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Social norms and the fertility transition

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Abstract

This paper provides a norm-based explanation for two features of the fertility transition that have been observed in many different settings: the slow response to external interventions and the wide variation in the response to the same intervention. Most societies have traditionally put norms into place to regulate fertility. When the economic environment changes, individuals gradually learn through their social interactions about the new reproductive equilibrium that will emerge in their community. This characterization of the fertility transition as a process of changing social norms is applied to rural Bangladesh, where norms are organized at the level of the religious group and interactions rarely cross religious boundaries. Consistent with the view that changing social norms are driving changes in reproductive behavior in these communities, we find that the individual's contraception decision responds strongly to changes in contraceptive prevalence in her own religious group within the village whereas cross-religion effects are entirely absent. Local changes in reproductive behavior occur independently across religious groups despite the fact that all individuals in the village have access to the same family planning inputs.

JEL classification: D100; D830; J130; Z130

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1. Introduction

Countries at similar levels of economic development are often seen to display very different patterns of fertility behavior (Bongaarts and Watkins, 1996). Although fertility rates have declined throughout the world over the past decades, long delays and wide differentials in the response to family planning programs have also been frequently observed, both across countries as well as within countries (see, for instance, Bulatao, 1998; Cleland et al., 1994; NRC, 1993). One explanation for these stylized facts is based on the idea that many aspects of individual behavior, including fertility, are socially regulated in a traditional economy. While such social regulation has advantages of its own, the drawback is that it may prevent individuals from responding immediately to new economic opportunities. Social norms are typically seen to emerge in environments characterized by multiple equilibria, to keep the community in a preferred equilibrium (Kandori, 1992). Changes in the economic environment, such as the availability of modern contraceptives, could reopen the possibility for such multiple equilibria, which would explain the slow response to external interventions, as well as the differential response to the same external stimulus, as each community gradually converges to a new reproductive equilibrium.[1]

The setting for this study is the fertility transition in rural Bangladesh. The International Centre for Diarrhoeal Disease Research, Bangladesh (ICDDR,B) launched a Maternal Child Health–Family Planning (MCH-FP) project in 1978, covering seventy villages in Matlab thana, Comilla district. The MCH-FP project is quite possibly the most intensive family planning program ever put in place: all households in the intervention area have been visited by a Community Health Worker (CHW) once every 2 weeks since the inception of the project in 1978, and contraceptives are provided to them free of cost. Despite these economic incentives, and the sustained pressure on the households to change their behavior, we still see long delays in the adoption of contraceptives. The family planning program was already well established in the intervention area by the time our data began in 1983. Nevertheless, contraception levels continued to increase steadily over the sample period (1983–93), from 40% in 1983 to 63% in 1993, with an accompanying decline in total fertility rates from 4.5 children per woman to 2.9 children over that period. Wide variation in long-run contraceptive prevalence is also observed across villages in the intervention area.

Most societies have traditionally put norms into place to regulate fertility. In rural Bangladesh, the traditional norm was characterized by early and universal marriage, followed by immediate and continuous child-bearing. Religious authority provided legitimacy and enforced the rules that sustained this equilibrium. In such a social environment, the unexpected availability of modern contraceptives through the family planning program would have opened up the possibility for new equilibria, in which a

[1] As Ray (1998, p. 323) remarks, also in the context of the fertility transition, “The very strength of such [traditional] norms becomes a weakness when the environment of the society begins to change. Accepted, appropriate practice over many centuries may now become inappropriate, but once this happens, social practice is often slow to alter. It becomes necessary to coordinate on some new norm, but such coordination requires many people to move in unison.”

sufficient fraction of the women in the village ignored the religious sanctions and began to regulate fertility. The point of departure for our simple model of fertility change, following the exogenous economic intervention, is a social uncertainty: the individual does not know what level of contraceptive prevalence will ultimately be sustained in her community. This uncertainty is slowly resolved over time as women in the village interact sequentially with each other from one period to the next, which explains the gradual change in contraceptive prevalence that we see in the data, as well as the convergence to different levels of contraceptive use across communities.

While this characterization of social change as a learning process explains the broad stylized facts that we described above, it also allows us to endogenously derive the individual's decision rule during the transition from the traditional equilibrium to the modern equilibrium: The contraception decision in any time period is determined by the individual's lagged decision and the lagged level of contraceptive prevalence in the community. However, this prediction by itself has little bite since it is well known that a spurious correlation between the individual's decision and her neighbors' past decisions could be obtained when unobserved determinants of the contraception decision are correlated across neighbors and over time (Manski, 1993). For example, neighbors' decisions could simply proxy for changes in economic opportunities or the effectiveness of the MCH-FP project itself.

Our strategy in this paper to provide additional support for the view that changes in contraceptive prevalence were driven by changes in underlying social norms takes advantage of the institutional background that we will provide in Section 2. Female mobility in Bangladesh has traditionally been severely restricted by the institution of purdah. Young married women will rarely leave the homestead (bari), and when they do, it will typically be to visit extended family or kin. While the two major religious groups in rural Bangladesh, Hindus (who constitute 18% of the population in our villages) and Muslims, share a common language and a common Bengali culture, female interactions almost never cross religious boundaries even within the village. Changes in social norms must thus occur independently across religious groups within the village.

We test these implications of the model with a unique data set, which includes contraceptive use information as well as demographic and socioeconomic characteristics for all the women residing in the 70 villages in the intervention area over an 11-year period (1983–93). Consistent with the preceding prediction, we present the striking result in Section 5 that while individuals respond strongly to contraceptive prevalence within their own religious group in the village, cross-religion effects are entirely absent in the data. In contrast, when we partition the village by other variables, such as age or education, we consistently observe large and significant cross-group effects. We will also show in Section 5 that omitted determinants of the individual's contraceptive decision must be completely uncorrelated across religious groups within the village to spuriously generate the within-religion and cross-religion patterns that we just described. We will argue in that section that standard omitted variables, such as unobserved program effects or economic change, which complicated the interpretation of the estimated contraception decision rule above, are unlikely to satisfy this condition. For example, while health inputs and information signals supplied by the MCH-FP project may have varied across religious groups within the village, it is difficult to imagine that they were uncorrelated across these groups. After all, it is the same agency, and the same CHW, that is providing these inputs.[2]

The paper is organized in six sections. Section 2 describes the institutional setting, paying special attention to the social restrictions that prevented the immediate adoption of contraceptives in the intervention area. Section 3 describes the village level data: we see a gradual change in contraceptive prevalence over time as well as sorting across villages to different long-run contraceptive prevalence levels. Section 4 presents a simple model of social change that is consistent with these stylized facts. The individual's (optimal) decision rule is also derived in this section. Section 5 subsequently presents the data and the estimation results that support the view that religion-specific social interactions gave rise to the changes in reproductive behavior that we see in the data. Section 6 concludes the paper.

2. The institutional setting

Our primary objective in this section is to describe the social restrictions that prevented the rapid spread of contraception in the intervention area. By making modern contraceptives available for the first time, the MCH-FP project ran counter to the practice of early and universal marriage followed by immediate and continuous child-bearing, followed traditionally throughout rural Bangladesh (Arthur and McNicoll, 1978). Not surprisingly, the MCH-FP project faced strong opposition from community elders and local religious leaders, who were responsible for safeguarding the traditional norms. Apart from this social opposition, the spread of contraception was also hindered by the institution of purdah, which promotes the seclusion of women and rigidly segregates labor activities along gender lines (Amin, 1997). Purdah severely restricts the mobility of young married women, which would have reduced social interactions between them, slowing down the process of social change and with it, the diffusion of modern contraceptives.

Neither the Koran nor the Hindu religious scriptures take a firm position on contraception. Thus, the attitude of the community in Bangladesh will typically follow the view of the local religious leader (Amin et al., 1997). Regulation of reproduction was seen to be contrary to religious principles by local leaders, and religious views opposing any fertility control persist in the intervention area to this day. Simmons (1996) describes conversations with women in the intervention area who retained their religious objections a decade after the institution of the MCH-FP project. As one of the women put it, "God has given the mouths and he will feed them. Therefore, we have nothing to do with it (contraception)."

While appeal to a "higher order" can have a powerful influence on individual behavior, stronger incentives may be required when the optimal action, from the individual's perspective, deviates significantly from customary behavior. Thus, norms are often

[2] The observed changes in reproductive behavior could in principle have been motivated by changes in preferences at the level of the social group (as in Pollak, 1976). However, we choose to maintain the classical economic assumptions that the individual's preferences are exogenously determined and stable in this paper (see Postlewaite (1998) for an elaboration of this view).

associated with social sanctions, which may take the form of peer pressure, ridicule and even ostracism in extreme cases. Women using contraceptives in the intervention area did in fact face considerable overt pressure, although from our conversations with MCH-FP project field-staff, this social opposition has weakened in recent years.

The MCH-FP project enlisted young married women residing in the local area as Community Health Workers (CHWs), to visit each household in their designated area (roughly the size of a village) twice a month providing contraceptives and health inputs. Since their job required them to venture outside the home without an appropriate chaperon, the CHWs directly violated the rules of purdah. Simmons et al. (1992) interviewed a small sample of CHWs in 1987–88 to study the social pressure that they faced at the outset of the MCH-FP project. The response from the community was initially extremely hostile. As one worker put it, "Many people used to say many bad things. They used to say that a khanedarjal (devil) has come to the village in order to destroy the women. They would not even look at us, or used to tease us whenever we passed their houses."

The hostile community response to the CHWs only reinforced the opposition to contraception in general. One woman interviewed by Simmons, Mita and Koenig describes the villagers' initial reaction in the following manner: "They used to think that she is doing the people harm. Why should she stop fertility? Let the embryo develop. God is the creator and he is giving birth. So she has no right to give tablets, injections, and other methods and stop pregnancy."

A further explanation for the religious opposition to fertility regulation is based on the idea that modern contraceptives reduce the risk that a woman's extramarital relations will be revealed. This is very important in a conservative society where such relations are severely punished when detected.[3] We would expect that the religious establishment, which enforces the moral code, would oppose the introduction of modern contraceptives on the grounds that they would encourage promiscuity and artificially alter the "natural order." This is indeed what appears to have happened; religious leaders in the intervention area went so far as to link contraceptive use, even by married women, to promiscuity in the early years of the MCH-FP project.

Although the religious resistance that we have described may be very persistent, its effectiveness weakens as a greater fraction of the community gradually deviates from the traditional social rules. Since this introduces a strategic aspect to the contraception decision, information about neighbors' decisions is clearly valuable. Unfortunately, access to such information is severely restricted by purdah. Patrilinearly related households are grouped together in homesteads or baris in Bangladesh, and groups of baris in turn form a village. Women in rural Bangladesh are confined to the bari and the area immediately

[3] Illegitimate birth is severely punished in the intervention area. Koenig et al. (1988) found that no pregnancy outside wedlock in Matlab resulted in a live-birth over the 1976–85 period; either due to abortion of the foetus, death of the mother as a result of abortion, or death of the mother from violence related to the pregnancy. In another study carried out in Matlab, Fauveau et al. (1989) show that despite the low occurrence of illicit coitus, 8% of all maternal deaths take place among unmarried women. 70% of these deaths result from unsuccessful abortion, while the balance is attributed to violence.

surrounding it, and their contacts with the world outside of the family are extremely limited (Schuler and Hashemi, 1994).

Cain et al. (1979), in a well-known study, collected detailed time allocation information for men and women in one village (Char Gopalpur) in Mymensingh District of Bangladesh between 1976 and 1978. They found that both men and women work roughly 8.3 h per day, but that men allocated 85% of their time to income-earning activities, while women allocate 81% of their time to home production. All the activities grouped under home production, with the possible exception of firewood collection, take place within the bari. A disproportionate share of women's income-earning time is allocated to handicrafts and hut construction, which also occur within the bari. Cain et al. (1979, pp. 428) thus conclude that "The physical limits of the market for a woman's labor are described by a circle with a radius 200–400 meters, with her homestead [bari] at the center of the circle."

These spatial patterns of female work activity do not appear to have changed appreciably over time, and more recent studies such as Amin's (1997) survey of two villages in Mohanpur Thana in 1991 show that women's work opportunities continue to be severely limited in rural Bangladesh. Opportunities for women to travel outside of work are also extremely limited in Bangladesh. For instance, while the women in Cain, Khanam, and Nahar's study have complete responsibility for preparing meals at home, they do not themselves go to the local market to make purchases.

To assess the general level of female mobility in rural Bangladesh, Schuler et al. (1997) conducted a survey of 1300 married women under age 50 in 1992 in which respondents were asked whether they had ever gone to the market, a medical facility, the movies, and outside the village. Each respondent was given one point for each place she had visited accompanied by someone else, and two points for each place she had visited alone. The mean score for the women in the sample was just 2.1 (out of a maximum of 8), reflecting the extremely low levels of mobility among the women. Note that while purdah is generally associated with Muslim societies, this concept of seclusion applies to both Hindus and Muslims in Bangladesh. It has been suggested that this is because the specific construction of purdah in Bangladesh, and its connections with gender-demarcated work patterns, are peculiar to Bengali culture (Rosario, 1992).

About the only opportunity for young married women to travel in rural Bangladesh is on suitably chaperoned social visits to other baris in the village. But baris are geographically dispersed, and during the monsoon months, they are often only accessible by boat. The infrequent interaction with friends, married sisters, and sisters-in-law, nevertheless slowly disseminates information through the community. A young woman in Mita and Simmons (1995) describes how her peer group discussed "how many children we would have, what method would be suitable for us . . . whether we should adopt family planning or not, all these topics ... We used to know from people that they used (contraceptives). If a couple takes any such method, the news somehow spreads." This slow diffusion of information matches well with the gradual change in contraceptive prevalence over time that we will observe in the next section, which will in turn motivate the learning-based model of social change that follows in Section 4. Women venture outside the bari to meet their kin, and Hindus and Muslims never inter-marry in rural Bangladesh, so female interactions occur exclusively within religious groups. This observation will also help explain the absence of cross-religion social effects, within the village, that we later observe in Section 5.

3. Aggregate patterns in the data

We now describe two important features of the data, which will motivate the model of social change that we present later in Section 4: the gradual increase in contraceptive prevalence over time and the sorting among the villages to different long-run levels of contraceptive prevalence.

We begin by describing the gradual change in contraceptive use over time. Contraceptive use information for all eligible women, 15–49 years, married and capable of conceiving, is available at two points in each year (June 30 and December 31) over an 11-year period from 1983 to 1993. Note that only women capable of conceiving enter the data set at each point in time. Thus, while a woman will typically appear in the data set over many periods, she will not appear in those periods in which she is pregnant, nursing, or otherwise incapable of conceiving. Average contraceptive prevalence, measured as the proportion of all eligible women who use contraceptives, is presented over the sample period in Fig. 1.[4] Contraceptive prevalence increases slowly but steadily over time, although it does begin to flatten out after 1990.

Fig. 1 also plots contraceptive prevalence separately for Hindus and Muslims (these are the dashed lines in the figure). While Hindus maintain higher levels of contraceptive prevalence throughout the sample period, the gap between the two communities remains roughly unchanged. It is interesting to note that while the aggregate trajectories for Hindus and Muslims may track together, we will later observe absolutely no local interaction between these religious groups, within the village.

Turning to the second stylized fact that we wish to describe, Quah (1997) suggests using a simple transition matrix to study sorting among the villages to different long-run levels of contraceptive prevalence. While individual level data, with information on age and religious affiliation, are available from 1983 to 1993, aggregate village level contraceptive prevalence (the proportion of eligible women in each village who use contraceptives in any given year) is available over a longer period, starting from the inception of the MCH-FP project in 1978. The transition matrix in Table 1 thus allows us to study changes in the distribution of contraceptive prevalence from 1978 to 1993.

The numbers to the left of the box in Table 1 describe the distribution of contraceptive prevalence across the 70 villages in the intervention area in 1978, while the numbers above the box describe the corresponding distribution in 1993. The mean of the distribution increases from 0.27 to 0.55 over this period, consistent with the pattern that we saw earlier

[4] Women are more likely to use contraceptives as they get older. However, we have both refreshment and attrition in our data since the sample is restricted to women aged 15–49 and capable of conceiving, at each point in time. This leaves us with a constant average age over the sample period. In a previous version of the paper, we adjusted for age effects at the individual level without changing the aggregate contraceptive prevalence patterns reported in Fig. 1.

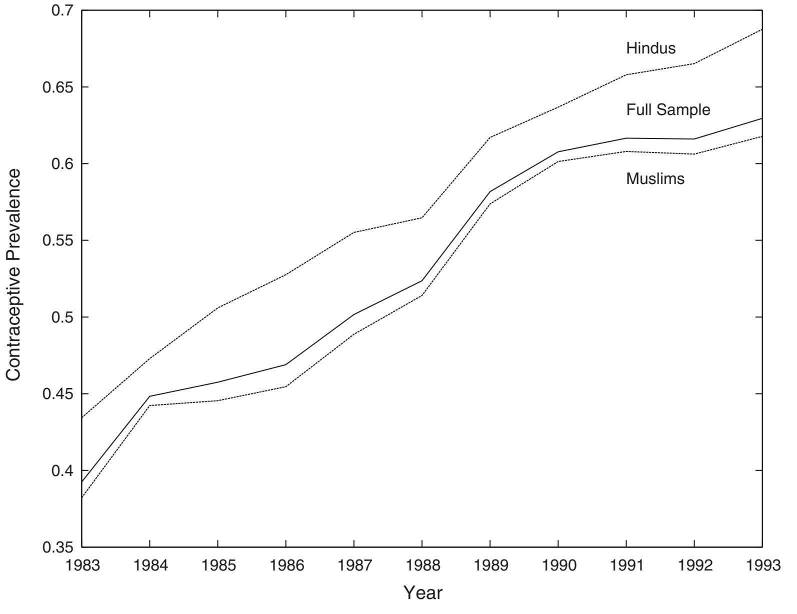

Fig. 1. Contraceptive prevalence over time.

in Fig. 1.[5] Notice, however, that the shape of the distribution, measured by the standard deviation and the inter-quartile range (the difference between the 0.25 and the 0.75 quantiles), is roughly the same in 1978 and 1993.

While the shape of the distribution may not have changed significantly over time, this stability could still mask mobility within the distribution, as villages re-sort, leaving the overall distribution intact. To study such sorting, we turn to the cells within Table 1, which cover all possible transition possibilities in this simple system. For example, the number in the top left hand cell represents the probability that a village which began in the bottom quartile of the distribution in 1978 will remain in the same quartile in 1993. More generally, the numbers along the diagonal of the matrix represent the probability that villages remain in the same quartile that they began in. In the extreme case without state dependence, all the numbers in the transition matrix would be 0.25. Conversely, with complete state dependence, the diagonals would be one and all other cells would be zero. While the diagonal cells, and the cells (horizontally and vertically) adjacent to the diagonal cells, tend to be somewhat larger than 0.25 in Table 1, there is nevertheless a high level of mobility: the probability of remaining in the same quartile is 0.27 on average, and never exceeds 0.33.[6]

[5] The 1993 contraceptive prevalence in Table 1 differs slightly from the corresponding 1993 statistic in Fig. 1 because we are computing the (unweighted) mean across villages, rather than across individuals, in the table.

[6] By way of comparison, Quah (1993) constructs a 5×5 transition matrix describing the change in the distribution of real per capita GDP for 118 countries over a 23-year period (1962–1984). With no state dependence, the probabilities along the diagonals would be 0.20, but in fact, these probabilities are as high as 0.60 on average.

Table 1
Inter-quartile transition probabilities

1978 Distribution, mean 0.27, std.dev. 0.09 \ 1993 Distribution, mean 0.55, std.dev. 0.06		0.25 quantile 0.51	.50 quantile 0.56	0.75 quantile 0.60
	0.33	0.33	0.06	0.28
0.25 quantile 0.21	0.35	0.29	0.24	0.12
0.50 quantile 0.27	0.22	0.22	0.22	0.33
0.75 quantile 0.31	0.12	0.12	0.53	0.24

The intra-distributional mobility that we have just described suggests that initial conditions will not completely describe a village's position, within the contraceptive prevalence distribution, in 1993. Looking down any column in Table 1, we observe a fairly substantial contribution from each row, as expected. This tells us that villages are being drawn from across the 1978 distribution to fill each segment (quartile) of the 1993 distribution. The uncertainty about the reproductive equilibrium that the village will ultimately end up in serves as the starting point for the model of social change that we describe in Section 4.[7]

4. A simple model of social change

Our first objective in this section is to present a model of decentralized social change that can explain the two stylized facts that we described above. The point of departure for the model is a social uncertainty following the introduction of the family planning program: the individual does not know the reproductive equilibrium that her community will ultimately converge to. We will see that this uncertainty is gradually resolved as individuals interact sequentially with each other over time.

There are only two types of individuals in our simple model, which is constructed so that only two possible equilibria can emerge in the long-run. No one regulates fertility prior to the intervention. While this continues to remain a potential equilibrium, we show that a new equilibrium in which a sufficient fraction of the community regulates fertility could also emerge. Much of this section is devoted to studying the process by which some

[7] While contraceptive prevalence increased from 40% to 63% over the 1983–93 period, it had only reached 70% in 1999 (the last year for which official data are available). It thus seems reasonable to assume that individual villages were close to their long-run level at the end of the sample period in 1993.

communities gradually make the transition from the traditional equilibrium to the modern equilibrium, while others remain where they were.

The model can explain both the gradual change as well as the sorting across communities to different long-run contraceptive prevalence levels that we described in Section 3. It also allows us to derive the individual's optimal decision rule during the transition period, which we will later estimate in Section 5.

4.1. Individual payoffs and social equilibria

Each community consists of a continuum of individuals in our simple model of reproductive behavior with social regulation. An individual chooses from two actions at the beginning of each period: the traditional (t) action corresponding to unchecked fertility and the modern (m) action, which refers to fertility control. Subsequently, she is randomly matched with a member of the community.

When reproductive behavior is socially regulated, the individual's payoff from a particular action depends not only on the intrinsic utility that she derives from that action, but also on the social pressure or sanctions that go with it. In our framework, which closely matches Kandori's (1992) characterization of social norms, the individual's payoff depends on her own action, as well as her partner's action, which determines the social sanction that she will face in that period.

Since there are two possible actions, and the individual matches with a single partner in each period, we must consider payoffs corresponding to four combinations of actions:

$$V_i(m,m) = U_i$$

$$V_i(m,t) = U_i - l$$

$$V_i(t,t) = 0$$

$$V_i(t,m) = g.$$

V_i is individual i's payoff at the end of the period, where the first term in parentheses refers to the individual's own action, and the second term refers to her partner's action. U_i is the intrinsic utility that the individual derives from the modern action. There are two types of individuals in our simple model, conformists and reformists, with reformists comprising a fraction P of the community. Conformists have very strong religious convictions, and we take it that they have internalized the religious opposition to reproductive control that we described in Section 2. Thus, they derive lower intrinsic utility from the m action than the reformists; $U_i = v$ for the conformists and $U_i = w > v$ for the reformists.

l and g refer to the punishment and rewards that have been put in place, perhaps by the religious establishment, to regulate reproductive behavior. When a woman who chooses the modern action meets another woman who continues to follow the traditional action, she faces some sort of social censure, which is presumably connected to the religious restrictions that we described in Section 2. The reward g may be associated with enhanced social standing, possibly within a very restricted peer group, for having punished a deviator. Notice that there are no social sanctions when two deviators meet each other.

We impose the following conditions on the payoffs prior to the external intervention: $v>0$, $w-l<0$, $w<g$. Under these conditions, it is easy to verify that a unique equilibrium is obtained in each period, in which both conformists and reformists choose the t action.[8]

Subsequently, we introduce an external intervention, which would correspond to the MCH-FP project in this application. We suppose that the availability of modern contraceptives reduces the inconvenience associated with fertility control, increasing the individual's intrinsic utility from the *m* action by an amount *S*. The conditions on payoffs in the post-intervention regime are the same as what we described above, with one important exception: $v+S>0$, $w+S-1<0$, $w+S>g>v+S$.

It is easy to verify that the traditional equilibrium, without fertility control, continues to be sustainable after the intervention. A new modern equilibrium can also be sustained if the proportion of reformists in the community *P* is sufficiently large. In this equilibrium, all the reformists choose *m* and all the conformists choose *t*. A reformist will not deviate from this equilibrium if the expected payoff from choosing *m* exceeds the expected payoff from choosing *t*

$$P(w+S)+(1-P)(w+S-l)\geq Pg. \tag{1}$$

Simplifying the expression above, a necessary condition to sustain the modern equilibrium is obtained as $P\geq P^*=(l-(w+S)/l-g)$.[9] Communities with $P\geq P^*$ must choose between two equilibria, while only the traditional equilibrium can be supported in communities with $P<P^*$.

4.2. Social uncertainty

The preceding discussion provides an explanation for the divergence across communities, to different reproductive equilibria, following an external intervention. To explain the gradual transition to the long-run equilibrium in each community, we now introduce a social uncertainty. The basic source of uncertainty in our model is that the proportion of reformists *P* is not known to begin with, since each individual's type is private information and both conformists and reformists chose the same traditional action prior to the intervention. To simplify the equilibrium dynamics, we assume that there are two types of communities: stable communities with $\underline{P}<P^*$ reformists and unstable communities with

[8] Each individual's payoff in this equilibrium is zero. No individual will deviate from this equilibrium since $v-1<w-1<0$. Further, it is easy to verify that an equilibrium in which any group of individuals chooses the m action is unstable, since any member of that group would do better by deviating to the *t* action.

[9] Note that $l-(w+S)<l-g$ since $w+S>g$. We also assumed $w+S-l<0$ above. This ensures $0<P^*<1$. All the conformists choose *t* and all the reformists choose *m* in the modern equilibrium. It is easy to verify that no conformist ever wishes to deviate and choose *m* since $v+S-l<0$, $v+S<g$. Note that a modern equilibrium in which only some of the reformists choose *m* is unstable. Take the case of a community with $P>P^*$, where only P^* of the individuals (all of whom are reformists) choose *m*. Clearly, any reformist choosing t in this situation would prefer the *m* action, since the proportion of deviators has reached the P^* threshold.

$\bar{P} > P^*$ reformists. We will see below that information about P is gradually revealed over time as individuals interact with each other, with unstable communities moving to the modern equilibrium while stable communities remain where they were.[10]

While we focus on uncertainty about social fundamentals (the underlying social structure of the community), a model based on strategic uncertainty could also deliver the aggregate patterns that we see in the data. Suppose, for example, that all the communities are unstable, with $\bar{P} > P^*$ reformists. We are still left with a coordination problem, since both the traditional and the modern equilibrium can be sustained in these communities. The standard approach to model this coordination problem would be to perturb the system by exogenously switching a fraction of the community to the m action in period 0. If we assume that individuals mimic their partner's action (in the next period) with a fixed probability, then we are essentially describing the beginning of a contagion. It is well known that if the initial perturbation is sufficiently large, then the community will "tip over" to the modern equilibrium, if not it will return to the traditional equilibrium after a temporary deviation.[11] Thus, the contagion model can explain both the gradual change in behavior as well as the initial uncertainty about the long-run outcome across communities.

There are two reasons why we prefer our model, based on social fundamentals, to this alternative model, based on strategic uncertainty. First, one of the important objectives of this paper is to explain why different communities respond so differently to the same external intervention. For example, every attempt was made to standardize the MCH-FP program across villages, yet we see significant variation in contraceptive use across communities that otherwise look fairly similar. We believe that differences in the underlying social structure, measured by the P parameter in the model, may explain much of the variation in the response to external variations that is typically observed in developing countries. In contrast, the contagion model must rely on differences in the initial perturbation (the external intervention) to generate different long-run equilibria across communities.

A second advantage of our model is that social learning about P occurs in a Bayesian setting (as in Banerjee, 1992, 1993; Bikhchandani et al., 1992). While previous research on social norms (Kandori, 1992; Okuno-Fujiwara and Postlewaite, 1995; Ellison, 1994) has studied how patterns of cooperative behavior can be sustained when any two individuals in the community do not interact repeatedly with each other, to the best of our knowledge, this is the first attempt, using a Bayesian framework, to investigate how the community actually moves from one social equilibrium to the other. The individual's (optimal) decision rule is derived endogenously in our case, and is not simply assumed as in the contagion models described above, or the social interactions literature (Glaeser et al., 1996; Topa, 2001).

[10] While we focus on interactions among the women in this paper, contraception decisions will also in general depend on the attitudes of the men in the community. Since women bear most of the costs of child-bearing and child-rearing, they are typically at the forefront of efforts to regulate fertility in most traditional societies. It may thus be convenient to think of male attitudes as being aligned with those of the local leaders and the religious establishment. Moreover, since there are few restrictions on male mobility, we might expect to see relatively little variation in male attitudes within the village. In terms of the model, these (common) male attitudes may then be seen to determine, in part, the social rules l and g.

[11] For example, see Eshel et al. (1998), or the references cited in Banerjee (1993).

4.3. Equilibrium dynamics

The analysis of the equilibrium dynamics proceeds in three steps. We begin by describing the exogenous perturbation, associated with the MCH-FP project, that is needed to initiate the transition. Subsequently, we describe the change in the distribution of beliefs α, the probability that $P=\bar{P}$, in both stable and unstable communities over the course of the transition. We will show that the distribution of beliefs shifts gradually until $\alpha=0$ for all individuals in the stable communities and $\alpha=1$ for all individuals in the unstable communities in the long run. We finally proceed to map these changes in beliefs into changes in actions (the proportion of m's in the community), deriving the dynamic path from the traditional to the modern equilibrium in the unstable communities, as well as the return to the traditional equilibrium (after some temporary deviation) in the stable communities.

4.3.1. Initiating the transition

All communities are in the traditional equilibrium prior to the external intervention. Immediately following the intervention, they continue to remain in that equilibrium. Since the ICDDR,B has exogenously increased the payoffs from the m action, it is evidently interested in making sure that the reformists in the unstable communities take advantage of the new opportunities that are available. To achieve this objective, it employs Community Health Workers (CHWs) to persuade individuals to choose the modern action.

We make the following assumptions about the exogenous perturbation. First, the CHW remains permanently in place in our model. When describing the contagion model in the previous section, we discussed how an initial perturbation in period 0 was required to move unstable communities to the modern equilibrium. In a Bayesian setting, we will see that beliefs about P, and subsequent decisions, change relatively slowly, so it is necessary to keep the CHWs in place for multiple periods.

While we keep each CHW permanently in place, we maintain the temporary nature of the perturbation by assuming that her ability to influence the individuals that she comes in contact with is temporary. Thus, our second assumption is that the CHW visits a fraction θ of the community in each period, drawn at random, and persuades any reformist that she meets to switch to the m action, but for a single period only. Since there is a continuum of individuals in each community, this implies that a constant fraction θP of the community, where $P=\bar{P}$ in unstable communities and $P=\underline{P}$ in stable communities, deviates exogenously in each period. We will see that this exogenous deviation provides the seed for subsequent endogenous deviation in the unstable communities, which ultimately moves them to the new social equilibrium.

Finally, our third assumption is that the value of θ is common knowledge. If the actions in the community (a fraction θP of the individuals choose m) were also common knowledge, then P would be revealed in the first period itself. Instead, we follow the standard set up in the social norms literature in which each individual matches with a single partner in each period. The decision whether or not to use contraceptives has serious implications for the household's future welfare, and while this decision may change over time, it is difficult to imagine that it will change very frequently. There is also a technological constraint on the frequency with which women can change their fertility behavior; the dominant method of contraception in the intervention area – injectables – is effective for a period of 3 months. Given the severe restrictions on female mobility that we described in Section 2, and the possibility that not all meetings will result in conversations about contraception, it is plausible that the frequency of decision-making and the frequency of social interactions have similar magnitudes in this setting. These low frequencies imply that the sequence of matches over time will only gradually reveal the proportion of reformists in the community.[12]

4.3.2. The change in beliefs

Once we have described the exogenous perturbations to the system, the next step in the analysis is to derive the evolution of beliefs over time. We make the standard rational expectations assumption that the individual correctly predicts the proportion of m's that will be realized in stable and unstable communities at each point in time over the transition. The only source of uncertainty for the individual is the type of community that she belongs to. Let $\alpha_t \in [0, 1]$ be the individual's belief about the state of the world, the probability that $P = \bar{P}$, in period t. The individual uses Bayes' Rule to update her belief from one period to the next, based on her partner's action and the proportion of m's in stable and unstable communities that she knows will be realized in that period. Thus, different individuals will have different beliefs at each point in time, depending on their particular history of matches.

It will be convenient in the discussion that follows to assume a continuous distribution of beliefs in the community at each point during the transition process, although this assumption is relaxed in the simulations that we present later.[13] Let the distribution of beliefs among the reformists in period t be characterized by c.d.f. $\bar{F}_t$, $\underline{F}_t$, in unstable and stable communities respectively.[14]

While the value of P may not be revealed immediately, no one is systematically misinformed through their social interactions in our model. Thus, we would expect that in the long run, beliefs in the unstable communities would pile up at $\alpha = 1$, and in the stable communities at $\alpha = 0$.[15] This process, in which the mass of the distribution shifts to the

[12] If the CHW observes all the individual decisions, then P would be revealed to the external agency in the first period itself. Immediate withdrawal by the external agency would signal in turn whether a community was stable or unstable. In our setting, the ICDDR,B must maintain a permanent standardized program across all the 70 villages to satisfy the research objective of the MCH-FP project. More generally, the external agency may prefer to maintain a long-term presence even in the stable communities in an effort to change preferences (P) or the social rules (l, g), which we treat as stable in our model.

[13] This assumption is clearly inconsistent with the matching process specified in our model. For example, starting with a degenerate belief distribution in period 0, we would have a bimodal distribution in period 1 and it would be many periods before the distribution started to fill out. The assumption that the distribution of beliefs is continuous will, however, simplify the analysis that follows considerably, and we will see that our analytical results match the simulations that we present later (which allow for a discrete distribution) very well.

[14] There is no need to characterize the distribution of beliefs among the conformists since they will choose the traditional action in any case.

[15] The process of learning that we describe in this paper is conceptually related to Banerjee's (1993) characterization of a rumor process. In his model, the delay before individuals meet reveals the state of the world. In our case, individuals match every period; it is the sequence of partners' decisions that ultimately reveals the type of community that the individual belongs to.

right in the unstable communities, and in the opposite direction in the stable communities, is described in Fig. 2.

Let the belief distribution in period t span the range $[\alpha_{Lt}, \alpha_{Rt}]$, where we know from Fig. 2 (and will see below) that the support of the distribution is the same in both stable and unstable communities. Next, denote beliefs α'_{Lt}, α'_{Rt} such that a single match moves the individual's belief from α'_{Lt} to α'_{Lt}, and similarly from α'_{Rt} to α_{Rt}. A belief α is said to lie in the tail of the distribution if $\alpha \in [\alpha_{Lt}, \alpha'_{Lt}]$ or $\alpha \in [\alpha'_{Rt}, \alpha_{Rt}]$. The dynamics that we describe in Fig. 2 can then be expressed as follows:

Proposition 1. *At any belief α, except in the tail of the belief distribution, the flow of beliefs to the right will dominate the flow to the left in unstable communities, $\bar{F}_{t+1}(\alpha) - \bar{F}_t(\alpha) < 0$, whereas the direction of the flow is reversed in stable communities $\underline{F}_{t+1}(\alpha) - \underline{F}_t(\alpha) > 0$.*

The proof is provided in the Appendix. Since the individual matches with a single m or t in each period, the change in beliefs from one period to the next is very restricted. Applying Bayes' Rule, we can define a neighborhood around α, bounded by beliefs $\alpha(L)$ and $\alpha(R)$, which is relevant when determining $\bar{F}_{t+1}(\alpha) - \bar{F}_t(\alpha)$, $\underline{F}_{t+1}(\alpha) - \underline{F}_t(\alpha)$. Only individuals with beliefs in $[\alpha(L), \alpha]$ in period t can shift to the right of α (with a single match) in period $t+1$. Similarly, it is only individuals in $[\alpha, \alpha(R)]$ in period t who can shift to the left of α in period $t+1$. Deriving the probability of shifting and the size of each of these neighborhoods, in stable and unstable communities, it is easy to verify Proposition 1.

As noted, we make the standard rational expectations assumption that the individual correctly predicts the proportion of m's in any unstable community $\bar{x}_t$, as well as the corresponding proportion in any stable community $\underline{x}_t$, when she updates her belief about the type of community that she belongs to in any period t. Proposition 1 is obtained without placing any other restrictions on $\bar{x}_t$, $\underline{x}_t$: for both $\bar{x}_t > \underline{x}_t$ as well as $\bar{x}_t < \underline{x}_t$. Later in this section, we will proceed to map the changes in beliefs that we have just derived into changes in actions, to generate $\bar{x}_t$, $\underline{x}_t$, and complete the characterization of the equilibrium dynamics.

The only complication that is introduced when deriving these changes in beliefs during the transition is that the differences across communities do not apply to beliefs in the tail of

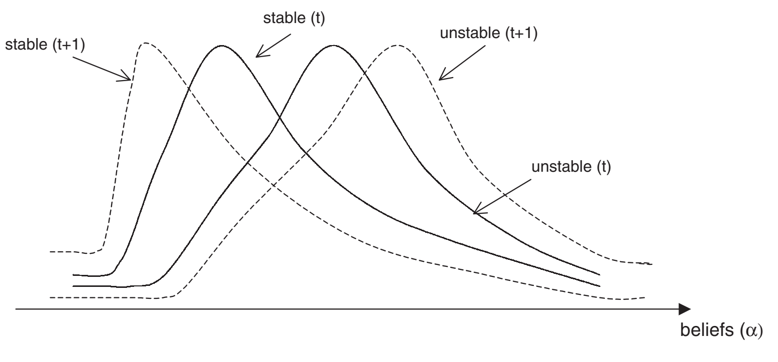

Fig. 2. Change in beliefs over time.

the distribution in any period. For example, consider the lowest belief in the support of the distribution in period t, α_{Lt}. Some individuals just to the right of this belief will certainly shift to the left of it in period $t+1$, depending on whom they match with. Since there are no beliefs to the left of this minimum belief, in period t, the net flow must be to the left in both stable and unstable communities. Similarly, net flows must be to the right of the maximum belief α_{Rt} in both types of communities. This restriction on the change in beliefs is also saying that the support of the distribution of beliefs must be spreading over time in both types of communities, just as we described in Fig. 2. This observation will come in useful below when deriving the change in actions over the transition.

4.3.3. The change in actions

Once we have described how beliefs change over time in the two types of communities, the final step in characterizing the equilibrium dynamics is to map beliefs into actions. Specifically, we want to derive the change in the proportion of m's, $\bar{x}_t$, $\underline{x}_t$, in unstable and stable communities over the transition.

It is convenient to begin with a degenerate distribution of beliefs α_0 in period 0, in both stable and unstable communities, such that no reformist deviates endogenously. Thus, we only observe exogenous deviation in the first few periods: the (constant) proportion of m's in the unstable communities is given by $\bar{x}_t = \theta\bar{P}$, with a corresponding proportion $\underline{x}_t = \theta\underline{P}$ in the stable communities. While contraceptive prevalence might be constant in these early periods, the distribution of beliefs within each community will spread out over time as different individuals are faced with a different sequence of matches.

To derive the evolution of individual beliefs during these early periods without endogenous deviation apply Bayes' Rule to an individual with belief α_t in period t who matches with an m in that period. Her belief α_{t+1} in the subsequent period is then expressed as:

$$\alpha_{t+1} = Pr\left(P = \bar{P}|m\right) = \frac{\alpha_t\left(\theta\bar{P}\right)}{\alpha_t\left(\theta\bar{P}\right) + (1-\alpha_t)\left(\theta\underline{P}\right)}. \tag{2}$$

Since the term in the denominator of Eq. (2) is a weighted average of $\theta\bar{P}$ and $\theta\underline{P}$, it is easy to verify that $\alpha_{t+1}/\alpha_t > 1$. As the individual matches with m's in the community, her belief that $P = \bar{P}$ grows. The right-hand support of the distribution in any period t is thus defined by the beliefs of the individuals in the community who have matched with a continuous sequence of m's up to that period, and so will shift steadily over time.

A reformist will choose the m action in any period, without persuasion from the CHW, if the expected probability of matching with an m exceeds P^* (from Eq. (1)). The expected probability of matching with an m in these early periods is simply $\alpha(\theta\bar{P}) + (1-\alpha)(\theta\underline{P})$, where α is the individual's belief that $P = \bar{P}$. This expected probability is evidently increasing in α. As long as $\theta\bar{P} > P^*$, there exists a threshold belief α^*, for which the individual is indifferent between the t and the m action, satisfying the following condition:

$$\alpha^*\left(\theta\bar{P}\right) + (1-\alpha^*)\left(\theta\underline{P}\right) = P^*. \tag{3}$$

If the individual's belief that $P=\bar{P}$ exceeds α^*, then the expected probability of matching with an m will exceed P^*, and she will deviate endogenously. If not, she will only choose m when she meets the CHW. Following the discussion above, the support of the belief distribution will shift steadily over time in the early periods until ultimately the right-hand support reaches α^*. The first wave of endogenous deviators will now appear, at the same time in both stable and unstable communities.[16]

To describe actions in the community after the first wave of endogenous deviators appears, it will be convenient initially to fix the threshold belief α^* to be the same in every period. The proportion of reformists that has crossed the threshold in any period t is simply $1-\bar{F}_t(\alpha^*)$, $1-\underline{F}_t(\alpha^*)$ in the unstable and stable communities. The outcomes that we are interested in, $\bar{x}_t$, $\underline{x}_t$, measure the proportion of m's in the entire community, so we need to normalize by the proportion of reformists in each case. Taking into account the exogenous deviators who have yet to cross the belief threshold as well, $\bar{x}_t=\bar{P}[1-(1-\theta)\bar{F}_t(\alpha^*)]$, $\underline{x}_t=\underline{P}[1-(1-\theta)\underline{F}_t(\alpha^*)]$. From Proposition 1, we know that beliefs shift to the right in unstable communities $\bar{F}_{t+1}(\alpha^*)<\bar{F}_t(\alpha^*)$, whereas the direction of the flow is reversed in stable communities $\underline{F}_{t+1}(\alpha^*)>\underline{F}_t(\alpha^*)$. It follows directly from the expressions for $\bar{x}_t$, $\underline{x}_t$ above that $\bar{x}_{t+1}(\alpha^*)>\bar{x}_t(\alpha^*)$, $\underline{x}_{t+1}(\alpha^*)<\underline{x}_t(\alpha^*)$: the proportion of m's is monotonically increasing (decreasing) in unstable (stable) communities.

While the result that we have just derived holds for α^* almost everywhere in the distribution of beliefs, recall that Proposition 1 cannot be applied when α^* lies in the tail of the distribution. This would be the case when the first wave of endogenous deviators appears, since we noted earlier that the right-hand support of the distribution α_R just reaches α^* at that point. Beliefs must flow to the right in both types of communities immediately following the first wave, so $\underline{x}_t$ must increase temporarily as well. However, once the support of the distribution has shifted sufficiently to the right of α^*, the result that we derived above begins to apply and $\underline{x}_t$ will decline monotonically thereafter.

The discussion up to this point treated the threshold belief as constant over time. More generally, this threshold belief would be derived endogenously in each period, and α^* would be replaced by α_t^* in the expressions above. Once we allow α_t^* to change over time, we cannot describe the details of the equilibrium dynamics without characterizing the distribution of beliefs at each point in time. We can, however, continue to say something about the early periods, as well as the long-run equilibria, in both types of communities. We know from Proposition 1 that the mass of the distribution of beliefs in the unstable communities will pile up at $\alpha=1$, so as long as α_t^* remains strictly in the interior of the unit interval, the proportion of m's will begin at $\theta\bar{P}$ and end up at $\bar{P}$. Similarly, the stable communities will begin at $\theta\underline{P}$, increase temporarily, and then ultimately return to where they began.

[16] Note the coordinating assumption $\theta\bar{P}>P^*$ embedded above in Eq. (3), which is necessary to support this initial endogenous deviation. Just as with the contagion model, a sufficiently large perturbation (θ) is required to jolt the community to a new equilibrium. Without this coordinating assumption, the equality in that equation would never be satisfied, the first wave would never emerge, and both stable and unstable communities would remain in the traditional equilibrium.

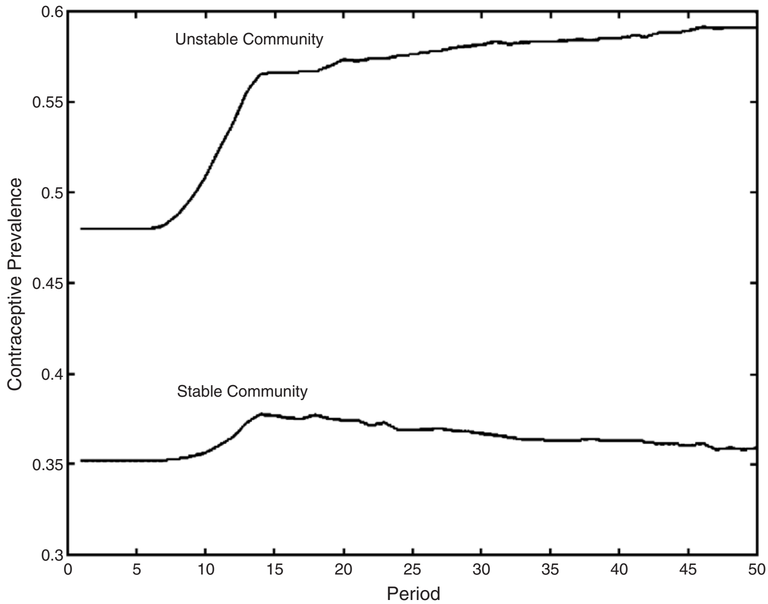

Fig. 3. Simulated contraceptive prevalence—two types.

To fully characterize the equilibrium dynamics, we solve the following system of equations:

$$\alpha_t^* \bar{x}_t + (1 - \alpha_t^*)\underline{x}_t = P^* \tag{4}$$

$$\bar{x}_t = \bar{P}\left[1 - (1 - \theta)\bar{F}_t(\alpha_t^*)\right] \tag{5}$$

$$\underline{x}_t = \underline{P}\left[1 - (1 - \theta)\underline{F}_t(\alpha_t^*)\right]. \tag{6}$$

While the model cannot be solved analytically, it is fairly easy to simulate the equilibrium dynamics, since the system of Eqs. (4)–(6) can be solved independently in each period. Starting with a degenerate distribution of beliefs in the first period, we only need to keep track of each individual's beliefs over time, rather than the entire history of matches, so the simulated distribution of beliefs can be used directly to solve iteratively for α_t^*, $\bar{x}_t$, $\underline{x}_t$ in each period. These simulation results, presented in Fig. 3 above, are very robust to the choice of parameter values and match the general predictions of the model:[17]

Proposition 2. *After an initial delay, the proportion of m's in unstable communities increases over time, starting at $\theta\bar{P}$ and converging to $\bar{P}$ in the long run. After the same*

[17] Parameter values are set at $\theta=0.75$, $\underline{P}=0.375$, $\bar{P}=0.625$, $P^*=0.45$, $\alpha_0=0.4$ with 400 individuals in each community, for the simulations reported in Fig. 3.

delay, and a temporary increase, the proportion of m's in stable communities begins to decline and ultimately returns to $\theta\underline{P}$.

The model with two types can be readily extended to multiple types. In a previous version of the paper, we reported simulations with three types and the convergence to three distinct equilibria. In general, N long-run equilibria can be sustained with N types. In practice, with many types, we would expect to see wide variation in the response across communities to the same external intervention.

4.4. The individual decision rule

Uncertainty about the social fundamentals is resolved over time as individuals interact with each other, and we saw above that communities gradually separate to different long-run equilibria. In the discussion that follows, we will derive the individual decision rule during this transition. The discussion in this section restricts attention to reformists, since conformists always choose the t action.

The individual's decision in period t is determined by her belief, relative to the threshold belief α_t^*. If her belief lies to the right (left) of α_t^*, she will choose the m (t) action. The individual's belief in period t is in turn determined by her belief in period $t-1$, augmented by the change in this belief through the social interaction in that period. It is easy to see that matching with an m will shift her belief to the right, by returning to Eq. (2) and replacing $\theta\bar{P}$, $\theta\underline{P}$ with $\bar{x}_{t-1}$, $\underline{x}_{t-1}$. We saw that $\bar{x}_{t-1} > \underline{x}_{t-1}$ in Fig. 3, and this result is obtained without exception with all the parameter values that we experimented with in that figure. This implies that $\alpha_t / \alpha_{t-1} > 1$ when the individual matches with an m.

There is a high level of state dependence in this system, since it is only individuals with beliefs in a left window $[\alpha(L)_{t-1}^*, \alpha_{t-1}^*]$ or a right window $[\alpha_{t-1}^*, \alpha(R)_{t-1}^*]$, around the threshold belief α_t^*, who can change their actions from period $t-1$ to period t. Individuals in $[\alpha(L)_{t-1}^*, \alpha_{t-1}^*]$ choose the traditional action in period $t-1$, but will switch to the modern action if they match with an m. Similarly, individuals in $[\alpha_{t-1}^*, \alpha(R)_{t-1}^*]$ will switch from the modern to the traditional action if they match with a t. Individuals with beliefs outside $[\alpha(L)_{t-1}^*, \alpha(R)_{t-1}^*]$ will not change their actions, regardless of whom they match with in period $t-1$.[18]

The preceding discussion tells us that the individual's decision in any period will be determined by her belief at the beginning of the previous period, and her social interaction in that period. Since beliefs are unobserved by the econometrician, we will proceed to derive the individual's decision rule in terms of her lagged decision in the discussion that follows.

An additional difficulty that arises when deriving the individual decision rule is that the response to neighbors' decisions will vary within the community at each point in time, depending on each individual's location in the belief distribution (relative to the threshold belief). We will consequently derive the decision rule for a representative individual, drawn randomly from the community, at each point in time during the transition.

[18] $\alpha(L)_{t-1}^*$, $\alpha(R)_{t-1}^*$ can be derived using a straightforward application of Bayes' Rule, as in the Appendix.

Let $y_{it}=1$ if individual i chooses the m action in period t, and let $y_{it}=0$ if she chooses the t action. The probability that $y_{it}=1$, conditional on $y_{it-1}=0$, is the product of two probabilities; the probability of lying in the left window (conditional on $y_{it-1}=0$), and the probability of matching with an m. Since the individual is selected randomly from the community, the probability that her belief will lie in the left window is simply $\Delta F(L)_{t-1}/F_{t-1}(\alpha^*_{t-1})$, where $\Delta F(L)_{t-1} \equiv F_{t-1}(\alpha^*_{t-1}) - F_{t-1}(\alpha(L)^*_{t-1})$. Note that we no longer distinguish between stable and unstable communities, to simplify the exposition. Further, since individuals match randomly with each other within the community, the probability of matching with an m in period $t-1$ is simply x_{t-1}, the proportion of m's in that period.

$$Pr(y_{it} = 1|y_{it-1} = 0) = \frac{\Delta F(L)_{t-1}}{F_{t-1}\left(\alpha^*_{t-1}\right)} x_{t-1}. \tag{7}$$

By the same type of argument, it is easy to derive the corresponding expression for the probability that $y_{it}=1$, conditional on $y_{it-1}=1$. The probability that the randomly selected individual will occupy the right window, conditional on having chosen m in the previous period, is expressed as $\Delta F(R)_{t-1}/1 - F_{t-1}(\alpha^*_{t-1})$, where $\Delta F(R)_{t-1} \equiv F_{t-1}(\alpha(R)^*_{t-1}) - F_{t-1}(\alpha^*_{t-1})$. Recall that individuals who chose m in period $t-1$ will continue with that action unless they lie in the right window and match with a t. Thus, we have

$$Pr(y_{it} = 1|y_{it-1} = 1) = 1 - \frac{\Delta F(R)_{t-1}}{1 - F_{t-1}\left(\alpha^*_{t-1}\right)}(1 - x_{t-1}). \tag{8}$$

Eqs. (7) and (8) are special cases of a general individual decision rule, expressed in terms of the lagged decision and lagged contraceptive prevalence in the community:

$$\begin{aligned} Pr(y_{it} = 1|y_{it-1}) = {} & \frac{\Delta F(L)_{t-1}}{F_{t-1}(\alpha^*_{t-1})} x_{t-1} + \left[1 - \left\{\frac{\Delta F(L)_{t-1}}{F_{t-1}(\alpha^*_{t-1})} x_{t-1}\right.\right. \\ & \left.\left. + \frac{\Delta F(R)_{t-1}}{1 - F_{t-1}(\alpha^*_{t-1})}(1 - x_{t-1})\right\}\right] y_{it-1}. \end{aligned} \tag{9}$$

While the lagged decision y_{it-1} and lagged contraceptive prevalence x_{t-1} are observed by the econometrician, the coefficients in the decision rule are expressed in terms of unobserved underlying beliefs. These beliefs will in general shift over the course of the transition and so we will take care to verify that the main empirical result of the paper – strong within-religion effects and completely absent cross-religion effects within the village – is obtained over the full sample period.[19] An alternative (equivalent) specification of the decision rule separates out the $y_{it-1} \cdot x_{t-1}$ interaction term in Eq. (9). Later in the

[19] These changes in the coefficients on y_{it-1}, x_{t-1} distinguish our Bayesian model from the alternative contagion model, which assumes that individuals mimic their neighbors' actions with a fixed probability (ϕ). With the contagion model, $Pr(y_{it}=1|y_{it-1}=0)=\phi x_{t-1}$, $Pr(y_{it}=1|y_{it-1}=1)=1-\phi(1-x_{t-1})$, and hence, $Pr(y_{it}=1|y_{it-1})=\phi x_{t-1}+(1-\phi)y_{it-1}$. The unobserved beliefs in Eq. (9) must be simulated prior to generating $\bar{x}_{t-1}$, $\underline{x}_{t-1}$ in Fig. 3. In a previous version of the paper, we consequently plotted the change in the coefficients on y_{it-1}, x_{t-1} over the transition period and subsequently empirically verified that these coefficients did in fact shift over time as predicted by the learning model.

empirical section, we will verify that the main result is obtained with this alternative specification of the contraception decision rule as well.

5. Individual level empirical analysis

This section begins with a brief description of the data in Section 5.1. Subsequently we discuss the identification problem in Section 5.2. A spurious relationship between the individual's contraception decision and neighbors' lagged decisions could be obtained if unobserved determinants of contraceptive use are correlated within the village. However, our characterization of the fertility transition as a process of changing social norms implies that the relevant social interactions should be restricted to the individual's religious group within the village. The village is consequently partitioned by religion in Section 5.3. Strong within-religion effects are obtained, while cross-religion effects are completely absent, as predicted. In contrast, strong cross-group effects are consistently obtained when the village is partitioned by age and education in Section 5.4. These empirical results, taken together, allow us to rule out alternative explanations for the estimated social effects in Section 5.5.

5.1. The data

Descriptive statistics for the women in our sample are presented in Table 2. Recall that the sample consists of all women, 15–49 years, married and capable of conceiving, residing in the intervention area at each point in time over the 1983–93 period. We provide these statistics for the full sample, as well as for sub-samples in which the women are divided by religion and by level of education, since these variables will later be used to partition the village in the contraception regression.

Starting with individual characteristics in panel A, we see that the women are on average 29 years old, with 2.4 children. Note that the number of children under-estimates the ultimate family-size since many households will continue to produce children in the future. The women in our sample have roughly 2 years of education, while their husbands have on average 1 more year of schooling. Looking across columns in panel A, we see qualitatively similar statistics for Hindus and Muslims, as well as for illiterate versus literate women.

Next we turn to the occupation of the household head in panel B, using data from a Socioeconomic Census that was conducted by the ICDDR,B in Matlab thana in 1982. Starting with the full sample in Column 1, the traditional occupations, farming and fishing, maintain their importance, followed by business, which in this setting refers essentially to petty trade. Looking across columns, the occupational choices are roughly comparable, with one exception: 26% of the Hindus and less than 2% of the Muslims are fishermen. Comparing Column 1 with Columns 4 and 5, we also see that fishermen are disproportionately illiterate. From our conversations with MCH-FP field-staff, it appears that the fishermen tend to be socially conservative and may form a distinct group, which we will take account of later in the estimation section.

Finally, we look at asset ownership, also obtained from the 1982 Census, in panel C. Land, cows and boats are the main assets, and once more, we see similar patterns across religious groups and education categories.

Table 2
Descriptive statistics

	Full sample	Hindus	Muslims	Illiterate	Literate
	(1)	(2)	(3)	(4)	(5)
Panel A: Individual characteristics					
Age	29.44 (8.01)	29.91 (8.00)	29.34 (8.01)	30.49 (8.18)	27.75 (7.44)
Number of children	2.41 (1.99)	2.18 (1.79)	2.45 (2.03)	2.57 (2.05)	2.14 (1.86)
Education	2.12 (3.12)	1.48 (2.68)	2.26 (3.19)	0.00–	5.53 (2.55)
Husband's education	3.21 (4.00)	3.07 (3.81)	3.24 (4.04)	1.53 (2.62)	5.91 (4.34)
Panel B: Occupation of household head (%)					
Farming	34.48	23.45	36.88	30.32	41.16
Fishing	5.80	26.18	1.37	8.07	2.15
Business	6.75	8.37	6.40	6.30	7.47
Housework	10.46	6.81	11.26	10.00	11.21
Other	42.51	35.20	44.10	45.31	38.01
Total	100.00	100.00	100.00	100.00	100.00
Panel C: Asset ownership					
Land (hectares)	1.00 (2.55)	0.72 (1.39)	1.06 (2.74)	0.82 (2.41)	1.29 (2.74)
Cows	1.06 (1.57)	0.81 (1.42)	1.11 (1.59)	0.91 (1.46)	1.28 (1.70)
Boats	0.55 (0.61)	0.63 (0.76)	0.54 (0.57)	0.55 (0.61)	0.56 (0.60)
No. of Observations	21,570	3847	17,723	13,288	8282
Panel D: Contraceptive prevalence					
Probability of using contraceptives	0.55 (0.50)	0.59 (0.49)	0.54 (0.50)	0.53 (0.50)	0.57 (0.50)
No. of Observations	144,186	26,414	117,772	91,727	52,459

Means (standard deviations) in panel A, panel C and panel D.
The individual is the unit of observation in panels A–C. The individual-year is the unit of observation in panel D. All statistics in this table are computed over the full 1983–93 sample period.

While we could reject the hypothesis that the means across religious groups are equal for most of the variables in Table 2, these statistics are generally of comparable magnitude. The two religious groups display qualitatively similar demographic characteristics, occupational patterns, and asset ownership, yet we will later see what appears to be absolutely no interaction, with regard to contraceptive use, within the village.

We complete this section by reporting average contraceptive prevalence, for the full sample as well as for the different groups of women in panel D. Contraceptive prevalence is roughly 55% over the sample period, and it is about 5 percentage points higher for the Hindus and the literate women, relative to their respective comparison groups (these differences are statistically significant).[20]

[20] Annual (December 31) data are used to compute the statistics in panel D. The number of observations in panel D is larger than the number of observations in the regressions that we report later using annual data because we compute all the statistics in panel D over the full 1983–93 sample period. In contrast, we must drop the first year (1983) in the regressions since the lagged decision and lagged contraceptive prevalence are included as regressors.

5.2. The identification problem

The model assumes implicitly that the individual would choose to use contraceptives in every period if the social environment is favorable. In practice, women who have not achieved their desired family-size will periodically discontinue using contraceptives to produce children, even when social restrictions are absent. Since the frequency of such temporary discontinuation will be strongly (negatively) correlated with the woman's age, we augment Eq. (9) by including age and age squared as additional controls in the contraception regression.

Further, the model assumes that the only change in the intervention area is caused by the introduction of modern contraceptives. But unobserved changes in the MCH-FP project or the economic environment over the sample period could also (spuriously) generate a role for neighbors' past decisions (x_{t-1}) in the contraception regression; neighbors' decisions simply proxy for the unobserved changes in this case. Since contraceptive prevalence information is available across multiple villages, we will control for secular changes by including time effects in some of the regressions that we report.

Unobserved individual characteristics could also generate a spurious role for neighbors' past decisions in the contraception regression to the extent that these characteristics are correlated within the village. Since we have panel data, we will check the robustness of all our results by including individual fixed effects in the contraception regression. Fixed effects control for observed time-invariant characteristics, such as religion and education, as well as for the woman's unobserved type; recall from Section 4 that while reformists change their behavior over the transition period, the conformists never use contraceptives.[21]

An augmented version of the individual decision rule, Eq. (9), that includes the control variables described above as well as unobserved determinants of the contraception decision, but treats the coefficients on y_{it-1}, x_{t-1} as being stable over time, can be written as

$$y_{it} = \alpha + \gamma y_{it-1} + \beta E_{t-1,v}(y_{it-1}) + X_{it}\eta + C_t^v + \xi_{it} \tag{10}$$

where $E_{t-1,v}(y_{it-1})$ is the expected level of contraceptive prevalence in the village in period $t-1$, which corresponds to x_{t-1} in the model. X_{it} is a vector of control variables, which includes the woman's age, age squared, and (in some cases) time effects and individual fixed effects. C_t^v is any unobserved determinant of the contraception decision that varies across villages and over time. In this setting C_t^v reflects unobserved individual characteristics that are correlated within the village, as well as changes in the economic

[21] We are thus identified in the fixed effects regressions from changes in behavior among the non-conformists alone. It would not make much sense to include fixed effects and the lagged dependent variable if we did not observe switches, in both directions, between contraceptive use and non-use from 1 year to the next. Computing sample statistics for all possible transition probabilities over the 1983–93 period, we obtain: non-use to non-use 33%, non-use to use 13%, use to non-use 10%, and use to use 44%.

environment or the MCH-FP project that are village specific. ξ_{it} is a mean-zero disturbance term. Since the individual decision rule, Eq. (9), is linear in variables, it is appropriate to use the Linear Probability model for estimation.[22]

To see the identification problem that arises in this case, lag Eq. (10) by one period and take expectations across individuals within the village,

$$E_{t-1,v}(y_{it-1}) = \alpha + (\gamma + \beta)E_{t-2,v}(y_{it-2}) + E_{t-1,v}(X_{it-1})\eta + C^{v}_{t-1}. \tag{11}$$

It is easy to verify from Eqs. (10) and (11) that $E_{t-1,v}(y_{it-1})$ will proxy for C^v_t when the omitted variable is auto-correlated. In general, a role for neighbors' decisions cannot be identified when the omitted variable is correlated across individuals in the village and over time. We avoid this problem to some extent by including individual characteristics in X_{it}; the fixed effects in particular will control for any time-invariant determinants of the contraception decision. Time effects will also control for secular changes that are common to all the villages. But we cannot control for unobserved village-specific variation over time.[23]

Our solution in this paper, to provide additional support for the view that social interactions shift social norms and, hence, reproductive behavior takes advantage of the institutional background that we presented in Section 2. Social norms will be organized at the level of the religious group in rural Bangladesh and we noted in that section that the very infrequent female social interactions in these villages will almost never cross religious boundaries. Thus, we would expect individuals to respond to contraceptive prevalence within their own religious group within the village, while cross-religion effects should be completely absent.

To test these predictions of our norm-based theory of reproductive change, we will estimate separate contraception regressions for each religion, allowing for within-religion and cross-religion effects. Muslim (M) individuals are identified by an i subscript, with a j subscript for Hindus (H). $E_{t-1,\mathrm{M}v}(y_{it-1})$ represents the average adoption among the eligible Muslims in village v in period $t-1$. $E_{t-1,\mathrm{H}v}(y_{jt-1})$ represents the corresponding statistic for Hindus in the village. Note that we now allow for religion-specific omitted variables $C^{\mathrm{M}v}_t$, $C^{\mathrm{H}v}_t$ in the contraception regressions.

$$y_{it} = \alpha_{\mathrm{M}} + \gamma_{\mathrm{M}} y_{it-1} + \beta_{\mathrm{MM}} E_{t-1,\mathrm{M}v}(y_{it-1}) + \beta_{\mathrm{MH}} E_{t-1,\mathrm{H}v}\left(y_{jt-1}\right) + X_{it}\eta_M + C^{\mathrm{M}v}_t + \xi_{it}. \tag{12}$$

[22] An additional advantage of the linear probability model over the more standard discrete choice models in this application is that the lagged dependent variable, individual fixed effects and time-varying characteristics can be included in the contraception regression (Maddala, 1987). As a robustness check, we also experimented with a logit model to estimate Eq. (10). Our estimates are qualitatively the same with the logit and the linear probability model.

[23] The health component of the MCH-FP project was very successful, with child mortality rates (per thousand live births) declining from 170 deaths in 1983 to 85 deaths in 1993. We included village-specific child mortality in the contraception regressions to check the robustness of our results. While these results are not reported here, the coefficient on mortality is negative and significant as expected, but the other coefficients in the regression are completely unchanged. While this test allows us to control for village-specific change along one dimension, we cannot control for other unobserved determinants of contraceptive behavior that could vary across villages and over time.

$$y_{jt} = \alpha_{\mathrm{H}} + \gamma_{\mathrm{H}} y_{jt-1} + \beta_{\mathrm{HM}} E_{t-1,\mathrm{M}v}(y_{it-1}) + \beta_{\mathrm{HH}} E_{t-1,\mathrm{H}v}(y_{jt-1}) + X_{jt}\eta_H + C_t^{\mathrm{H}v} + \xi_{jt}. \tag{13}$$

Following the discussion above, we would expect that $\beta_{\mathrm{MM}}>0$, $\beta_{\mathrm{HH}}>0$, $\beta_{\mathrm{MH}}=\beta_{\mathrm{HM}}=0$. We will see later that the estimation results precisely match these predictions, providing strong support for the view that social interactions, within each religious group, gave rise to changes in contraceptive use. These results are also useful in ruling out the possibility that neighbors' decisions simply proxy for unobserved determinants of the contraception decision $C_t^{\mathrm{M}v}$, $C_t^{\mathrm{H}v}$. In the discussion that follows, we derive conditions that these omitted variables must satisfy to spuriously generate the observed within-religion and cross-religion effects. Later in Section 5.5, we will argue that the omitted variables that we would expect to encounter in this setting are unlikely to satisfy these conditions.

Consider an alternative model without social interactions:

$$y_{it} = \alpha_{\mathrm{M}} + \gamma_{\mathrm{M}} y_{it-1} + X_{it}\eta_M + C_t^{\mathrm{M}v} + \xi_{it} \tag{14}$$

$$y_{jt} = \alpha_{\mathrm{H}} + \gamma_{\mathrm{H}} y_{jt-1} + X_{jt}\eta_H + C_t^{\mathrm{H}v} + \xi_{jt}. \tag{15}$$

$E_{t-1,\mathrm{M}v}(y_{i-1})$, $E_{t-1,\mathrm{H}v}(y_{jt-1})$ no longer belong in the contraception regressions, but could the $E_{t-1,\mathrm{M}v}(y_{it-1})$ term in Eq. (12) and the $E_{t-1,\mathrm{H}v}(y_{jt-1})$ term in Eq. (13) simply proxy for the unobserved $C_t^{\mathrm{M}v}$, $C_t^{\mathrm{H}v}$ terms in this case? They could, for exactly the same reason that we described above for the village-level regression. Taking expectations in Eq. (14) and lagging one period, $E_{t-1,\mathrm{M}v}(y_{it-1})$ is correlated with $C_{t-1}^{\mathrm{M}v}$. Similarly, $E_{t-1,\mathrm{H}v}(y_{jt-1})$ would be correlated with $C_{t-1}^{\mathrm{H}v}$. So spurious $\hat{\beta}_{\mathrm{MM}}$, $\hat{\beta}_{\mathrm{HH}}$ estimates could be obtained if $C_t^{\mathrm{M}v}$, $C_t^{\mathrm{H}v}$ are auto-correlated.

But what about the cross-religion effects? $E_{t-1,\mathrm{M}v}(y_{it-1})$ cannot perfectly proxy for $C_{t-1}^{\mathrm{M}v}$ on account of the $E_{t-2,\mathrm{M}v}(y_{it-2})$ and $E_{t-1,\mathrm{M}v}(X_{it-1})$ terms that correspond to y_{it-1} and X_{it} in Eq. (14), once we have lagged that equation by one period and taken expectations. This leaves room for $E_{t-1,\mathrm{H}v}(y_{jt-1})$ to appear as an additional proxy for $C_{t-1}^{\mathrm{M}v}$. Cross-religion effects in the Muslim regression can only be absent if $E_{t-1,\mathrm{H}v}(y_{jt-1})$ provides no information about $C_{t-1}^{\mathrm{M}v}$. A necessary condition for this result is that $C_t^{\mathrm{M}v}$ and $C_t^{\mathrm{H}v}$ should be orthogonal. Similarly, if $E_{t-1,\mathrm{M}v}(y_{it-1})$ has no role to play in the Hindu regression, then $C_t^{\mathrm{M}v}$, $C_t^{\mathrm{H}v}$ must be orthogonal.

To explain the estimated pattern of weights $\hat{\beta}_{\mathrm{MM}}>0$, $\hat{\beta}_{\mathrm{HH}}>0$, $\hat{\beta}_{\mathrm{MH}}=0$, $\hat{\beta}_{\mathrm{HM}}=0$ without social effects, the omitted variables $C_t^{\mathrm{M}v}$, $C_t^{\mathrm{H}v}$ must be orthogonal within the village. We will argue later in Section 5.5 that it is difficult to imagine that potential omitted variables such as program effects or economic change are completely uncorrelated across religious groups within the same village. In contrast, the social norms that lie at the heart of our story of social change are organized at the level of the religious group within each village.

5.3. Estimation results: partitioning the village by religion

Contraceptive prevalence, separately for Hindus and Muslims, together with the individual's lagged decision are now included as determinants of the contraception decision. The contraception regression will be estimated separately for Hindus and

Table 3
Partitioning the village by religion

	Dependent variable: contraception							
	All villages		More than 5% Hindus/Muslims		More than 15% Hindus/Muslims		Annual data	
	Muslims	Hindus	Muslims	Hindus	Muslims	Hindus	Muslims	Hindus
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged contraceptive prevalence (own group)	0.217	0.161	0.193	0.169	0.207	0.168	0.312	0.246
	(0.013)	(0.014)	(0.016)	(0.017)	(0.018)	(0.020)	(0.023)	(0.023)
Lagged contraceptive prevalence (other group)	0.008	0.009	0.007	0.024	− 0.001	0.019	0.009	0.006
	(0.006)	(0.007)	(0.011)	(0.016)	(0.013)	(0.024)	(0.011)	(0.012)
Lagged contraception	0.698	0.712	0.704	0.710	0.706	0.717	0.498	0.517
	(0.003)	(0.005)	(0.004)	(0.005)	(0.004)	(0.006)	(0.005)	(0.008)
R^2	0.513	0.559	0.520	0.558	0.521	0.565	0.281	0.338
Number of observations	139,875	43,101	79,927	29,771	49,730	20,756	70,787	21,419
Box–Pearson Q statistic	0.000	0.003	0.001	0.002	0.002	0.006	0.003	0.008

Standard errors in parentheses.
Standard errors are robust to heteroskedasticity and correlated residuals within each village-period.
$Q \sim X_1^2$ under H_0: no serial correlation. The critical value above which the null is rejected at the 5% significance level is 3.84.
Columns 1–2: Sample includes all mixed-religion villages.
Columns 3–4: Sample restricted to villages with more than 5% Hindus and Muslims.
Columns 5–6: Sample restricted to villages with more than 15% Hindus and Muslims.
Columns 7–8: Annual data.

Muslims, in most of the specifications that we consider in this section. Age and age squared are included as control variables. The coefficient on the individual's age is positive, the coefficient on age squared is negative, and both these coefficients are very precisely estimated, without exception.

The first regression in Columns 1–2 of Table 3 considers all villages and we see that strong within-religion effects are obtained, while cross-religion effects are entirely absent, both for Hindus and Muslims. While these results are very promising, one cause for concern is that villages may be predominantly of one religion or the other. In the extreme case, all the within-religion effects could be obtained from villages that consist exclusively of households belonging to a particular religion, which would leave no room at all for cross-religion effects. Although we do not see this sort of segregation in the data, some villages are dominated by a single religion. We consequently proceed to remove all villages with less than 5% Hindus or Muslims from the sample in Columns 3–4. Thereafter, we discard villages with less than 15% Hindus or Muslims in Columns 5–6. The sample size declines substantially over the course of this exercise, and is less than half the size of what we began with. Yet we see that the estimated within-religion and cross-religion effects, for both Hindus and Muslims, remain remarkably stable across the different sample sizes in Table 3.[24]

[24] In a related robustness test, we also verified that the size of the village, measured by the total number of eligible women, has no effect on the estimated within-religion and cross-religion effects.

We have contraception data at two points in the year, June 30 and December 31, and so most of the regressions in this paper are estimated using 6-monthly data. The major disadvantage of using relatively high frequency 6-monthly data is that we are left with a narrow belief window in each period, $\Delta F(L)$, $\Delta F(R)$ are small in Eq. (9), which results in an extremely high level of state dependence. Annual data permit individuals with beliefs in a wider range around the threshold belief to change their behavior from one period to the next, increasing the response to neighbors' decisions but otherwise leaving all the implications of the previous section intact. We complete Table 3 by running the contraception regression with annual data in Columns 7–8. Comparing the estimates using annual data with the corresponding estimates using 6-monthly data in Columns 1–2, we see that the coefficient on the lagged decision declines substantially, while there is a corresponding increase in the within-religion effect, as expected. Nevertheless, the usual pattern of strong within-religion effects and absent cross-religion effects continues to be obtained for both Hindus and Muslims.

Subsequently, we check the robustness of our results to alternative specifications of the contraception regression in Table 4. While we have assumed this far in the empirical analysis that the coefficient on the lagged decision (y_{it-1}) and lagged contraceptive prevalence (x_{t-1}) are stable, Eq. (9) tells us that these coefficients should actually shift over the course of the fertility transition. We consequently proceed to partition the sample

Table 4
Partitioning the village by religion—alternative specifications

	Dependent variable: contraception							
	1983–1986		1987–1989		1990–1992		With interactions	
	Muslims	Hindus	Muslims	Hindus	Muslims	Hindus	Muslims	Hindus
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged contraceptive prevalence (own group)	0.157	0.137	0.237	0.129	0.191	0.109	0.308	0.256
	(0.025)	(0.023)	(0.024)	(0.028)	(0.034)	(0.032)	(0.021)	(0.023)
Lagged contraceptive prevalence (other group)	− 0.025	0.004	0.028	− 0.010	0.007	0.021	0.013	0.030
	(0.013)	(0.016)	(0.012)	(0.009)	(0.010)	(0.013)	(0.011)	(0.012)
Lagged contraception	0.744	0.752	0.682	0.701	0.681	0.691	0.798	0.831
	(0.004)	(0.007)	(0.005)	(0.007)	(0.005)	(0.008)	(0.014)	(0.017)
Lagged prevalence–lagged contraception (own group)	–	–	–	–	–	–	− 0.180	− 0.182
							(0.027)	(0.030)
Lagged prevalence–lagged contraception (other group)	–	–	–	–	–	–	− 0.011	0.031
							(0.014)	(0.018)
R^2	0.564	0.609	0.483	0.535	0.481	0.518	0.513	0.560
Number of observations	37,985	12,531	45,705	14,637	56,185	15,933	139,875	43,101
Box–Pearson Q statistic	0.033	0.043	0.004	0.000	0.004	0.002	0.000	0.001

Standard errors in parentheses.
Standard errors are robust to heteroskedasticity and correlated residuals within each village-period.
$Q \sim X_1^2$ under H_0: no serial correlation. The critical value above which the null is rejected at the 5% significance level is 3.84.
Columns 1–6: Sample is partitioned into shorter time periods.
Columns 7–8: Lagged contraceptive prevalence–lagged contraception interaction included as additional regressor.

into three periods: 1983–86, 1987–89, 1990–92, and then verify that a strong within-religion effect continues to be obtained in each period, whereas cross-religion effects are absent, in Table 4, Columns 1–6.

We mentioned earlier that Eq. (9) could be re-specified to include an additively separable interaction term $y_{it-1} \cdot x_{t-1}$. Table 4, Columns 7–8, include y_{it-1}, x_{t-1}, $y_{it-1} \cdot x_{t-1}$ as regressors and the usual within-religion and cross-religion patterns continue to be obtained as expected.

As a further check on the robustness of the results, we include time effects and then individual fixed effects as controls in the contraception regression in Table 5, Columns 1–4. The estimated coefficients when a full set of 6-monthly dummies is included in Table 5, Columns 1–2 are very similar to what we obtained without these additional controls in Table 3, Columns 1–2. In contrast, all the coefficients decline in size when the individual

Table 5
Partitioning the village by religion—robustness tests

	Dependent variable: contraception									
	Time period dummies		Fixed effects		With bari adoption		Without fishermen		CHW effect	
	Muslims	Hindus	Muslims	Hindus	Muslims	Hindus	Muslims	Hindus	CHW's religion	Other religion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged contraceptive prevalence (own religious group)	0.206 (0.016)	0.137 (0.016)	0.142 (0.022)	0.113 (0.025)	0.194 (0.013)	0.140 (0.015)	0.220 (0.013)	0.161 (0.016)	0.236 (0.011)	0.149 (0.015)
Lagged contraceptive prevalence (other religious group)	0.009 (0.006)	0.008 (0.007)	0.006 (0.008)	0.020 (0.012)	0.007 (0.006)	0.008 (0.007)	0.006 (0.006)	0.019 (0.010)	− 0.001 (0.005)	0.054 (0.015)
Lagged decision	0.698 (0.003)	0.712 (0.005)	0.484 (0.002)	0.497 (0.004)	0.697 (0.003)	0.711 (0.005)	0.697 (0.003)	0.705 (0.005)	0.702 (0.003)	0.715 (0.005)
Bari adoption	–	–	–	–	0.028 (0.004)	0.028 (0.006)	–	–	–	–
R^2	0.514	0.560	0.479	0.525	0.513	0.559	0.511	0.548	0.527	0.547
Number of observations	139,875	43,101	139,875	43,101	132,132	40,869	136,847	32,064	152,535	39,630
Box–Pearson Q statistic	0.000	0.004	0.019	0.027	0.000	0.001	0.001	0.001	0.002	0.009

Standard errors in parentheses.
Standard errors are robust to heteroskedasticity and correlated residuals in each village-period.
$Q \sim X_1^2$ under H_0: no serial correlation. The critical value above which the null is rejected at the 5% significance level is 3.84.
Columns 1–2: Full set of (6-monthly) time period dummies included as control variables.
Columns 3–4: Individual fixed effects included as control variables.
Columns 5–6: Include bari level contraceptive prevalence.
Columns 7–8: Fishermen dropped from the sample.
Column 9: Individuals that share the same religion as the CHW. Column 10: Individual and CHW have different religions.
Age, age squared are included as control variables in all regressions.

fixed effects are included in Table 5, Columns 3–4, although the basic within-religion and cross-religion patterns continue to be obtained.[25]

Continuing with these robustness tests, while the village is treated as the social unit for much of the analysis in this paper, it may be less important as a social institution in Bangladesh as compared with the rest of South Asia (Arthur and McNicoll, 1978). On average ten households form one bari, and since all the households in a bari share the same religion, within-religion effects could simply proxy for underlying heterogeneity at the level of the bari. We consequently include bari-level contraceptive prevalence as an additional regressor in the contraception equation. While positive and statistically significant bari effects are obtained in Columns 5–6 of Table 5, the estimated within-religion and cross-religion effects remain very stable when compared with Columns 1–2 of Table 3.[26]

Further, we noted in Table 2 that fishermen, who display relatively low levels of education and tend to be socially conservative, are disproportionately Hindu. One possibility in this case is that the observed within-religion and cross-religion effects simply proxy for an underlying occupation effect. We have already accounted for any characteristics that do not vary over time in the fixed effects regressions, but a more stringent test would exclude fishermen entirely from the sample. Comparing the coefficients in Columns 7–8 with the coefficients in Table 3, Columns 1–2, we see that the estimates are very robust to the omission of the fishermen.

Finally, suppose that social interactions are absent but that the Community Health Worker (CHW) can only induce members of her own religious group to change their behavior over time.[27] Changes in within-religion contraceptive prevalence will then proxy for changes in the CHW's persuasive ability, but only among women who share her religion. Within-religion effects will be absent among the women in the village who do not share the CHW's religion. Further, cross-religion effects will be absent for all women. CHWs are typically drawn from the dominant group in the village, so most women in the

[25] One explanation for the decline in the point estimates when fixed effects are included is that we are controlling for unobserved heterogeneity, which may have previously biased the coefficient on the lagged decision as well as the response to neighbors' decisions. However, it is also well known that within-estimation to eliminate fixed effects gives rise to inconsistent estimates when the lagged dependent variable is included as a regressor. Correlation of the order $(1/T)$, where T is the number of time periods, is created between the lagged dependent variable and the residuals in the transformed model (Hsiao, 1986). Since $T=6$ on average in our data, this bias could be significant.

[26] Along the same lines, we experimented with the twice-lagged individual decision as an additional regressor in the contraception regression. The coefficient on this variable is precisely estimated, although small in magnitude, presumably because it is picking up unobserved heterogeneity in the contraception equation. The estimated within-religion and cross-religion effects, however, are completely unaffected by the inclusion of this additional variable.

[27] The assumption that the CHW completely ignores the members of the other religious group, or that they completely ignore her, is very strong. Later in Section 5.5, we will argue that it is difficult to imagine that she would provide orthogonal inputs to the two religious groups within the village or, more generally, that she would have an orthogonal impact on the two groups.

Table 6
Alternative partitions of the village—age and education

	Dependent variable: contraception							
Cut-off:	0.50 quantile age		0.75 quantile age		Literacy		0.75 quantile education	
Group:	< 0.50	> 0.50	< 0.75	> 0.75	Illiterate	Literate	< 0.75	> 0.75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged contraceptive prevalence (own group)	0.206	0.116	0.217	0.055	0.154	0.126	0.174	0.084
	(0.017)	(0.011)	(0.012)	(0.011)	(0.012)	(0.016)	(0.011)	(0.019)
Lagged contraceptive prevalence (other group)	0.097	0.030	0.045	0.043	0.067	0.083	0.040	0.128
	(0.016)	(0.011)	(0.010)	(0.013)	(0.011)	(0.016)	(0.009)	(0.021)
Lagged contraception	0.620	0.793	0.661	0.851	0.714	0.684	0.712	0.675
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)
R^2	0.401	0.652	0.466	0.738	0.544	0.495	0.539	0.481
Number of observations	121,050	119,585	182,762	57,873	154,077	86,558	185,092	55,095
Box–Pearson Q statistic	1.200	0.125	0.048	0.221	0.008	0.002	0.007	0.007

Standard errors in parentheses.
Standard errors are robust to heteroskedasticity and correlated residuals in each village-period.
$Q \sim X_1^2$ under H_0: no serial correlation. The critical value above which the null is rejected at the 5% significance level is 3.84.
Columns 1 to 4 : Partition the village by age.
Columns 1–2: 0.5 age quantile cut-off. Columns 3–4: 0.75 age quantile cut-off.
Columns 5–8: Partition the village by education.
Columns 5–6: Literacy cut-off. Columns 7–8: 0.75 education quantile cut-off.

sample will share the same religion as the local CHW.[28] The unobserved CHW-effect that we have just described could, in principle, have generated both the within-religion effects, as well as the absence of cross-religion effects, that we see in the data.

To rule out this possibility, individuals from both religions are pooled together in Columns 9–10 of Table 5. Column 9 restricts attention to individuals that share the same religion as the CHW and Column 10 restricts attention to individuals who do not share her religion. Strong within-religion effects continue to be obtained with both groups of individuals, ruling out the alternative CHW-based explanation, while the cross-religion effects are absent as usual.

5.4. Estimation results: alternative partitions of the village

We complete the empirical analysis by partitioning the village, separately by age category and by level of female education, in Table 6. What within-group and cross-group effects would we expect to see with these alternative partitions of the village? There are two independent mechanisms that generate particular within-group and cross-group patterns in this case.

[28] 85% of the village-periods in our panel are characterized by a Muslim-majority population. 83% of the CHWs in village-periods with a Muslim majority are Muslim. 92% of the CHWs in village-periods with a Hindu majority are Hindu.

First, while we assume for simplicity that individuals match randomly within the village, peer groups tend to consist of individuals with similar characteristics in practice. We would thus expect individuals to place more weight on their own group in the contraception regression, everything else being equal.

Second, in our Bayesian setting, the weight that an individual places on her partner's decision in each period will depend on the amount of information that she receives, from that interaction, about the nature of the social equilibrium that will ultimately prevail. Partition the community into G groups with different observed characteristics, and apply Bayes' Rule to derive the posterior belief when any individual with belief α matches with an m from some group g:

$$Pr(P = \bar{P}|m_g) = \frac{1}{1 + \left(\frac{1-\alpha}{\alpha}\right)\underline{x}_{tg}/\bar{x}_{tg}}$$

where $\underline{x}_{tg}$, $\bar{x}_{tg}$ refers to the proportion of m's among the members of the g group in stable and unstable communities respectively. Clearly a lower $\underline{x}_{tg}/\bar{x}_{tg}$ implies a stronger response to the m-match. In general, a group whose behavior is less sensitive to the type of community will wield less social influence. In the extreme case, if $\underline{x}_{tg}=\bar{x}_{tg}$, then it is easy to verify from the expression above that the posterior belief will be equal to the prior belief, no information will be provided through the social interaction, and the members of that group will carry zero weight.

In general, we would expect groups with a greater propensity to choose the m action (with a lower P^* in the model) to be less sensitive to the type of community they belong to. Since older women and more educated women are more likely to use contraceptives at each point in time over the sample period, our learning model predicts that they should have less influence in the contraception regression, everything else being equal.

As usual within-group and cross-group contraceptive prevalence, and the lagged decision, are included as regressors in the contraception equation. Control variables include the woman's age and age squared.[29] The village is divided into two age categories in Columns 1–2 of Table 6, using the median age in the sample (30 years) as the cut off. Young women typically use contraceptives for birth-spacing, so there will be switches in the early years between use and non-use, even for individuals that have crossed the belief threshold. The level of state dependence, measured by the coefficient on the lagged decision, is consequently increasing with age. Turning to the social interactions, while both young and old women put more weight on their own group, cross-group effects are substantial and statistically significant.

To further explore these results, we partition the village using the 0.75 age quantile (37 years), computed using the full sample of women, as the cut off. Essentially the same pattern that we saw above continues to be obtained in Columns 3–4. As we noted in Section 2, social interactions tend to occur within peer groups of the same age, which would explain the dominance of the within-group effect in Columns 1–4.

[29] Since we are now partitioning the sample by age (and education is highly correlated with age), the age effects in Table 6 are difficult to interpret. While we observe the usual pattern with a positive coefficient on age and a negative coefficient on age squared in some cases, the opposite pattern is also obtained.

Turning to the second partitioning variable, the village is divided into literate and illiterate women in Columns 5–6 of Table 6. The coefficient on the lagged decision is now roughly the same, for both groups of women. Within-group effects are larger while cross-group effects are substantial and statistically significant, both for literate and illiterate women, just as we saw above when the village was partitioned by age. But notice now that the literate women place relatively more weight on the other group in Column 6. This pattern is accentuated when we partition the village using the 0.75 education quantile (4 years of schooling), computed using the full sample of women, as the cut off. Both groups of women put more weight on the less educated women in Column 7 and Column 8. This result is consistent with the view that social interactions occur freely across these groups, and more importantly that less educated women (who have a lower propensity to use contraceptives) provide more information through their social interactions. We are used to thinking of educated women as being more influential in the community, presumably due to their higher social status.[30] The results that we have just described go in the opposite direction to this view but are perfectly consistent with the predictions of the model, providing additional independent support for our learning-based theory of social change.

The results that we have presented in Table 6 are very different from what we saw earlier when the village was partitioned by religion. While within-group effects tend to be larger than cross-group effects, these cross-group effects are nevertheless substantial and statistically significant in the table. In sharp contrast, while strong within-religion effects were also obtained, cross-religion effects were entirely absent across all the specifications that we experimented with in Tables 3–5.

5.5. Alternative explanations for the estimation results

We conclude the empirical analysis by discussing alternative explanations for the results described in this section. We will discuss unobserved program effects, economic change, and learning about new contraceptive technology below.

1. Program effects: Cross-sectional variation in the MCH-FP project is captured by the individual fixed effects in the contraception regression. Secular changes in the program are accounted for by the time-period dummies. However, changes across villages and over time could generate a spurious role for neighbors' decisions in the contraception regression. For example, the Community Health Worker (CHW) may become more effective in persuading individuals to adopt contraceptives with experience. If CHWs improve at different speeds, then neighbors' decisions could simply proxy for an unobserved CHW-effect.

To rule out the CHW-effects, and program effects more generally, we appeal to the within-religion and cross-religion results. Recall that omitted variables must be orthogonal across religious groups within the village to spuriously generate the patterns that we saw in

[30] Educated women could also be more influential if they had access to superior information, through the media for instance. While this argument would make sense if the women were learning about a new contraceptive technology, it does not apply when the community is learning about local social fundamentals, since there is no reason why educated women should have better information about the social equilibrium that will ultimately prevail.

the data. While project inputs and information signals may have varied across religious groups within the village, it is difficult to imagine that they were uncorrelated across these groups. Remember that it is the same agency, and the same CHW, that is providing these inputs. The absence of cross-religion social effects thus rules out an important potential source of bias. Note that this result does not imply that the MCH-FP project was ineffective in bringing about change. What this says is that there was little cross-village variation in project inputs.

2. Economic change: It is well known that fertility rates have historically responded to changes in income and returns to human capital investment (Schultz, 1988; Rosenzweig, 1990). There has, however, been little economic change in the intervention area over time. Matlab thana was chosen as the setting for the early cholera-vaccine trials in the 1960s by the ICDDR,B precisely because it was so isolated. We saw in Table 2 that traditional agriculture and fishing continue to be the main occupations, and no new technologies for these activities have been introduced. Apart from fishing, which we controlled for in Table 5, Columns 7–8, there does not appear to be a religious aspect to occupational choice among the men. As discussed in Section 2, women, from both religions, rarely work outside the home in rural Bangladesh.

Moreover, local segregation by occupational activity, along religious lines, is not observed in the data. The choice of occupational activities is positively correlated across religions within the village. Computing the share of each occupational activity by religion within the village, the correlation coefficient across religions is found to be 0.48 for farming, 0.66 for fishing and 0.37 for business. Thus, even if economic change did occur, it is very likely to have been correlated across religious groups within the village. While female social interactions may not cross religious boundaries, there are no such restrictions on male interactions; Hindu and Muslim men mix freely in the marketplace and in other public areas. We can therefore use our cross-religion result once more to rule out economic change as a source of spurious correlation.

3. Learning about contraceptive technology: The model of social change that we present in this paper assumes that both preferences (P) and social rules (l, g) are exogenous and stable. However, within this framework, uncertainty about the performance of the new contraceptive technology (measured by S in the model) could still generate many of the patterns that we see in the data.

The MCH-FP project introduced modern contraceptives in the intervention area for the first time. While the main contraceptive method promoted by the ICDDR,B – injectables – appears to have been a well understood and well established technology by the time our sample begins in 1983, there was some initial uncertainty as to whether a woman who had previously used injectables for birth-spacing would be able to conceive in the future.

Both neighbors' decisions, as well as their experiences, will typically provide information about a new technology. For instance, a neighbor's (unexpected) decision to use a particular contraceptive method reveals that she must have received a favorable signal about its performance. This signal extraction process would generate a link between the individual's decision and her neighbors' past decisions (as in Munshi, 2004). Uncertainty as to whether the new injectable technology was reversible would also have begun to be resolved when women that used injectables for birth-spacing discontinued and subsequently conceived.

We have already argued that external information signals and program inputs will be correlated across religious groups within the village, so the signal extraction process described above cannot explain the complete absence of cross-religion effects that we see in the data. However, information generated within the community, through individuals' experiences with the new technology, could give rise to these patterns if information generated internally fails to cross religious boundaries within the village.

While there is a wealth of anecdotal evidence suggesting that religious restrictions led to substantial delays in the adoption of contraceptives in the intervention area, we are unaware of any study that points to persistent concerns about the performance of the new technology as an explanation for these delays. In general, we were unable to uncover independent supplemental evidence supporting the alternative view that individuals were learning about a new technology. For instance, it is possible to identify women in the data who used injectables for birth-spacing and then subsequently conceived. We found that the number of post-injectable births in the village, or within each religious group in the village, in any period had absolutely no effect on subsequent contraceptive use in the community during the sample period. This absence of an experience effect contrasts with the results from our own previous research on the adoption of new agricultural technology (Munshi, 2004), where we find that neighbors' experiences (crop yields) had a strong effect on the individual grower's subsequent acreage decision in the Indian Green Revolution.

6. Conclusion

This paper provides a norm-based explanation for two features of the fertility transition that have been observed in many different settings: The slow response to external interventions and the wide variation in the response to the same intervention. Most societies have traditionally put norms into place to regulate fertility. When new opportunities become available, individuals gradually learn through their social interactions about the specific reproductive equilibrium that will emerge in their community.

This characterization of the fertility transition as a process of changing social norms implies that the relevant social interactions in our rural Bangladeshi setting should be restricted to the individual's religious group. As predicted, individuals respond strongly to changes in contraceptive prevalence within their own religious group in the village, while cross-religion effects are entirely absent. Local changes in reproductive behavior occur independently across religious groups despite the fact that all individuals in the village receive the same family planning inputs.

The MCH-FP project is quite possibly the most intensive family planning program ever put in place. Community Health Workers meet each woman at her home once every 2 weeks, in an attempt to circumvent the restrictions on female mobility associated with purdah in rural Bangladesh. But we see at the end that there appears to be no substitute for the social interactions among the women. And since these are very infrequent, contraceptive prevalence ultimately changed very slowly in the intervention area. With hindsight, a program that encouraged women to meet at the primary health clinic, instead of delivering services to their homes, might have been more effective despite the initial resistance and delays in adoption that would almost certainly have occurred.

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Appendix A

Proof of Proposition 1. We make the usual rational expectations assumption that each individual correctly predicts the proportion of m's in both stable communities $\underline{x}_t$ and unstable communities $\bar{x}_t$, at each point in time during the transition, but is unsure about the type of community that she belongs to. We place no other restrictions on $\bar{x}_t$, $\underline{x}_t$, and the shifts in beliefs will be derived below for both $\bar{x}_t > \underline{x}_t$ and $\bar{x}_t < \underline{x}_t$.

Case 1: $\bar{x}_t > \underline{x}_t$

Consider any belief α in the support of the distribution. Applying Bayes' Rule, define a neighborhood $[\alpha(L), \alpha(R)]$ around α, which is relevant to determining $\bar{F}_{t+1}(\alpha) - \bar{F}_t(\alpha)$, $\underline{F}_{t+1}(\alpha) - \underline{F}_t(\alpha)$. Begin by deriving an expression for $\alpha(L)$, which lies to the left of α. Since there are more m's in an unstable community at each point in time, $\bar{x}_t > \underline{x}_t$, matching with an m will shift beliefs to the right. Thus, an individual with this belief in period t who matches with an m just reaches α in the subsequent period

$$\alpha = Pr\left(P = \bar{P}|m\right) = \frac{\alpha(L)\bar{x}_t}{\alpha(L)\bar{x}_t + (1-\alpha(L))\underline{x}_t}.$$

Solving for $\alpha(L)$ we obtain:

$$\alpha(L) = \frac{\alpha\underline{x}_t}{(1-\alpha)\bar{x}_t + \alpha\underline{x}_t} = \frac{\alpha\underline{x}_t}{X_t}$$

where X_t is a weighted average of $\bar{x}_t$ and $\underline{x}_t$, with the weight α on $\underline{x}_t$. Since $\bar{x}_t > \underline{x}_t$, it is easy to verify that $\alpha(L) < \alpha$. From the preceding expression we obtain:

$$\alpha - \alpha(L) = \frac{\alpha(1-\alpha)(\bar{x}_t - \underline{x}_t)}{X_t}. \tag{16}$$

A similar exercise allows us to solve for $\alpha(R)$. An individual with belief $\alpha(R)$ in period t who matches with a t just reaches α in the subsequent period. To derive an expression for $\alpha(R)$, we apply Bayes' Rule as before:

$$\alpha = Pr\left(P = \bar{P}|t\right) = \frac{\alpha(R)(1-\bar{x}_t)}{\alpha(R)(1-\bar{x}_t) + (1-\alpha(R))(1-\underline{x}_t)}.$$

Solving for $\alpha(R)$ as above, and then for $\alpha(R) - \alpha$, we finally obtain:

$$\alpha(R) - \alpha = \frac{\alpha(1-\alpha)(\bar{x}_t - \underline{x}_t)}{1 - X_t}. \tag{17}$$

The flow to the right of α is determined by the measure of individuals in $[\alpha(L), \alpha]$ who match with an m in period t. Similarly the flow to the left of α is determined by individuals in $[\alpha, \alpha(R)]$ who match with a t. Deriving the net flows is relatively straightforward in this case because the range of beliefs $\alpha - \alpha(L)$ and $\alpha(R) - \alpha$ is extremely narrow: a single m (or t) will shift beliefs from $\alpha(L)$ (or $\alpha(R)$) to α. We can therefore assume that the distribution of beliefs is approximately uniform in $[\alpha(L), \alpha(R)]$. Starting with the unstable communities, the net flow to the right is given by:

$$\bar{F}_{t+1}(\alpha) - \bar{F}_t(\alpha) = -\left[\bar{f}_t(\alpha)(\alpha - \alpha(L))\right]\bar{x}_t + \left[\bar{f}_t(\alpha)(\alpha(R) - \alpha)\right](1 - \bar{x}_t) \tag{18}$$

where $\bar{f}_t(\alpha)$ is the density of the distribution at α. Substituting expressions for $\alpha - \alpha(L)$ from Eq. (16) and $\alpha(R) - \alpha$ from Eq. (17), Eq. (18) can thus be simplified as

$$\bar{F}_{t+1}(\alpha) - \bar{F}_t(\alpha) = -\bar{f}_t(\alpha)\cdot\frac{\alpha(1-\alpha)\left(\bar{x}_t - \underline{x}_t\right)}{X_t}\cdot\bar{x}_t + \bar{f}_t(\alpha)\cdot\frac{\alpha(1-\alpha)\left(\bar{x}_t - \underline{x}_t\right)}{1 - X_t}\cdot\left(1 - \underline{x}_t\right). \tag{19}$$

Collecting terms and simplifying Eq. (19),

$$\bar{F}_{t+1}(\alpha) - \bar{F}_t(\alpha) = \frac{\bar{f}_t(\alpha)\cdot\alpha(1-\alpha)\left(\bar{x} - \underline{x}_t\right)(X_t - \bar{x}_t)}{X_t(1 - X_t)}.$$

Recall that X_t is a weighted average of $\bar{x}_t$ and $\underline{x}_t$. Since $\bar{x}_t > \underline{x}_t$, $\bar{F}_{t+1}(\alpha) - \bar{F}t(\alpha) < 0$.

Turning to the stable communities, note that the expressions for $\alpha - \alpha(L)$ and $\alpha(R) - \alpha$ are unchanged. The expression corresponding to Eq. (19) is therefore

$$\underline{F}_{t+1}(\alpha) - \underline{F}_t(\alpha) = -\underline{f}_t(\alpha)\cdot\frac{\alpha(1-\alpha)\left(\bar{x}_t - \underline{x}_t\right)}{X_t}\cdot\underline{x}_t + \underline{f}_t(\alpha)\cdot\frac{\alpha(1-\alpha)\left(\bar{x}_t - \underline{x}t\right)}{1 - X_t}\cdot\left(1 - \underline{x}_t\right).$$

Simplifying as before,

$$\underline{F}_{t+1}(\alpha) - \underline{F}_t(\alpha) = \frac{\underline{f}_t(\alpha)\alpha(1-\alpha)(\bar{x}_t - \underline{x}_t)(X_t - \underline{x}_t)}{X_t(1 - X_t)}.$$

Since $\bar{x}_t > \underline{x}_t$, $X_t - \underline{x}_t > 0$ and, hence, $\underline{F}_{t+1}(\alpha) - \underline{F}_t(\alpha) > 0$.

Case 2: $\bar{x}_t < \underline{x}_t$

This case is very similar to the previous case except that matching with an *m* will now shift beliefs to the left, since there are fewer *m*'s in an unstable community at each point in time, $\bar{x}_t < \underline{x}_t$. Thus, to derive the expression for $\alpha(L) < \alpha$, the individual must match with a t to reach α. Similarly, an individual with belief $\alpha(R) > \alpha$ who matches with an m just reaches α. Once we have derived these beliefs, it is straightforward to derive the new flow; note that matching with a t now shifts beliefs to the right.

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