Transition to parenthood: The role of social interactions and endogenous networks

Paper Prepared for PAA 2007 Annual Meeting

Belinda Aparicio Diaz
Thomas Fent
Alexia Prskawetz
Vienna Institute of Demography, Austrian Academy of Sciences

Laura Bernardi
Max Planck Institute for Demography, Rostock

March 1, 2007

Abstract

This paper investigates how the decision of having an additional child is influenced by an individuals peer group. We show via agent based simulations how social interaction creates interdependencies in the individual transition to parenthood and its timing. 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. The agents compare the share of agents with a higher parity than their own within their peer group with the same share on the aggregate level. Our numerical simulations indicate that accounting for social interactions is important to explain the shift of first birth probabilities in Austria over the period 1984 to 1994.

1 Introduction

Human behavior, including childbearing behavior, is performed by socialised actors deeply rooted in a web of social relationships like those created by kinship, love, power, friendship, competition, or interest. Beliefs, norms, services and goods are exchanged, traded, negotiated, and enforced within informal social networks constituted of personal communities (Mitchell 1973). From a theoretical point of view different behavioural theories, or action theories, agree on the importance of 'relevant others' for explaining individual behaviour. Economic theory highlights the importance of others as source of information and of sanctions (Kohler 2001). Theories of rational behaviour consider the individual perception of the expectations of relevant others to be an essential determinant of behaviour even when others do not impose any sanction on behaviour. The simple fact that individuals know or believe that others have expectations is translated in subjective norms and influences action (Ajzen and Fishbein1973, Ajzen 1988, Ajzen 1991). Socio-psychological theories stressing the predominant role of normative affective factors over rational consideration as a cause for action, relevant others are potential sources of emotional input (Etzioni 1992, 1999). Social interaction approaches root the definition of the social actor in the process of social interaction. Social interaction is the locus where meanings of actions, words, objects are defined and constantly recreated (Blumer 1969). 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.

Interpersonal interactions among these relatively small groups of individuals produce social effects observable in macro patterns of behaviour and demographic research on union and family formation has concentrated on the latter. Empirical evidence increasingly suggests the interdependency among individual union and fertility behaviour and indicates 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 2001). 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)

In socio-demographic research the consideration of social determinants due to social interaction gained relevance when the empirical evidence provided by the European demographic history of the last century showed that regional patterns of fertility decline conformed very closely to linguistic, ethnic and religious territorial boundaries. Some socio-demographers interpreted these patterns as the result of an undergoing ideational change diffusing ideals about smaller family size across political borders and following cultural lines (Watkins 1986; Bongaarts and Watkins 1996). A similar interpretation applies to the diffusion pattern observed in contemporary populations in developing countries, where the adoption of modern contraception and correspondent fertility decline follow the typical S-shaped curve that characterises epidemiological contagion models (Rogers and Kincaid 1981; Retherford and Palmore 1983; Knodel et al. 1982, Montgomery and Casterline 1993, Rosero Bixby and Casterline 1994, Bocquet Appel and Jacobi 1998).

As a consequence of these findings, the way in which attitudes, values, and norms spread within a population became central in research of family and fertility. The effects of social interaction mechanisms are explored by using formal micro–analytical models, their effects are studied through non–agent–based simulations, whose fit with observed fertility trends confirm the potential explanatory power of social interaction mechanisms. (Rosero-Bixby and Casterline 1993, Montgomery and Casterline 1996, Kohler 2000, Kohler 2001).

In all these applications, social interaction enters fertility explanations, both at the micro and at the macro level. Individual and population fertility are interdependent because the aggregation of individual fertility behavior produces externalities (like the erosion of norms, pressure to conform, path dependency of the information exchange). Kohler (2002) 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 behavior 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

It alters the distribution of knowledge and of attitudes towards union and childbearing, contributing to the modification of preferences and norms concerning family formation behaviour. Likewise, the power of informal social institutions, as social norms, to influence individual behaviour, is shown to be dependent on the structure and the intensity of social interaction (Kohler 2002). 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 irrealistic model of social learning and social influence mechanisms (Chattoe 2003). As noted by Montgomery and Casterline this refined modelling of the social processes reposes on a weak conceptualisation: “little is known about learning mechanisms and the formation of perceptions in respect to demographic behaviour. We are aware of no systematic investigation of what would seem to be a central issue" (Montgomery and Casterline 1996:159). Not only the social mechanisms are not specified in a satisfactory way; similar problems exist to define which are the influential relationships on childbearing decision-making and how the structure of informal social interaction vary across different sub-populations.

This lack of precision seems to constitute a general problem in the development of demographic behavior theory. Specifically, there is a certain agreement that demography suffers from a poor level of precision in the theoretical construction, a statistical modelling 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 modelling simulations and systematic and comparative in–depth investigations offer new possibilities to develop cognitive valid behavioral 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., 2006).

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 section 2 we introduce the theory and hypothesis of fertility transitions and social interaction and endogenous networks. Section 3 is devoted to the implementation of the model. First preliminary results are presented in section 4.

2 Social Interaction and fertility: theory and hypothesis

Studies on fertility timing in developed countries contribute a strong explanatory role to individual life course transitions. These include educational, occupational, partnership and geographical mobility histories. The postponement and increasing variability in these processes has often been associated with the observed delay in childbearing. To account for fertility preferences in general, family background variables, or more generally early life experiences, constitute key indicators (Axinn et al. 1994).

Individuals' fertility behaviour does not only depend on family background variables, and life course paths, but also on the behaviour and characteristics of other individuals transmitted through social networks. Several authors have emphasized the importance of social interactions for fertility choices (Bongaarts and Watkins 1996; Montgomery and Casterline 1996; Bernardi 2003). As Bongaarts and Watkins (1996) argue, social interactions have at least three aspects: the exchange of information, the joint evaluation of its meaning and social influence that constrains or encourages action. A comprehensive survey on fertility and social interactions is documented by Kohler (2001). To understand the divergence in the demographic behaviour of different populations with relatively similar environmental conditions he argues for a combination of economic fertility theory (based on individual optimal and rational decision rules) and theories on social interaction (which incorporates the behaviour of other members of the community/society). Another contribution which emphasizes the relevance of social interactions in the context of low fertility is Kohler, Billari and Ortega (2002). They find that all lowest low fertility countries, i.e. all countries with TFR less that 1.3 have experienced a sharp increase of the age of first birth and argue that this observation cannot be explained by changing socioeconomic incentives alone: Social interactions (either impersonal through e.g. the labour market or personal ones through e.g. peer groups) must have induced multiplier effects or multiple equilibria. Lyngstad and Prskawetz (2006) investigate the influence of siblings on fertiliy. Their results indicate that cross–siblings effects are relatively strong for the respondent's first births, but weak for the second parity transition. In an empirical study based on survey data from Bulgaria and Hungary Philipov et al. (2006) found that the older the first child, the less likely are women to intend to have a second child. A further interesting demonstration how social interaction affect demographic behaviour is given by Åberg (2003) who examined how the high-school peers of young Swedes influenced their propensity to marry. She found positive effects of the proportion of peers' married on the marriage rate, indicating that social interaction is in part driving individuals' marital decisions.

For an individual, the set of "relevant others" consists of people who are close to her/him, i.e. the member of her/his "social network". Closeness is a general feature we shall exploit in what follows. In our context, the term "close" refers to a distance that may represent a spatial distance (that is, neighbours constitute relevant others), but might as well represent a distance in terms of kinship, age, education, professional occupation, and so on. Closer individuals are more likely to be relevant others. The size and characteristics of an individuals' social network may themselves depend on the individuals' characteristics. For instance, the number of relevant others increases with age during youth and adulthood, at least up to ages that are important for processes such as getting married or having children (Micheli, 2000). The literature on social networks has further shown dependencies on further individual characteristics and conditions under which the social network change:

Age. The aging process produces a reduction in the size but an increase in the density of network partners since non kins drop out (Wagner and Wolf 2001). But these changes seem to reflect life course transitions rather than aging itself.

Marital status and parental status.: There is extensive and consistent evidence on the variation of network by marital and parental status, from cross section comparative studies and longitudinal studies. Wellman et al. (1997) have analyzed the changes in intimate ties of individual informal social networks in Toronto between 1968 and 1978. They find that the intimate relationships are relatively unstable over ten years. The median network has retained only one quarter of its initial members and those family situations rather than aging itself account for this turnover. Not surprisingly, marital change (getting married or divorced) seems to be the main triggering process for changes in the network: those who experienced it replaced almost all (94%) of their network. Immediate and distant kin are most persistent ties compared to friends and neighbors. The transition to parenthood seems to affect the circle of non-kin, whose members change already in the short one-year time after pregnancy (Ettrich and Ettrich 1995). The shift in the composition of the social networks consequent to the transition to parenthood is consistent with the results from three similar studies in the US and England, where parents' networks versus non-parents networks are compared (Hammer et al. 1982). In addition to the positive association between rearing of children and increased emphasis on kin connections, the non-kin network composition shifts by including a higher number of friends versus working relationships.

Employment status.: More interestingly, Hammer et al. (1982) find that the network size of the non-working mothers is substantially reduced in the lowest social classes compared to non-mothers.

Education and gender.: Moore (1990) finds that most differences between gender in the social network composition of men and women in the US disappears when one controls for age, employment, marital and parental status. Higher education or professional/managerial occupation entails a larger share of the network composed of non-kin (p. 732, table 3). The only difference that persists is that women are more "kin-keepers" (the kin share that characterizes women networks is larger compared to men in similar structural positions).

Relevant others, chosen because of their closeness in any characteristic, influence the behaviour of an individual through interaction. In our model, we assume that as the share of mothers within the social network increases, also the influence that the relevant others exert on an individual increases. The desire to give birth is intensified or alleviated depending on the others' behaviour. We model the closeness of individuals in terms of a hierarchic structure of social groups, where each individual is part of one group for each relevant characteristic. However, we reduce the number of characteristics to four, namely age, education, intended education, and parity. Thus, each individual is part of three social groups. Individuals who share one group are close, and therefore more likely to become a relevant other than others.

3 The model implementation

To demonstrate the role of social networks for fertility behaviour we develop a one–sex model through which we aim to simulate the different life cycle stages of females. Although partnership plays a major role in the transition to parenthood, we refrain from including mate-search into our model since it would increase the complexity of the model and complicate the interpretation of the results.

Each individual agent has an identity number *id*, four characteristics, and a social network which includes friends, siblings and the agent's mother.[1] 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 to 15 and respectively 49 years and the maximum age of our agents equal to 95 years. Though agents older than 49 cannot give birth, they still may influence other agents. Education is an influential factor for social network formation and size (Moore 1990, Hammer et al. 1982) and thus our second characteristic. For this simulation we assume all children, that is individuals younger than 15, to have no education at all (i.e. to have only compulsory education), hence their education is zero. For older individuals 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. (The argument to include intended education in addition to attained education is closely related to the "anticipation effect" in demographic analysis.) Based on these three characteristics – age, education and intended education – an adult agent chooses on average s 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. We use six stages of parity, 0 to 5+. An individual that gives birth to a child increases her parity by one. The agent's desire to give birth, that is to increase parity, is weakened or intensified by the influence of the social network snw. A summary of the agent's characteristics is shown in Table 1.

Initial population

We initialize the simulation with N individuals. To start with a realistic population structure we use Austrian data for assigning the characteristics to the initial agents. For the age structure of our initial population we use the Austrian female age distribution (see section 4). The level of education of individuals aged 15 or older is assigned according to the Austrian age–specific female educational distribution (cf. section 4). On the basis

[1] The agent's mother and siblings are not known for the initial population.

Table 1: Summary of the Agent's characteristics.

Agent variables		values
Identity number	id	0 - ..
Age	x	0 - 95
Education	e	0 - 3
Intended education	ie	0 - 3
Parity	p	0 - 5+
Age at birth	a	15 - 49
Identities of children	cid	0 - ..
Social network	snw	0 - ..

of the assigned age and education, each agent is assigned her parity according to the Austrian age and education specific parity distribution of females (cf. section 4).

Since most people finish their education before they turn 30, we assume that the educational distribution at age 30 in 1981 determines intended education at earlier ages.[2] From the census we obtain the shares q_1, q_2, and q_3 of women aged 30 with level of education $e = 1, 2$, and 3, respectively. To consider that the parity level at age 30 is higher than at younger ages we need to include the parity distribution at younger ages. Therefore, we use the parity distribution by age and education from the census (see section 4). We denote $q_{xe}(p)$ the share of women at parity p within the group of women at age $x \in [x, x+5)$ and at the level of education e. The shares of the parity groups are then multiplied by the share of the according educational level at age 30 to determine the probability for each level of intended education. Thus, for all agents aged 15 to 29 with the current level of education equal to 1 the probabiliy to get assigned an intended education $ie = 1, 2$, or 3 is given as

$$p(ie = i) = \frac{q_i q_{xi}}{\sum_{j=1}^{3} q_j q_{xj}}.$$

We do not allow an intended education ie lower than the already achieved education e. Therefore, agents with $e = 2$ get their intended education $ie = 2$ or 3 according to

$$p(ie = i) = \frac{q_i q_{xi}}{\sum_{j=2}^{3} q_j q_{xj}}.$$

[2]Of course there are some individuals who finish secondary or tertiary education later than at the age of 30. Therefore, it seems to be favourable 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 — in particular for females.

and agents with $e = 3$ get assigned $ie = 3$. Agents younger than 15 do not get assigned an intended education and for all individuals above the age of 28 the intended education ie is set equal to the actual education.[3] Moreover, individuals at the educational level 1 and older than 20 also get assigned their actual education 1 as their intended education since transition between level 1 and 2 practically happens solely until age 20. Thus, the intended education is assigned randomly. It is based on the educational distribution of females at age 30 in 1981 and the following restrictions:

$$\begin{array}{ll} ie \geq e & \text{for all agents} \\ ie = e & \text{if } (x > 28) \text{ OR } (x > 20 \text{ AND } e = 1). \end{array}$$

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 4). 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 according to these characteristics (age, education and intended education).

Simulation steps

During each simulation step, each agent ages by one year and dies off at age 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 feature a social network consisting of their mother and siblings.[4] Though children do not exhibit their own social network of friends, they can nevertheless be part of one. When an agent turns 50, we assume that childbearing ceases. However agent's older than 50 may still influence adults of childbearing age.

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

[3] 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.

[4] 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.

etra for Austria (see section 4). 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 the following multiplier

$$w(c) = \frac{ppae(x, e+1, p) * f(e+1, ie)}{a(c) \sum_{x,p,ie} ppae(x, e+1, p) * f(e+1, ie)},$$

where $a(c)$ is the share of agents with the 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. The multiplier $f(e+1, ie)$ captures this assumption. It makes sure that within the set of agents who progress from the level of education e to $e+1$ the share of those with intended education ie less than $e+1$ is smaller than the share of those with ie greater or equal $e+1$.

For the transition from education level 1 to level 2 we apply the weights

$$f(2, ie) = \begin{cases} \frac{1}{25} & \ldots \text{ if } ie = 1 \\ \frac{12}{25} & \ldots \text{ if } ie = 2 \\ \frac{12}{25} & \ldots \text{ if } ie = 3 \end{cases}$$

and for the transition from level 2 to level 3 we apply

$$f(3, ie) = \begin{cases} \frac{1}{10} & \ldots \text{ if } ie = 1 \\ \frac{1}{10} & \ldots \text{ if } ie = 2 \\ \frac{8}{10} & \ldots \text{ if } ie = 3 \end{cases}.$$

In detail, in the group progressing from level 1 to level 2 the share of agents with $ie = 1$ is 4 percent (i.e. 1/25) and the shares with $ie = 2$ and $ie = 3$ are 48 percent each (12/25), while in the group progressing from level 2 to 3 the shares with $ie = 1$ and $ie = 2$ are 10 percent each (i.e. 1/10) and the share with $ie = 3$ is 80 percent (8/10), provided there are enough agents with each particular intended education.

As empirical data evidence that mothers have a lower transition rate to higher education we apply the multiplier $ppae(x, e+1, p)$ which represents the empirical proportion of women with parity p at age x and education $e+1$. Since these data are only available for five year groups we assume that half of the births happened after the transition to $e+1$ and the other half before the transition.

Endogenous social network

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 the like. Thus, we have agents living in a multidimensional space, where each dimension represents one characteristic. Watts et al. (2002) introduced a searchable network taking into account the fact that individuals partition the social world in more than one way. They applied this network to forward messages to a target person. In the sequel we will use a similar network structure for the diffusion of childbearing behaviour.

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 agent's 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. Branching ratio and group-size are exogenous parameters which, together with the number of individuals, determine the depth of the network hierarchy l. An agent is influenced by its social network *snw* concerning her childbearing behaviour.

Since the number of agents is continuously changing in our simulations, the hierarchy depth l needs to be recalculated in each simulation step. For this reason we suggest a slightly different variant as compared to the Watt's procedure. We fill the hierarchic groups sequentially with agents instead of literally splitting the population into groups. Through this approach we avoid missing groups and fluctuating group sizes which would occur due to the changing population size. 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. For instance agents i and j in figure 1 are in different groups which are not directly connected. To find the lowest common ancestor we need to trace back the branches two levels upwards. Therefore, the distance between i and j, d_{ij} is equal to three. The probability of acquaintance (i.e. the probability of a link) between two individuals with a distance d is given by

$$p_1(d) = c \exp(-\alpha d), \tag{1}$$

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.

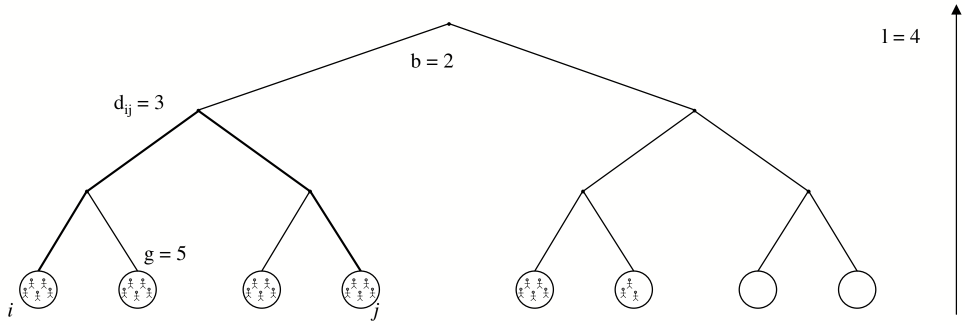

Figure 1: Partitioning of the population into groups of size $g = 5$

However, if the parameter α gets 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)[5] and then picks a friend uniformly among all individuals with distance d. This procedure is repeated until an average number s of friends are found. The mean network size is an exogenous parameter. The actual number of friends for an agent is log-normally distributed.

Since individuals belong to three groups (age–group, education group, and intended education group) the procedure described in the previous paragraph is repeated for each characteristic. 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 part of her peer group. The social network *snw* of agents in the initial population only consists of members chosen through the way of the above algorithm, whereas the social network of agents that are created during the simulation also contains their mother and siblings.

Further, each adult may exchange one or more members of her social network, since networks are known to be unstable over time. Wellman (1997) found that after ten years the median network retains only one quarter of its initial members. If an agent exchanges each member of her network with a probability p_2, the probability for an initial member to

[5]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).

still belong to the network after ten years is $(1-p_2)^{10}$. One quarter of the initial members should remain in the network, that is $(1-p_2)^{10} = 0.25$. Thus, for each member of the particular agents social network the annual probability to be exchanged is $p_2 = 0.129$. To implement these observed network changes we proceed as follows. Since there are $\binom{s_i}{n}$ possibilities to choose n agents out of a network of size s_i, the probability to exchange exactly n network members is given as

$$p_3(n) = \binom{s_i}{n} p_2^n (1-p_2)^{s_i - n}. \tag{2}$$

According to this probability distribution each individual removes n randomly chosen members from her network and chooses n new members analogous to the choice of members during the first construction of the network.

Social influence and parity transition

An adult agent (aged between 15 and 49) may give birth to a child, whereas her decision to change her parity status is influenced by her social network. Thereby the share of mothers within the network, *rop*, is translated into a social influence *si*. This social influence is used as a multiplier for the probability of giving birth, which depends on the age– and parity–specific birth probabilities *ppr* of Austria (see section 4).

To calculate the social influence *si* that the social network *snw* exerts on an agent i, we compute the share of network members at a greater parity than agent i's parity p, $rop(p)$, and the share of agents with a greater parity who had their first birth before the current age of agent i, $rop(p, x)$. For the first birth we consider the shares

$$rop(p) = \frac{\#\{j : p_j > p \text{ AND } j \in snw\}}{\#snw}$$
$$rop(p, x) = \frac{\#\{j : p_j > p \text{ AND } a_j \leq xANDj \in snw\}}{\#snw},$$

where p_j denotes the current parity of agent j who is a member of agent i's social network snw, $\#\{j : p_j > p \text{ AND } j \in snw\}$ is the number of network members with parity greater p, a_j is the age at first birth of agent j, and $\#\{j : p_j > p \text{ AND } a_j \leq x \text{ AND } j \in snw\}$ is the number of network members with parity greater p and age at first birth less or equal to x.

For higher order births we ignore those agents within the peer network who are not yet mothers[6] and compute

$$rop(p) = \frac{\#\{j : p_j > p \text{ AND } j \in snw\}}{\#\{j : p_j > 0 \text{ AND } j \in snw\}}. \tag{3}$$

We do not consider age at birth for higher order births, since the literature indicates that age of youngest child as opposed to age of the mother acts as the duration variable in models of higher order birth intensities.

Likewise, we compute the share of agents with parity greater p (and age at birth less than x), $ROP(p)$ ($ROP(p,x)$), on the aggregate level:

$$\begin{aligned} ROP(p) &= \frac{\#\{i : p_i > p\}}{N} \\ ROP(p,x) &= \frac{\#\{i : p_i > p \text{ AND } a_i \leq x\}}{N} \end{aligned}$$

and for higher order births:

$$ROP(p) = \frac{\#\{i : p_i > p\}}{\#\{i : p_i > 0\}}$$

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 $ppr(x,p)$. We distinguish four different types of social influence, where we model social influence as an s-shaped function with slope β. To achieve this we compute the multipliers,

$$si_1(p) = \frac{\exp(\beta * (rop(p) - ROP(p)))}{1 + \exp(\beta * (rop(p) - ROP(p)))} + 0.5 \tag{4}$$

$$si_2(p) = \frac{\exp(\beta * (rop(p,x)) - ROP(p)))}{1 + \exp(\beta * (rop(p,x)) - ROP(p)))} + 0.5 \tag{5}$$

$$si_3(p) = \frac{\exp(\beta * (rop(p,x) - ROP(p,x)))}{1 + \exp(\beta * (rop(p,x) - ROP(p,x)))} + 0.5 \tag{6}$$

$$si_4(p) = \frac{\exp(\beta * (rop(p) - ROP(p,x)))}{1 + \exp(\beta * (rop(p) - ROP(p,x)))} + 0.5, \tag{7}$$

where β determines the slope of the function.

[6]Bernardi et al. 2007 found that women who already have children do not refer to childless peers concerning former fertility decisions.

The multiplier $si_1(p)$, considers parity but ignores age at birth, the second multiplier, $si_2(p)$, considers age at birth only at the micro level, and the third multiplier, $si_3(p)$, considers age at birth at the macro and at the micro level. The multiplier $si_4(p)$ compares $rop(p)$ ignoring age at birth at the micro level with $ROP(p, x)$ considering age at birth at the macro level. Thus, for young agents the multiplier $si_2(p)$ is biased to low levels because it compares $rop(p, x)$ with $ROP(p)$ and $si_4(p)$ is biased to higher values for young agents. These multipliers are then used to correct the empirical age– and parity–specific birth probability, $ppr(x, p)$, to take the social influence into account. Thus, an agent i at age x gets assinged a probability of birth,

$$ppr_k(x, p) = ppr(x, p)si_k(p), \tag{8}$$

with $k \in \{0, .., 4\}$. The multipliers given in (4), (5), (6) and (7) ensure that the birth probability $ppr(x, p)$ 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 is equal to one and hence, the agent does not changes its birth probability. In this way we achieve that the social influence modelled at the individual level is "anchored" at the social influence we observe at the macrolevel.

The parameter β gives the intensity of the social influence when the individual share diverges from the one on the aggregate level. Choosing $\beta = 0$ results, like the multiplier $si_0(p)$, in a social influence of 1 in any case, which means that the influence of the social network is completely ignored.

Transition to parenthood: After transition to parenthood an agent changes her parity and the birth is added to the statistics. Since we do not include males to our model we use the Austrian sex ratio at birth *srb* (see section 4) 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 to adulthood (at age 15) when they choose their friends for the social network. During the childhood an agents network only consists of the agents mother and siblings, to whom the new agent is also added as a network member.

4 Data

Age Distribution: For the initial population we use the age–distribution of Austrian females in 1981.[7]

[7]Source: Demographisches Jahrbuch 2003 Table 8.7, Statistik Austria.

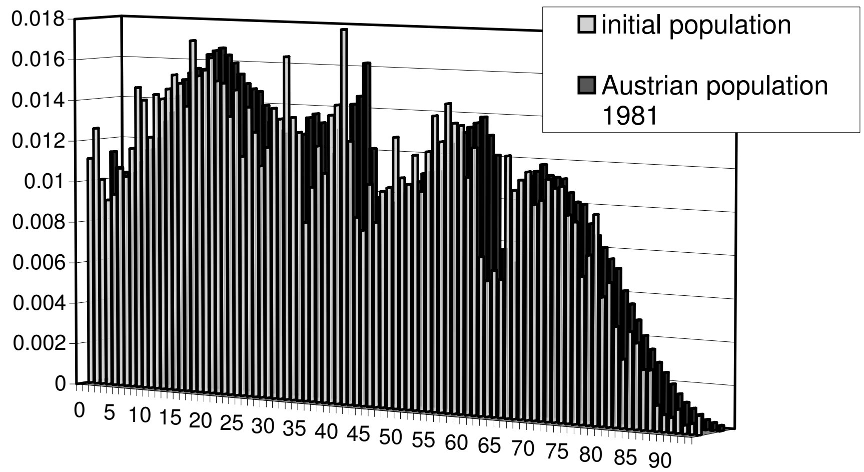

Figure 2: Age distribution for the Austrian female population in 1981 and for the initial population

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 1981.[8] We distinguish (for adult agents) three stages of education, whereas the Austrian data we use as input distinguish up to 6 stages. We therefore merged these groups as follows:

Allgemeinbildende Pflichtschule	Lehrlingsausbildung	Berufsbildende mittlere Schule	Allgemeinbildende höhere Schule	Berufsbildende höhere Schule	Universität, (Fach)-Hochschule
primary / lower secondary			upper secondary		tertiary

Distribution by Age, Education and Parity: The Austrian distribution by age, education and parity of 1981,[9] that we use to assign a convenient parity for the initial agents also distinguishes up to 6 education groups (analogous to the distribution by age and education).

[8]Source: Volkszählung 1981 Hauptergebnis II Table 13, Statistik Austria.
[9]Sources: Volkszählung 1981, Eheschliessungs- und Geburtenstatistik, Table 50, Statistik Austria.

Parity–specific Birth Probability by Age: The calculations done for the parity–specific birth probabilities of 1984, that are used in the model, are accomplished by Tomáš Sobotka.[10]

Education Transition Rate by Age: The age-specific transition rates for educational groups are based on period measures. We start from the age and educational structure of the population in 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:

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

By working with shares instead of absolute values we control for different cohort size. We then pretend 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.

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 2001. Since these data are only provided for five year age groups we interpolate the data with piecewise cubic hermite polynomials.

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[11] of 1981 for this purpose.

5 Simulation Results

In this section we discuss the results we obtained by running simulations with a population size of $N = 5000$. For assigning age, education and parity to the initial population we use data from 1981 and as the probability to give birth we use the parity-specific birth probability of 1984. Unfortunately we do not have the birth probabilities of 1981. We

[10]Source: EUROSTAT New Cronos, Census data 1991 and 2001 Census data for the period 2001+.

[11]Statistischen Jahrbuch Österreich 2004 Table 2.26.

nevertheless use for the first simulations data from 1981 and 1984 to allow a comparison of the results with empirical data.

We set the group size of the hierarchy equal to 5 individuals ($g = 5$) and the branching ratio b equal to 2. For the parameter α we choose 0.75. We assume that the average network contains 10 friends ($s = 10$, Fliegenschnee, 2006) and simulate the fertility behaviour over 10 years.

Model Parameters		default
Number of agents	N	5000
Number of simulation years	y	10
Mean size of social network	s	10
Branching ratio	b	2
Group size	g	5
Alpha	α	0.75
Beta	β	8
Multiplier type	k	3

Since transition to parenthood is of main interest to us, we obtain the probability of first childbirth and the mean age at first childbirth. In order to receive smooth curves we take the average of 500 simulation runs.

In the first set of simulations we compare the social influence types $k = 1 \ldots 4$ using $\beta = 8$ for the calculation and contrast the results with simulations where we ignore social influence ($\beta = 0$) and with empirical data. Figure 3 plots the probability of first childbirth among childless women for Austria in the years 1984 and 1994 and for a simulation run, where we ignore social influence ($\beta = 0$), thus we keep social influence equal to 1 at any time. Simulating 10 years without social influence results in roughly the same behaviour as in the base year. Whereas including social influence pushes the simulated probabilities closer to the observed birth probabilities of 1994. As expected, the second multiplier si_2 underestimates the probability for young ages, whereas the fourth multiplier si_4 overestimates the values for young agents (see figure 4.)

Further we test the outcome when varying model parameters. For that purpose we choose the former simulation using the third multiplier (where age at birth is considered at both, the individual and the aggregate level) as the benchmark case. We first compare different values for the slope of the social influence function $\beta = 2$, $\beta = 8$ (=benchmark) and

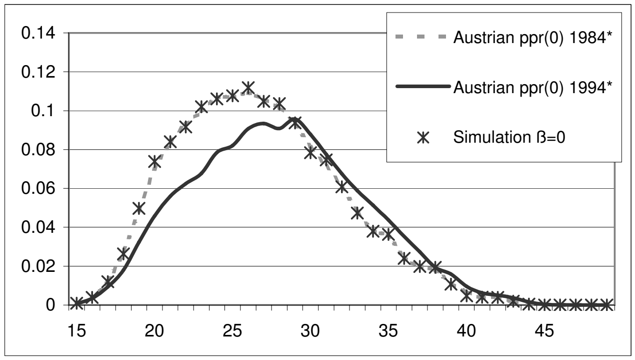

Figure 3: Probabilities of the first childbirth among childless women. Source: Parity-specific birth probabilities (see section 4.)

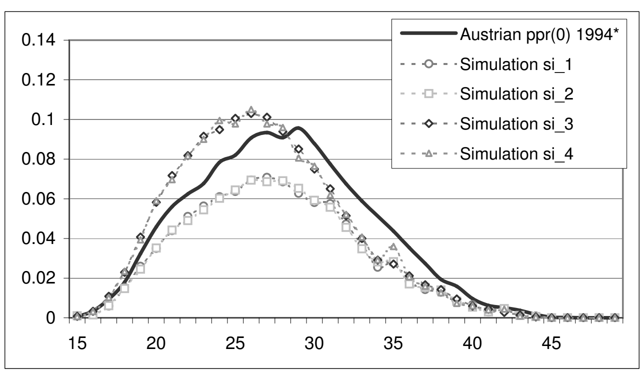

Figure 4: Probabilities of the first childbirth among childless women.

$\beta = 14$. The slope specifies the strength of the networks influence when the networks share of mothers rop differs from the share of mothers in the whole population ROP. The higher the slope β, the more intense is the influence exerted by the network. Figure 5 plots the respective social influence functions.

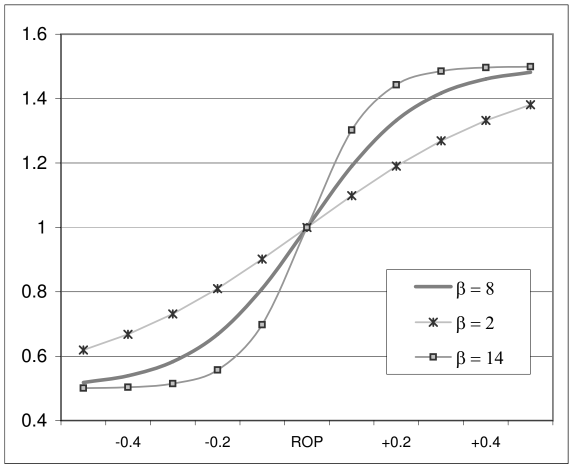

Figure 5: Functional form of social influence.

The effect of varying slopes of the influence function on the probability of first birth is shown in figure 6. A smooth social influence ($\beta = 2$) increases the probability for a first birth at young ages, while agents following a steeply increasing influence function ($\beta = 14$), seem rather to postpone their first birth.

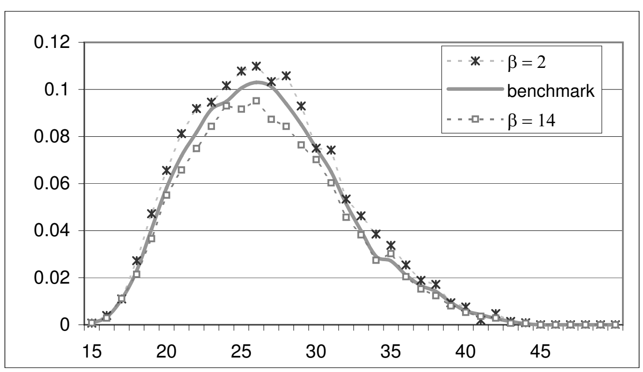

Figure 6: Probabilities of the first childbirth among childless women.

Further simulations showed that the parameters concerning the hierarchically structuring of the world, group size g, branching ratio b and α do not show a significant influence on the results. The mean network size s does not distort the results either.

Figure 7 plots the increasing mean age at first birth in Austria for the years 1984 to 2004. Our simulation results show a similar increase although the postponement of first birth is underestimated by our third influence type, especially in the first few years. The second influence type in turn overestimates the postponement in the last years.

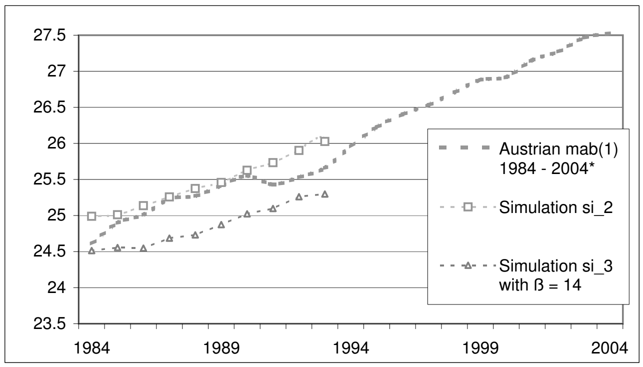

Figure 7: Mean Age at first childbirth.

References

[1] Aparicio Diaz, B., Fent, T. (2006). An Agent–Based Simulation Model of Age–at–Marriage Norms. In: Billari, F. C.; Fent, T.; Prskawetz, A., Scheffran, J. (eds.) Agent–Based Computational Modelling. Heidelberg: Physica Verlag, pp. 85–116.

[2] Bernardi, L. (2003). Channels of social influence on reproduction. Population Research and Policy Review 22, pp. 527–555

[3] Bernardi, L., Keim, S., von der Lippe, H. (2007). Social Influence on Fertility: A Comparative Mixed Methods Study in Eastern and Western Germany, Journal of Mixed Methods Research 1(1), pp. 23–47

[4] Billari, F., Fent, T., Prskawetz, A., Scheffran, J. (2006). Agent–Based Computational Modelling: Applications in Demography, Social, Economic and Environmental Sciences. Physica Verlag.

[5] Billari, F. C., Prskawetz, A. (2003), Agent-Based Computational Demography: Using Simulation to Improve Our Understanding of Demographic Behaviour. Physica-Verlag.

[6] Billari, F., Prskawetz, A., Fürnkranz, J. (2003). On the Cultural Evolution of Age-at-Marriage Norms. In: Billari, F. C.; Prskawetz (eds.) Agent–Based Computational Demography. Physica Verlag, pp. 139–158.

[7] Cleland, J. and Wilson, C. (1987), Demand theories of the fertility transition: an iconoclastic view, Population Studies 41(1): 5–30.

[8] Ettrich, C. and K. U. Ettrich, (1995) Die Bedeutung sozialer Netzwerke und erlebter sozialer Unterstützung beim Übergang zur Elternschaft - Ergebnisse einer Längsschnittstudie; Psychologie in Erziehung und Unterricht, 42(1), 29-39.

[9] Fliegenschnee, K. (2006). personal communication.

[10] Hammer, Gutwirth, Phillips (1982) Parenthood and Social Networks; Soc Sci Med. 1982;16(24):2091-100.

[11] Knodel, J. and van de Walle, E. (1979), Lessons from the past: policy implications of historical fertility studies, Population and Development Review 5(2): 217–245.

[12] Kohler, H.-P. (2001), Fertility and Social Interaction. An Economic Perspective. Oxford: Oxford University Press.

[13] Lyngstad, T.H., Prskawetz, A. (2006). Do siblings' fertility histories influence each other? mimeo.

[14] Montgomery, M.R. and Casterline, J.B. (1993), The diffusion of fertility control in Taiwan: Evidence from pooled cross-section time-series models, Population Studies 47(3): 457– 479.

[15] Montgomery, M.R.and Casterline, J.B. (1996), Social learning, social influence and new models of fertility, pp. 151–175 In: J.B. Casterline, R.D. and K.A. Foote (eds.), Population and Development Review (Supplement 22: Fertility in the United States: new patterns, new theories).

[16] Moore, G. (1990) Structural Determinants of Men's and Women's Personal Networks'; American Sociological Review 55(5): 726-735.

[17] Nazio, T. and Blossfeld, H.-P. (2002), The diffusion of cohabitation among young women in West Germany, East Germany and Italy. Working Paper. Globalife.

[18] Palloni, A. (1998), Theories and models of diffusion in sociology. Working paper. University of Wisconsin. Centre for Demography and Ecology.

[19] Philipov, D. Spéder, Z., Billari, F.C. (2006). Soon, later, or ever? The impact of anomie and social capital on fertility intentions in Bulgaria (2002) and Hungary (2001) Population Studies, 60(3), pp. 289–308.

[20] Pollak, R. and Watkins, S. (1993), Cultural and economic approaches to fertility: proper marriage or misalliance?, Population and Development Review 19(3): 467–496.

[21] Wagner,M. and Wolf, C. (2001). Altern, Familie und soziales Netzwerk; Zeitschrift für Erziehungswissenschaft, 4, 529–554.

[22] Watkins S. (1987), The fertility transition: Europe and the third world compared, Sociological Forum 2(4): 645–673.

[23] Watkins, S. (1986), Conclusions, pp. 420–449 in A Coale and S.Watkins (eds.), The Decline of Fertility in Europe. Princeton: Princeton University Press.

[24] Watts, D. J., Dodds, P. S., and Newman, M. E. J. (2002), Idendity and search in social networks. *Science*, 296(5571):1302–1305.