specific fertility rate as projected by our simulations for 2011 and 2021 is rather similar as the corresponding rates postulated by Statistik Austria with one exception. Fertility rates at

higher ages (above age 40) are projected to be lower in our simulations as compared to the assumptions underlying the projections by Statistik Austria. The reason for this difference is the assumption of Statistik Austria that currently low fertility at younger ages (postponement) will be partially offset by a higher fertility rate at higher ages (recuperation) in the future. Yet, there is no empirical evidence indicating to what extent recuperation indeed will take place and, consequently, our model solely based on age- and education-specific fertility rates of the past and mechanisms of social networks and social learning is not designed to capture expert opinions.

43. Figure 5 depicts age specific fertility rates in 2021 and Figure 6 illustrates the time trend of total fertiliy rate from 1991 to 2021. Both graphs are based on 542 simulations with a population size of N = 12000 agents initialized with data from 1991. Again a comparison with the projection of Statistik Austria is provided. In addition to Figures 2, 3, and 4, plotting the mean values of series of simulations, Figures 5 and 6 show the median value and the confidence intervals comprising 50%, 75%, and 95% of all simulations. Therefore, these graphs do not provide just one projection but also confidence intervals indicating the bandwith of uncertainty. Comparing the median value (labeled 0.500 in the legend) in Figure 5 with the standard projection again reveals a rather strong correspondence for young ages but a slight deviation beginning at the age of 35 and becoming more pronounced for the 40+ age groups. Within the age interval from 40 to 42 the line indicating the standard projection roughly coincides with the 75% confidence interval but for age groups above 42 it departures even further.

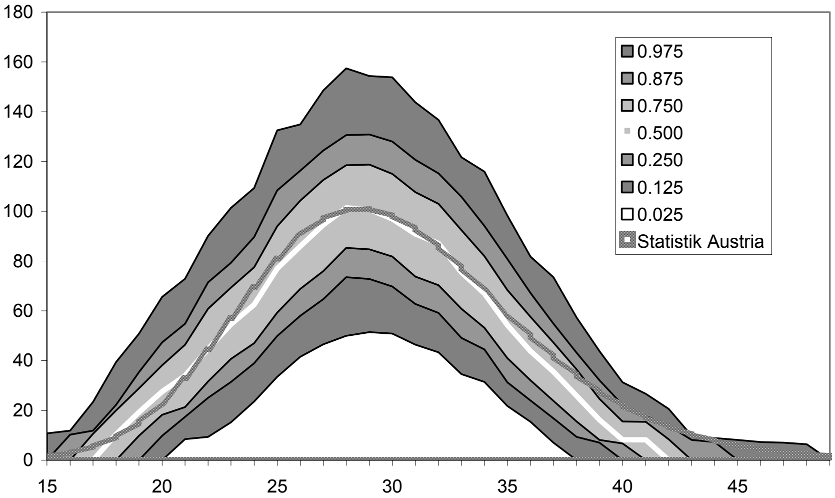

Figure 5: Age-specific fertility rate (births per 1000 women) in 2021

44. Figure 6 exhibits an apparent agreement for the time horizon up to 2002 but a pronounced departure starting in 2003. This is again due to the assumption of recuperation which is based on expert knowledge but cannot and should not be captured within a causal model of fertility. Nevertheless, the deviation in Figure 6 stays within the 75% confidence interval for most of the time.

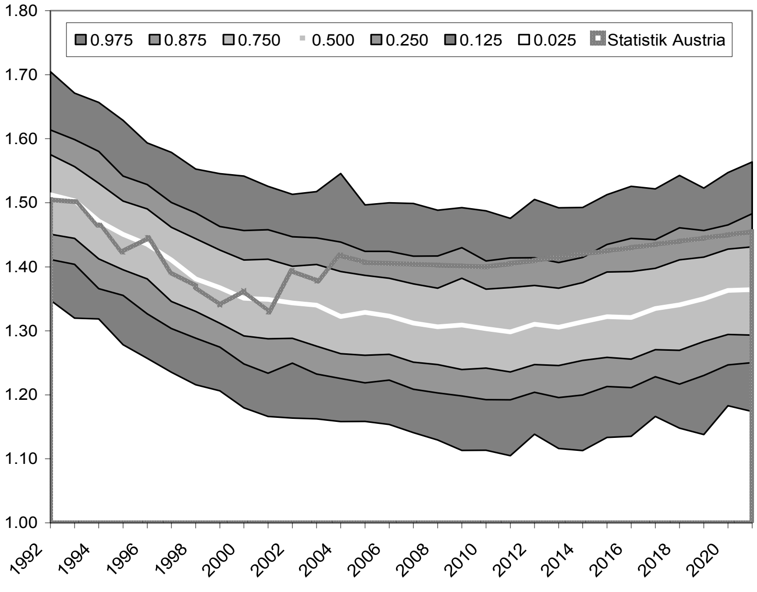

Figure 6: Total fertility rate 1991 - 2021

5. Conclusions

45. As recently shown by various authors (Kohler et al. 2002, Bernardi 2003) social learning and social influence play an increasing role in demographic explanations of observed family formation patterns also in contemporary Europe. The increasing inclusion of social interaction in the demographic theoretical framework however matches with a relatively unrealistic model of the mechanisms underlying those social interactions.

46. We propose to apply the methodology of agent-based models (ABMs) to study the role of social interaction for explaining observed demographic patterns. Such models allow "thought experiments that explore plausible mechanisms that may underlie observed patterns" (Macy and Willer 2002, p.147). Different to micro or macro simulations ABMS provide a theoretical bridge between the micro and macro level. The dynamic bottom up approach of ABMs – to explain global patterns by simple local interactions – is particularly useful when aiming to explain trends in fertility timing and quantum over the last decades.

47. Billari et al. (2007) developed a model taking into account the impact of social interactions within an individuals' peer group on her decision to get married. In this paper we present an ABM including endogenous formation of social networks. This model has the ability to capture the impact of social interaction – via peer groups – on the transition to parenthood. Calibrating our model to Austrian data we show that our model captures the observed changes in the timing and quantum of fertility over the last three decades to a high degree. Hence, one might argue that social interactions and their influence on childbearing decisions may be one driving force explaining recent fertility transitions.

48. Moreover, this model can also be used to project future trends of age- and education-specific fertility patterns. Thus, we apply our model to forecasts age-specific fertility rates in Austria for the next two decades. Different to common practice in population forecasts that are usually based extrapolations of past fertility trends combined with expert opinions, the agent based approach has a theoretical foundation. Our approach explains trends in timing and quantum of fertility by social interactions within an endogenous social network rather than continuing existing trends. The underlying network topology is based on a sound sociological

foundation. Sanderson (1998) argues that combining model-based forecasts including knowledge of the socio-economic determinants of population change with standard forecasts results in more accurate predictions if the forecast errors of the two different approaches are not highly correlated. Moreover, since an agent based model is per se probabilistic, this approach can also be used for probabilistic projections.

49. The next step is to apply our model to different European countries and test its validity. Within the framework of our ABM we can experiment with alternative mechanisms that may underly the timing and quantum of fertility in different social environments. The exploration of plausible mechanisms that underlie observed patterns is the main challenge demographers are confronted with in order to propose efficient explanations of past trends and provide reliable projections of future demographic developments. To demonstrate the feasibility of such an approach–by applying it to the topic of the transition to parenthood–is the main aim of the current paper.

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