

## Playing the Fertility Game at Work: An Equilibrium Model of Peer Effects

Federico Ciliberto	Amalia R. Miller	Helena Skyt Nielsen	Marianne Simonsen
Department of	Department of	Department of	Department of
Economics	Economics	Economics	Economics
University of Virginia	University of Virginia	and Business	and Business
		Aarhus University	Aarhus University

December 2012

**Abstract:** This paper studies workplace peer effects in fertility decisions using a game theory model of strategic interactions among coworkers that allows for multiple equilibria. Peer effects in fertility can be social or economic in nature and positive or negative. In addition to their direct effects on fertility, they can also amplify or dampen behavioral responses to policy changes. Using register-based data on fertile-aged women working in medium sized establishments in Denmark, we find that estimates depend crucially on modeling assumptions. Individual Probit models find positive peer effects that are confirmed in the basic structural model with no workplace-specific random effects. Allowing for these effects, however, reverses the sign of the average peer effect to negative. Further expanding the model allows us to uncover peer effects that are heterogeneous between different types of workers. Positive effects dominate across worker types defined by age or education, but the effects are negative within age groups and among low-education types. Our policy simulations show that these estimated effects make the distribution of *where* women work an important consideration, beyond simply *if* they work, in predicting population fertility. The empirical approach developed in this paper can be applied broadly to the study of social interactions with strategic elements.

**Acknowledgements:** We thank Steve Durlauf, Leora Friedberg, Bryan Graham, Ed Olsen, John Pepper and seminar and conference participants at the Nordic Summer Institute, Aarhus University, Mount Holyoke College, Rice University and the University of Houston for insightful comments and suggestions. We thank Søren Bundgaard Brøgger and Anders Tofthøj for excellent research assistance. This research was supported by the NIH National Institute for Child Health and Development under grant number 1R03HD061514, the Dean of the College of Arts and Sciences and the Vice President for Research and Graduate Studies at the University of Virginia, and the Danish Research Council under grant number 275-09-0020. Part of this work was completed while Miller worked as an Economist at the RAND Corporation. The contents of this paper are solely the responsibility of the authors and do not necessarily represent the official views of the NIH or other sponsors.

## I. Introduction

The demographic transition to lower fertility rates may have been a catalyst for sustained economic growth in previous centuries (Galor 2005), but sub-replacement fertility rates are now a major policy concern in much of the industrialized world. Fertility decisions affect the size and composition of the population. Reduced or delayed childbearing in the present leads to population aging and higher dependency ratios in the future. Hence, very low fertility rates present challenges for the financing of public and private pension schemes (Borsch-Supan 2000, Blake and Mayhew 2006), for redistribution under the welfare state (Rangel 2003), and for overall economic growth (Lindh and Malmberg 1999). Governments in Europe and elsewhere have sought to increase the size of the workforce by enacting policies that encourage fertility (through regulation or public spending, Grant et al. 2004; Mumford 2007) or that encourage women to enter the paid labor market. Because female labor market participation is generally associated with lower fertility, these two policies may be in conflict.

This paper studies peer effects in the fertility decisions of working women. Measuring workplace peer effects in fertility can improve our understanding of how female labor market participation affects population fertility rates. Furthermore, if (positive or negative) peer effects are important, their presence implies that a new workplace factor should be introduced into fertility models: *where* women work may matter as much as *if* they work. In addition to their direct effects, peer effects in fertility may be important for predicting the impact of policy changes on overall population fertility and fertility of different groups of women. Previous studies have discussed how positive peer effects can amplify or dampen fertility responses to changes in the policy or economic environment (e.g., Kohler 2001, Kravdal 2002, Bloom et al. 2008). An example of a dampening story is the argument in Moffitt (1998) and Murray (1993) that social stigma (associated with out-of-wedlock childbearing) reduced the short-term fertility responses to changes fertility incentives in US welfare policies. An amplification story is in Montgomery and Casterline (1998), who argue that multiplier effects from social learning and social influences hastened demographic transitions, through the diffusion of contraceptive technologies.

Following the economics literature on fertility, we model childbearing as a rational choice, responsive to financial incentives (Becker, 1960, Willis, 1973). However, unlike most of

that literature, which studies decisions at the level of individual women or couples,<sup>1</sup> we explore peer effects in an equilibrium framework for peer groups of women working at the same establishment. Our emphasis on peer interactions aligns with the shift in economic demography to consider social influences on fertility decisions. Recent studies have found evidence of peer effects using geographic areas or neighborhoods (Bloom et al. 2008; South and Baumer 2000; Crane 1991), schools (Evans et al. 1992), ethnic or religious groups (Manski and Mayshar 2003), families (Kuziemko 2006) and networks of friends (Behrman et al. 2002, Bernardi et al. 2007) as their primary social unit. A common feature of these studies is their focus on social or informational factors leading to *positive* peer effects. In contrast, this paper focuses studies interactions in fertility decisions among female coworkers at the same physical work establishment that could be positive *or* negative.

One motivation for studying the workplace is precisely this variation. Unlike the usual social effects that tend to lead to greater similarity among friends or neighbors, the workplace setting contains a complex mix of social and economic interactions the can produce peer effects in fertility among co-workers that are either positive or negative. A second motivation is the dramatic increase over the last half-century in the share of prime-age women working for pay, which has made the workplace an increasingly important setting in which to study women's fertility decisions. Third, the workplace provides well-defined peer groups of individuals who work for the same organization at the same physical location and are potentially exposed to one another for several hours a day. Although workplace peer groups are primarily structured around economic production goals, a new set of studies has found evidence of peer effects at the workplace involving various behaviors other than fertility, including productivity (Mas and Moretti 2009; Bandiera, Barankay, and Rasul 2010), charitable contributions (Carman 2003), retirement savings (Duflo and Saez 2003), and paternity-leave taking (Dahl, Løken and Mogstad 2012).<sup>2</sup>

---

<sup>1</sup> See Hotz, Klerman and Willis (1997) for a survey of the literature on the economics of fertility in developed countries. More recent studies have revisited the relationship between household income and demand for children (e.g., Mumford and Lovenheim, forthcoming) and the impact of redistributive policy on fertility (e.g., Kearney 2004).

<sup>2</sup> Dahl, Løken and Mogstad (2012) find peer effects both within families and workplaces.

In this paper, we develop and apply a novel empirical approach to studying peer effects. Estimation is based on a game theoretic framework that simultaneously considers fertility choices of all agents at the same workplace. We impose a self-consistency condition on outcomes at each workplace based on the Nash Equilibrium condition that each agent is enacting her own best response to her peers' behavior. The use of a self-consistency condition to address both individual and aggregate behavior in studies of social interactions is discussed in Brock and Durlauf (2001), who apply a notion of self-consistency based on a rational expectations rule in which average behavior conforms to expected behavior. By contrast, this paper uses a complete information setting and derives the self-consistency condition from the equilibrium condition of the fertility game. Our effective unit of analysis is the workplace, and our outcome of interest is the number of women having children.

The well-known potential for multiple equilibria in binary choice models of social interactions (e.g., Brock and Durlauf 2007; discussed in Section II.A below) presents a major estimation challenge. The approach in this paper builds on the methods developed in Ciliberto and Tamer (2009) to incorporate multiple equilibria in estimation without imposing any rules for equilibrium selection in the regions of multiplicity (as is done, for example, in Cohen, Freeborn, McManus 2011; Rennhoff and Owens 2012; Krauth 2006; Card and Giuliano 2011). Like Ciliberto and Tamer (2009), we estimate models that allow for heterogeneous interaction effects for different agents and market-specific (in our case, workplace-specific) common shocks.

Because we explicitly incorporate an equilibrium concept in our full structural model, we can compute marginal effects that incorporate both direct effects (from changes in individual characteristics and contextual effects) and those mediated through changes in peer behavior. Our model can also be used to identify workplaces with multiple equilibria consistent with the observable variables and error terms. In these areas, small policy shifts may trigger large behavioral shifts or "phase changes" (Brock and Durlauf, 2007) when many individuals change their behavior at once. Negative peer effects may dampen policy effects by preventing groups of coworkers from having children in the same period. The approach developed in this paper can be applied more broadly to other settings in which social interactions have strategic components.

We estimate our model using data drawn from detailed administrative records on the entire population of Denmark. These records allow us to link individuals to their coworkers and family members to construct a cross-sectional database of fertility outcomes and predictors for

2002 to 2005. We find evidence of positive interactions in fertility decisions among coworkers in individual Probit models with a variety of different sets of controls. These positive correlations are repeated in a simplified version of the structural model, but the addition of establishment-level random effects reverses the sign of the endogenous peer effects. We also find important evidence of heterogeneous effects for different types of workers: positive effects dominate across worker types defined by age or education, but negative effects dominate within age groups and among low-education types. In the models with heterogeneous peer effects, we find that nearly half of all workplaces are in a region of multiplicity, with more than one Nash Equilibrium outcome. The peer effects that we estimate are meaningful in magnitude, which suggests that where women work could affect their fertility outcomes. Indeed, our policy simulations show potentially large changes in fertility rates caused by reallocating workers across establishments.

This paper is organized as follows. Section II discusses the model and identification. Section III describes the data and reduced form estimates. Empirical results from the full model are presented in Section IV and Section V contains policy simulations. Section VI concludes.

## **II. Econometric Model of the Fertility Game at Work**

This section describes our game theoretic model of strategic interactions in fertility decisions among coworkers and then outlines our estimation approach.

### ***II.A Equilibrium in the Fertility Game***

Our theoretical model of the fertility game builds on the individual fertility model in Jones, Schoonbroodt and Tertilt (2011) by adding the possibility of peer effects from co-workers. Agents in the model are women of childbearing age who decide whether or not to have a child. Agents aim to maximize their utility, which is defined broadly to encompass consumption of market goods and services, engagement in activities that are personally or socially rewarding, and pleasure from motherhood. The direct utility from motherhood may depend on the quality (behavior or achievements) of the child, which in turn may depend on parental investments in child human capital and the productivity of those investments.

After deciding on childbearing, each agent chooses her time allocation and consumption bundle, including investment in child quality for women with children, to maximize her utility, subject to her budget constraint (represented by her income level  $y$ ) and her time constraint

(represented by  $t$ ). We define the maximum utility that an agent without a child achieves as  $u_{NK}(t, y, n)$  and the maximum utility achieved by an agent with a child as  $u_K(t, y, q, n)$ . Each of these functions depends on the exogenous variation in income and time available to the woman, and the utility from motherhood also depends on the woman's preference for child quality (or her productivity in producing child quality,  $q$ ).

The utility functions for both mothers and childless women also depend on  $n$ , the number of peers who have children in the period. The effects of peer fertility may flow through mainly social or economic channels. There may be positive social peer effects stemming from mimicry or a desire to conform to group norms (Bernheim 1994), where increasing the number of peers with children directly increases  $U_K$  (or decreases  $U_{NK}$ ).<sup>3</sup> Direct social effects on utility can be negative instead if agents want to be different from their peers, though these are less commonly studied (as they are less likely to occur with self-selected groups such as friends or neighbors that are usually used to define peers).

The economic channels for peer effects can also be positive or negative. Motherhood itself is associated with lower wages and wage growth (e.g., Waldfogel 1998 and Miller 2011 in the United States and Nielsen, Simonsen and Verner 2004 in Denmark). By reducing the negative signal to employers about the productivity of working mothers, coworker fertility can lead to positive financial spillovers for mothers. Alternatively, childbearing (and leave-taking) by coworkers can increase the incremental costs to the employer from hiring temporary replacements or rearranging work-flows, which would lead to negative spillovers (such as lower returning pay or an increased risk of job loss) for mothers. Competition in internal labor markets (Lazear and Rosen, 1981) may create positive spillovers to women who forgo childbearing while their coworkers have children if they find it easier to be promoted or otherwise advance professionally during their coworkers' absences, which could generate negative peer effects in

---

<sup>3</sup> This channel would correspond to "social influence" in Montgomery and Casterline (1996). The "social learning" channel (where individuals learn from the past experiences of their peers and resolve uncertainty about their own future payoffs from different actions) is not included in the peer effects we measure in our static model of complete information. However, to the extent that these factors are present (for example, if a woman at the establishment was especially successful or unsuccessful at balancing work and family in 2001 or 2002), they will appear either as common shocks to all women at the same work establishment or (imperfectly) correlated errors. We account for both of these possibilities in estimation of our full model.

fertility. Finally, there may be positive peer effects from scale economies in childcare if coworkers share information or coordinate childcare arrangements with one another (through the employer or outside of work).

We model these effects as a set of static games of complete information played once at each workplace and use the Nash Equilibrium solution concept. For each individual woman, the net utility gain from having a child can be represented as  $v(t, y, q, n) = u_K(t, y, q, n) - u_{NK}(t, y, n)$ , meaning that agents prefer to have a child if  $v(t, y, q, n) \geq 0$ . A set of fertility decisions (to have a child or not for each agent) is an equilibrium outcome of the game if no individual agent can improve her well-being by individually changing her action, taking the actions of all other agents at the workplace as given.

In the homogenous peer effects version of the model, the decisions of all other agents are summarized by a scalar  $n$  for each woman. In addition to this base case, we also consider cases with heterogeneous peer effects, in which women are grouped into discrete types and they potentially respond differently to the fertility decisions of other women of their same type and a different type (and this can also vary according to the type of the woman). This

A simple example with two identical agents ( $i = 1, 2$ ) is sufficient to illustrate some key features of the model. In this example, the economic problem can be summarized as:

$$d_1 = 1 \text{ if } v(t, y, q, d_2) \geq 0$$

$$d_2 = 1 \text{ if } v(t, y, q, d_1) \geq 0$$

Each agent has a child if her net utility from childbearing is positive. In this example, it is clear that although the Nash Equilibrium conditions reject outcomes in which either woman would prefer to deviate, it does not ensure that the equilibrium outcome is efficient or that there is a unique solution for any particular game. For example, there are two equilibria for the basic game with two identical agents with positive peer effects in which  $v(t, y, q, 0) < 0$ ,  $v(t, y, q, 1) > 0$ . Neither agent would want to deviate away from the equilibrium in which both agents have a child or from the one in which neither agent has a child.

Indeed, positive peers can generically lead to multiple equilibria in the fertility game with two or more agents. This means that for many workplaces, there may exist both lower-fertility and higher-fertility outcomes from which no individual woman wants to deviate. In the case of homogeneous interaction effects that are known to be negative, there may be multiple equilibria in the identity of agents who take the action of interest, but their number is uniquely determined

(Bresnahan and Reiss 1990). However, uniqueness is not guaranteed if the interactions are heterogeneous and there are more than two agents. For most of the workplaces in our study, this implies that multiple equilibria is a potential outcome that we need to address in estimation.

Although our model is robust in the sense of accommodating a range of positive and negative peer effects and the resulting multiplicity of equilibria, we are only able to accomplish this by focusing on a static game. This means that we assume that the game is played only once by the agents. While it is true that women make fertility choices many times in their lives, this research will focus on a single cross-section of data at a particular point in time. We assume that this cross-section captures the long run equilibrium of fertility decisions within each establishment, which means that we would obtain the same empirical results, regardless of the particular time period we selected. Our static game setup means that we do not model agents as playing repeatedly over time or responding dynamically to one another's decisions and outcomes. This may be reasonable in the context of fertility choices within a couple of years, because neither researchers nor coworkers observe the time when the decision to have a child is taken. We observe instead the timing of births. Variation in the time between the decision and actual conception makes it impossible to determine the exact decision date.<sup>4</sup> Thus, using data on births alone, we are unable to determine which agent made the decision to conceive first. Third, the game is played simultaneously. This means that all agents are assumed to make their fertility choices at the same time. In the case of fertility choices, this assumption seems particularly reasonable, because we do not observe the order with which agents made their fertility choices, and because the agents themselves are not immediately aware of their coworkers' decisions or pregnancies.

## ***II.B Empirical Specification of the Utility Function***

The fertility game is played separately at each establishment, which we index by  $e = 1, \dots, E$ . The agents in the model are women of childbearing age. Agents are indexed by  $i = 1, \dots, K_e$ , where  $K_e$  is the number of female employees of childbearing ages at that establishment. In our complete model, we allow for heterogeneous peer effects by worker type. In this model, the

---

<sup>4</sup> According to Juul et al. (1999), 40% of fertile couples conceive within the first month, while 84% conceive within a year. According to the same source, between 6 and 20% of European couples are infertile.

utility to an agent from having a child depends on the agent's own type and the fertility decisions of other agents at her workplace of each type.<sup>5</sup>

An individual  $i$  at establishment  $e$  gains net utility of  $v_{ie}(X_{ie}, n_e, \theta)$  from having a child. The variable  $n_e$  captures the peer effect experienced by each agent. In the single-type model, it is the count of other women at the establishment who have a child in the sample period. In the two-type extensions, it is a vector  $n_{ie} = (n_{ie1}, n_{ie2})$ , where  $n_{ie1}$  is the number of peers of type 1 who have a child in establishment  $e$ , and  $n_{ie2}$  is the number of peers of type 2 who have a child in establishment  $e$ . The variable  $N_e$  (or vector  $N_e = (N_{1e}, N_{2e})$  in the model with two types) is the endogenous outcome of the game. Here,  $N_e$  includes all agents, while  $n_e$  excludes includes only the peers of individual  $i$ .<sup>6</sup> The vector  $X_{ie}$  consists of a set of observable exogenous variables that determine the net utility of an agent from having a child. These variables control for heterogeneity in observables across agents.

We estimate a linear approximation of this function as follows:

$$v_{ie} = \alpha X_{ie} + \sum_{r=1}^{R_e} \delta_r^{r(i)} n_{re} + \epsilon_{ie} \quad (1)$$

Establishments are indexed by  $i = 1, \dots, K_e$  and worker types are indexed by  $r$ . Peer effects in fertility are captured by the  $\delta_r^{r(i)}$  coefficients that relate increases in the fertility of type  $r$  peers on the net utility from childbearing for a type  $r(i)$  agent. These terms measure peer effects within and between coworker types. In our empirical analysis, we allow  $\delta_r^{r(i)}$  to be positive or negative, and will estimate its sign.

The error term  $\epsilon_{ie}$  is the part of utility that is unobserved by the econometrician. We assume throughout that  $\epsilon_{ie}$  is observed by all players in peer group  $e$ . Thus, this is a game of complete information. We consider three components to the error term: a firm-specific component; an establishment-specific component; and an individual-specific component. These unobservables are all assumed to be drawn from normal distributions. In some specifications we

---

<sup>5</sup> This treatment of heterogeneous effects differs from that in Ciliberto and Tamer (2009) where each agent's entry decision was allowed to have a different effect on the utility of each other agent, because the same sets of airlines were observed as potential entrants in multiple geographic markets. This is not feasible in our context of establishment peer effects, as each agent is observed as a potential child bearer only in one establishment.

<sup>6</sup> Notice that the problem is different from Ciliberto and Tamer (2009), where the outcome is a vector of binary values.

allow the individual-specific components to be correlated within establishments and we estimate the variance-covariance matrix.

The outcome of the fertility game is defined in terms of types of agents rather than single agents. Thus, for a given value of the parameters, we will derive a predicted equilibrium outcome  $N_e = (N_{ie}, \dots, N_{R_3e})$ . Nevertheless, we will estimate the model and solve for equilibrium outcomes using individual utility functions.<sup>7</sup>

Three types of variables are included in the vector  $X_{ie} = (Z_{ie}, S_e, W_{ie})$ : individual characteristics ( $Z_{ie}$ ), establishment specific characteristics ( $S_e$ ), and instrumental variables ( $W_{ie}$ ).  $Z_{ie}$  is a vector of individual characteristics that enter into the net utility of all the workers in the peer group, for example individual productivity that affects overall firm performance and wages for all workers. Elements of the  $Z_{ie}$  vector are included in estimation directly as factors that affect individual fertility; their establishment-level average values comprise the  $S_e$  vector of establishment level variables.<sup>8</sup>  $W_{ie}$  contains individual characteristics that enter only into individual  $i$ 's utility. The values of  $W_{ie}$  for coworkers only influence the coworkers' utility from having a child, and do not directly influence the individual's own utility from having a child. This exclusion restriction allows us to separately identify endogenous and contextual fertility effects, which is why we refer to the variables as instruments.

### ***II.C Estimation and Simulation***

We estimate the parameters of the utility function in Section II.B with an approach that incorporates the possibility of multiple equilibria discussed in Section II.A by employing econometric methods developed in Ciliberto and Tamer (2009) to estimate parameter bounds. The key strength of this approach is that it allows for heterogeneous peer effects that can take either sign and does not impose assumptions to select a single equilibrium.

Our unit of observation is an establishment. In the single-type model, we separately

---

<sup>7</sup> The fact that our sample includes workplaces with only 1 agent allows us to identify the parameters on the individual effects.

<sup>8</sup> We use median values for each variable over the set of agents in the work establishment. It is also possible to include establishment- or firm-level variables that are not based on elements of  $Z_{ie}$  in  $S_e$ . In our reduced form analysis, we found that these additional establishment variables had little effect on the estimated peer effects and we omit them from the structural model.

consider establishments based on the number of women in fertile ages employed there,  $K_e$ . There could be as few as 1 and as many as 50 this number varies by establishment, and in practice, it never exceeds 38. The goal of our minimization routine is to find the parameters that minimize the distance between predicted and actual fertility at each establishment.

We simulate the distribution of the error term by drawing, for each woman at each establishment,  $S$  values of each of the (up to three) components of the error term described above for each woman in each establishment. Each draw is denoted by  $s \in \{1, \dots, S\}$ . Our minimization routine includes all  $S$  draws in the distance measure.

The possibility of multiple equilibria means that our economic model only allows us to partially identify the parameters of interest. Instead of point estimates, we compute upper and lower bounds for the parameters. For each set of parameter values, we initialize two establishment-specific vectors of lower and upper bound probabilities of each possible equilibrium outcome, which we denote by  $H_e^L$  and  $H_e^U$ . The dimension of these vectors of probabilities is given by the total number of possible equilibrium outcomes in each establishment (in terms of number of births). At the start of the simulation routine, we set both  $H_e^L$  and  $H_e^U$  equal to zero and update the vectors at each simulation round.

We then compute the  $\alpha_r X_{ie}$ , to which we add a simulated draw of the unobservable,  $\epsilon_{ie}^{(s)}$ ; this sum is the value of net utility when peer effects are neglected:

$$v_{ie}(X_{ie}, n_{1e}, \dots, n_{R_e e}) = \alpha_r X_{ie} + \epsilon_{ie} \quad (2)$$

We solve for the possible Nash Equilibria of the game by computing the hypothetical utility for each woman for any possible number of other women having a baby, here denoted by  $n_{re}$ ,  $r = 1, \dots, R_e$ . For example, if there are two women of the same type  $r$  in a given establishment  $e$ , then this means that we have two possible utility values for each one of these women; one would be given by  $\alpha_r X_{ie} + \epsilon_{ie}^{(s)}$  when the other woman does not have a baby. The other one would be given by  $\alpha_r X_{ie} + \delta_r^r + \epsilon_{ie}^{(s)}$  when the other woman does have a baby.

The number of possible outcomes in establishment  $e$  is given by the  $\prod_{r=1}^{R_e} (1 + n_{re})$ . As discussed above, the number of outcomes determines the cardinality of the vectors  $H_e^L$  and  $H_e^U$ . Thus, for example, in an establishment with two women, there are three possible outcomes: no women having children; one woman having a child; and both women having children. Notice that there are three possible outcomes because we only look at how many of the women are

having a child, not which individual woman is doing so. Thus, in this establishment with two women, the two vectors initially are  $H_e^L = (0,0,0)$  and  $H_e^U = (0,0,0)$ .

We determine all the equilibria of the fertility game in each establishment for each simulation draw,  $s$ . For an outcome to be an equilibrium, no individual woman could be better off by making a different choice. This means that it must be the case that every woman having a child must have a non-negative net utility function from childbearing, conditional on the choice of all the other women. This condition ensures that no woman who has a child wants to deviate by not having a child. For the outcome to be an equilibrium, it must also be the case that no woman without a child would prefer to have a child. We test this by ensuring that the net utility for all agents who do not have children is negative, conditional on the fertility of her coworkers.

Table 1 illustrates the possible equilibrium outcomes in the case of two women. The game has three potential outcomes, ranging from zero to two children. The outcome in which neither of the two women has a baby is an equilibrium as long as both  $\alpha_r X_{1e} + \epsilon_{1e}^{(s)} < 0$  and  $\alpha_r X_{2e} + \epsilon_{2e}^{(s)} < 0$ , as shown in the first row. The outcome where only one woman has a baby is an equilibrium if either  $\alpha_r X_{1e} + \epsilon_{1e}^{(s)} \geq 0$  and  $\alpha_r X_{2e} + \delta_r^r + \epsilon_{2e}^{(s)} < 0$ ; or  $\alpha_r X_{1e} + \delta_r^r + \epsilon_{1e}^{(s)} < 0$  and  $\alpha_r X_{2e} + \epsilon_{2e}^{(s)} \geq 0$ . The analysis becomes much more complex with more agents and with more than one type of agent, as the number of conditions increases but the principle is the same in all cases.

For every simulation draw  $s$  and establishment  $e$ , we count the number of equilibria consistent with the values of the observables and parameters. If there is a unique equilibrium, then we increase the corresponding entry in  $H_e^L$  and  $H_e^U$  by 1. If there is more than one equilibrium, then  $H_e^L$  is unchanged and all the entries in  $H_e^U$  corresponding to the equilibria are increased by 1. In the example with two women, let's suppose that for the simulation  $s = 1$  there are two equilibria, when no woman has a baby and when both women have babies (possible with relatively large and positive peer effects). Then,  $H_e^L = (0,0,0)$  and  $H_e^U = (1,0,1)$ . We repeat the steps above for all the  $S$  draws (and, of course, all of the establishments). After completing the simulations, we compute the lower and upper bounds on the probabilities of each potential outcome by dividing  $H_e^L$  and  $H_e^U$  by  $S$ .

Finally, we compare  $H_e^L$  and  $H_e^U$  with the empirical probability, the rate at which we observe each one of the possible outcomes at that establishment across the simulation draws. We

compute the distance function between observed and predicted fertility outcomes and minimize this function over the space of possible parameter values using simulated annealing. The distance function consists of the distance between the lower (upper) bound and the empirical probability if the empirical probability is smaller (larger) than the lower (upper) bound and zero if the empirical probability falls between the lower and upper bound. We iterate using different parameter values, and continue this process until we find the parameter set that minimizes the distance function. Finally, we apply the methods in Chernozhukov, Hong, and Tamer (2007) to construct confidence regions that cover the identified parameter with a 95-percent probability.

### ***II.D Identification***

The identification of social effects is challenging in any setting (see discussions in Manski 1993; Manski 1995; and Blume and Durlauf 2005). Manski (1993) identifies three reasons why individuals belonging to the same peer group may tend to behave similarly. First, individual behavior may be influenced by the behavior of other group members: endogenous effects. Second, individual behavior may respond to the exogenous characteristics of the group: contextual effects. These two comprise the social effects of interest. However, a third possibility is the presence of correlated effects in behavior that are unrelated to social interactions. This can occur if group members share similar observable or unobservable characteristics or face similar institutional environments. The fundamental problem of separately identifying these three effects from one another is denoted the reflection problem.

Even in the absence of correlated effects, the crucial novelty in our estimation framework is that we explicitly address the reflection problem by modeling the full system of individual equations. In the language of the peer effects literature, our parameter estimates separately capture endogenous effects and contextual effects. The endogenous effects are the direct effects of peer fertility on each individual’s net utility from fertility (captured in the  $\delta_r^{r(i)}$  parameters on the peer fertility measures  $n_{re}$ ). Contextual effects are estimated by including separate controls for individual values and establishment average values for elements of  $Z_{ie}$ . These are the individual factors that are assumed to predict both own and coworker fertility. In addition, because we estimate the variance-covariance matrix of the unobservables, we can also capture correlated effects in the unobservables. This is very different from Manski (1993), who studies the identification of a single equation model. It is also very different from most other empirical

studies of social interactions that aim at identifying the sum of peer effects (endogenous and exogenous) or by assuming that only one type of effect is present.

In order to empirically distinguish endogenous fertility effects, the strategic effects of interest, from contextual effects that stem from the direct effect of coworker characteristics on one's own fertility, we employ an exclusion restriction. Specifically, we exploit the presence of a factor that affects the agent's own net utility function but is not likely to affect her peers' net utility functions (the variable  $W_{ie}$ ). Specifically, we use the agent's *sister's* fertility. Recent evidence (Kuziemko, 2006) indicates that women are more likely to have children after their sisters have recently had a child. While a woman's own sister's fertility can increase her net utility from childbearing (because of social effects, scale economies in childcare and information), there is no reason to expect the fertility of a woman's coworkers to have any effect on her net utility from childbearing (other than the effect that runs through peer fertility).

We address the second potential challenge to identification from correlated errors within establishments in several stages, depending on the potential source of the correlation.<sup>9</sup> First, there may be random shocks at the establishment level or at the firm level that affect the utility from fertility for all women. The random utility shocks have a common firm specific, common establishment specific and an idiosyncratic individual component. Second, there may be correlations in the idiosyncratic shocks among women at the same establishment. In Section IV, we present estimates from models that allow for each of these types of random utility shocks.<sup>10</sup>

A final concern is from non-random sorting of individuals to work establishments related to their fertility preferences. In particular, one might be concerned that women with high intrinsic desire for children self-select into firms with favorable leave policies and family-friendly work environments. We address this by including controls for firm factors that are related to such policies, mainly the indicator for private sector firms and larger firms, but we also repeat our main estimations on sub-sample of public sector workers who face a homogeneous and favorable family-leave environment. We also add controls for peer characteristics such as

---

<sup>9</sup> Previous studies have addressed this problem by random assignment of individuals into peer groups (Sacerdote, 2001) or by exploiting exogenous between-group variation (Graham and Hahn, 2005). That source of variation is not available in our setting.

<sup>10</sup> Accounting for the possibility of random firm and establishment effects has a major impact on the estimates, but after including these random effects, allowing for correlated errors has a more modest impact on the estimates.

education and occupation that might be related to such policies.

### **III. Description of Administrative Data**

We estimate the fertility game using data on the population of Denmark, a country in which women can exert a high degree of control over whether and when to have children. Abortion is legal and socially accepted (the ratio of abortions to births is 1:4) and artificial insemination (AI) and in-vitro fertilization (IVF) are part of public health care that is generally provided at no cost (until 2011). The average age at first birth is 29 years and the average number of children per woman over the entire fertile age is 1.89. Roughly 12% of each cohort of women is voluntarily or involuntarily childless at age 49.<sup>11</sup>

We compile our dataset using several administrative registers that are maintained by Statistics Denmark. The primary data source is a merged employer-employee data set, which includes information on the entire population of Danes aged 15-70. The data set covers the period from 1980 to 2005. Using unique person and workplace establishment identifiers we link all coworkers at the establishment level. The data hold yearly information about socioeconomic variables such as gender, age, family status as well as family identifiers, education, labor market experience, tenure at current job, unemployment levels, leave-taking, and income. Of particular interest for our study, births are identified using exact birth dates from the national fertility register.

From this population we select the group of fertile-aged women (20 to 40) who worked at a given establishment within a firm in November 2002. Our sampling does not condition on employment status after November 2002, because this is endogenous and could bias our estimates. In our main analysis we focus on establishments with 10-50 employees thus excluding small establishments where it would be difficult to credibly distinguish peer effects from selection and large establishments where it would be difficult to identify groups of interacting coworkers. We observe 31,725 medium size establishments. Roughly 25% of employed women in the relevant age range worked in such medium sized establishments in November 2002 (151,494 out of 647,678 employed women).

---

<sup>11</sup> Source: <http://www.statistikbanken.dk>

We define coworkers as individuals at the same establishment -- that is individuals with the same employer and location of work, as of November 2002. Our fertility outcome is an indicator variable for having a child between December 2002 and November 2005. In our sensitivity analyses below we will investigate the robustness of our results to the choice of this particular time frame.

### *III.A Descriptive Statistics*

Panel A of Table 2 presents descriptive statistics for the individual level control variables used in our main estimates for the women in our sample, both overall and separately by fertility outcome. About 24 percent of the women in our sample gave birth in 2003 to 2005. The average age in our sample is about 30 years (mean age is 30.04 years, not reported in the table), and women above that age are more likely to have a child during the sample than those below it. Women with some college education are 30 percent of the full sample, but 40 percent of the sample of women with births. Like older women, women with more (above the mean of 6 years) work experience are more likely to have children.

On average, about half of the women in our sample were mothers prior to 2003. Previous fertility is a strong predictor of fertility during the sample period. Women with one child were far more likely to have a second during the sample period (they comprise over one-third of those giving birth during the sample period and less than 13 percent of those not giving birth), while those with 2 children were far less likely (comprising over 28 percent of the sample without births and less than 13 percent of the sample with births). This is consistent with a dominant two-child norm in Denmark and with birth spacing generally falling within three years. Women who gave birth in 2003 to 2005 were also, on average, younger and less educated. Finally, women with sisters who previously had a child were 23 percentage-points more likely to themselves have a child in the sample period. This is similar to the finding in Kuziemko (2006); it provides exogenous variation that we exploit for identification.<sup>12</sup>

Panel B of Table 2 presents descriptive statistics at the establishment level. The mean number of employees is about 20 but over 60 percent of establishments employed fewer than that

---

<sup>12</sup> Although not reported in the table, we did not find substantial differences in fertility between women with and without sisters also tested for variation in fertility based on other measures.

number of workers. Focusing on our peer group of interest, the average establishment employed roughly five women of reproductive age (20 to 40). Nearly 20 percent of establishments employed only one woman in the relevant age range. These women are not susceptible to workplace peer fertility effects, and they provide variation that is used to identify the effects of individual level explanatory variables. Figure 1 plots the full distribution of peer group size (number of female workers of fertile ages) across establishments in our sample. Although our selection rule could accommodate up to 50 fertile-aged women per establishment, in practice we observe no more than 38. Figure 2 plots the distribution of our main fertility outcome: the number of women at each establishment who have a child. Figure 3 shows the distribution of the ratio of these the variables: the share of women with births.

### ***III.B Individual Probit Estimates***

Before investigating the results from our main model that incorporates the strategic interactions in fertility decisions, we explore the key conditional associations in the data using a series of Probit models for the individual propensity to have a child. We estimate the model with different sets of covariates to explore the sensitivity of the estimated associations between own and peer fertility to the inclusion of different controls. Unlike the structural estimates in Section IV, this analysis is performed at the individual level.

Table 3 reports the marginal effect and standard error estimates for the peer fertility effects under different Probit models. In the basic model with only peer fertility and a constant term, the relationship is positive and significant. Each additional coworker that has a child increases the average fertility propensity by about 1 percentage-point, which is about 4 percent of the sample mean (of 23.7 percent, see Table 2).<sup>13</sup> The inclusion of individual characteristics as controls decreases the coefficient estimate to 0.3 percentage-points (still highly statistically significant), but the estimated effect remains relatively stable as other variables are added to the conditioning set. For computational feasibility, we limit the set of controls to a parsimonious set of key “basic” controls for individual characteristics (indicators for age, education, and

---

<sup>13</sup> The elasticity is similar in magnitude to the marginal effect, because the probability that an individual has a baby is close to the share of colleagues who have a baby. For example when the estimated marginal effect is 0.01, the elasticity is equal to  $(0.01/0.229) / (1/0.237) \approx 0.01$ .

experience categories, as well as previous own and sisters' fertility) and to a richer set that add controls for "contextual effects" (median age, education, experience and past fertility of peers). The marginal peer effect estimates from these models are also positive and highly statistically significant, at about 0.05 percentage-points.

We also explored the robustness of the Probit estimates to changing the sample definition. We found that considering public sector establishments only (that employ about two-thirds of the women in our sample) reduces the estimated peer effects, but only by a small amount. The reduction is most likely related to the fact that more generous family-friendly policies are in place in the public sector. However, whether the smaller effect is due to self-selection of a particular type of employees into the public sector or whether social interactions are actually less important in the presence of these policies is unclear. When we restrict the analysis to small establishments only, our coefficient estimates are strongly significant and conclusions are qualitatively unaltered. Similarly, our results are not sensitive to the choice of time period: considering births in 2003-2004 and births in 2003 only makes the estimates less precise, but does not qualitatively change the conclusions. When we restrict the analysis to women who stay in the same establishment in 2003-2004 or 2003-2005, the point estimates are slightly smaller, though there are no significant differences. However, these last estimates are difficult to interpret because leaving a company is likely an endogenous outcome that is related to negative career experiences, possibly following own or co-worker fertility. Therefore, in the main analysis, we define the peer group at only one point in time, the start of the period, November 2002.

#### **IV. Simultaneous Estimation of the Fertility Game**

This section presents estimates from the full structural model for the fertility game using the approach described in Section II. The unit of analysis is a work establishment and the outcome of interest is the total number of women having a child in the sample period (2003 to 2005). As described in Section II, our structural approach incorporates the Nash Equilibrium constraints requiring that each agent is enacting her own best response to her coworkers' fertility decisions, but does not make assumptions about which equilibrium will occur in cases of multiplicity. Hence, our results are bounds on the parameters rather than unique point estimates.

#### *IV.A Homogeneous Peer Effects*

Table 4 reports these parameter bounds for our initial structural specification for a single peer effect that is the same between all coworkers. Column 1 reports the basic model that only includes variables specific to the individual. Column 2 uses the same set of control variables but allows for common firm-level and establishment-level random effects in the overall error term. Including these effects has a dramatic change on the estimated peer effects. The bounds on the estimated change from positive in the model that assumes independent errors to negative when common unobservables are included. This reversal of the sign of the basic relationship in the model with the inclusion of random effects highlights the importance of firm-level and establishment-level unobserved heterogeneity in determining fertility outcomes at different workplaces.

Although the inclusion of the firm-level and establishment-level errors has a major effect of the peer effect estimates, it does not change the qualitative effects of the other controls. In both models presented in the first two columns of Table 4, women over the age of 30 are more likely to have a child in the sample period, as are women who are college-educated, those with more years of experience and with a single child born before 2003. Mothers with two children by 2003 are significantly less likely to have a child in the period, consistent with the two-child norm mentioned in Section III.A. Column 3 adds the variable for sister's fertility (an indicator for having a sister with a new child from 2000 to 2002) to the model; it is found to have a positive effect on fertility.

In the first 3 columns, all of the individual variables are included in the agent's own utility equation, but not in the net utility functions of the agent's coworkers, which means that the model treats all these variables as instruments for own fertility. The model effectively assumes that there are no contextual effects in that agents only affect their coworkers through the endogenous fertility decisions in the game. Although this may be a reasonable assumption, we relax it in the final column, where establishment-level median values of all of the variables except the designated instrument (sister fertility) are included in the model. Although several of these contextual effects are found to be relevant predictors of fertility, this expansion of the model leaves the estimated peer effects largely unchanged.

Once the random effects are included in the model, the homogeneous peer effects are found to be negative on average. Consistent with the theoretical result for models with

homogeneous peer effects that are negative, we did not uncover any cases of establishment with multiple equilibrium outcomes.

The parameter bounds in Table 4 reflect coefficients in the net utility function and there is no natural, direct interpretation for their magnitudes. Instead, we determine the quantitative importance of the effects by computing marginal effects from one-unit changes in each of the variables on average fertility rates for agents in the sample. These values are computed by comparing the predicted equilibrium fertility rates in the sample with each of the binary variables set to one or zero, and with the discrete experience measure set to its actual value or incremented by 1 unit (corresponding to 10 years).<sup>14</sup> The equilibrium fertility rates with higher and lower values for each control are shown in the first 2 columns of Table 5 and the marginal effect, the difference between these rates, is in the third columns. The top panel of the table reports these marginal effects with the peer effects assigned at their estimated parameter value and the bottom panel makes the same comparison but sets the peer effects to zero. The marginal effect of a unit increase in peer fertility (which can be seen by comparing the values for experience = 0 in the top and bottom panels) is a 5-percentage point decline in the share of agents who have a child in the sample period.

The finding of negative peer effects in fertility is consistent with several of the channels for peer effects described in the theoretical presentation in Section II.A. Specifically, although a desire to adhere to group norms or scale economies from information sharing and childcare coordination would yield positive peer effects, negative effects could come from a desire to distinguish oneself from one's peers, from scale diseconomies when multiple workers take leave at once, or from tournament competition in internal labor markets. The overall negative effects are also consistent with some of the positive channels operating, but the results indicate that the negative channels dominate in the overall population.

One concern about these results is that finding of negative average peer effects may in part be an artifact of our modeling decision (in Equation 1) for effects that increase linearly in the number of coworkers having a child. This model is appropriate if the incremental effect of each additional coworker having a child is constant and does not depend on the number of agents

---

<sup>14</sup> The parameter estimates in Table 4 are reported as bounds. In order to compute a single fertility rate outcome, we use the parameter values at which the distance function was minimized in estimation.

in the workplace. Appendix Table A2 reports estimates from an alternative version of the model, in which the peer effects enter the net utility function as a share rather than a count variable. This functional relationship is analogous to the usual peer effects measures in linear-in-means model of social interactions (Graham and Hahn 2005) where the average peer characteristic is what matters. The results are robust to this alternative measure of peer fertility. The model in column 1 with independent errors produces positive peer effects, but adding the random effects at the firm and work establishment in column 2 lead to negative peer effects.

The main finding in this section of *negative* workplace peer effects in fertility is novel, but the analysis is limited by its reliance on the assumption that all agents have the same influence on all other agents at their workplace. We relax the assumption of homogeneous peer effects in the next section by estimating heterogeneous peer effects for different types of agents.

#### ***IV.B Heterogeneous Peer Effects by Worker Type***

The different theoretical channels for peer effects in fertility, both social and economic, suggest that our model of homogeneous effect in the previous section may be too limiting. Social effects related to group norms might be expected to be stronger within group if agents care more about being similar to their closer peers, leading to overall effects that are more positive within subgroups rather than across them. Alternatively, if the subgroups differ in social status, the social effects could lead all agents to want to resemble one group but not the other. In that case, members of the lower status group would prefer to imitate the higher status peers, leading to positive peer effects across subgroups and negative effects within subgroup for agents in lower status subgroup. Scale economies from sharing information could similarly be stronger within subgroups if women are more likely to coordinate with their more similar peers, or stronger across groups if sharing is more likely with different types. The economic effects related to career competition could lead to more negative peer effects within subgroup (the set of closer competitors), particularly for subgroups engaged in more internal competition. The scale diseconomies for replacing a worker (and keeping their job open) could similarly be stronger (more negative) within subgroups that are related to job functions or tasks, and if these are large enough, workers who take leave at the same time as many similar coworkers may not have the option of returning to the same job at that employer after their maternity leave. This last effect can also differ across subgroups, in this case, depending on the scarcity of their skills and the

costs to the firm of replacing them.

In this section, we estimate expanded versions of our model that allow for heterogeneous peer effects by binary worker types defined based on education (defined by college education versus less than college) and then by age (over or under age 30). For each version of the model, we estimate four peer effect parameters: the effects of the low-type on the low-type, of the low-type on the high-type, of the high-type on the low-type and of the high-type on the high-type. Workplaces with multiple agents of a single type are used to identify the within-type parameters and those with agents of different types provide identification for the cross-type parameters.

The model with separate effects by education type in Table 6 reveals important heterogeneity in the peer effects across different subgroups of women. The first three columns of the table show 95-percent confidence parameter bounds for the peer effects (by type) and control variables in expanded versions of the specifications in Table 4, columns 2 to 4. The final column of Table 6 adds a specification that allows for correlated errors across agents within each workplace and estimates an additional parameter for that correlation. Across all specifications, the pattern of the peer effects is unchanged. The overall negative peer effects from the homogeneous model in Table 4 are reflected in the negative peer effects among lower education women; these women comprise over two-thirds of the sample, so it may not be surprising that their effects dominate the overall average. However, the peer effects among higher education women are found to be *positive*, as are both of the cross-type peer effects. Recall that all models in Table 6 include random effects for firms and establishments and column 4 also allows for correlated individual-specific errors. The inclusion of these terms provides some protection against a spurious finding of positive peer effects (as in the first column of Table 4), which makes the positive effects more credible when they occur.

What do these results indicate about the operative channels for peer effects? The negative peer effects for low-education women from the fertility of their low-education peers, but positive effects from the fertility of the higher-educated peers could indicate a social desire to mimic the higher-status, higher-education group. However, this pattern is not (exactly) what we find among higher-education women, who respond positively to fertility of both higher-educated and lower-educated peers. Similarly, the possibility of information spillovers being more valuable when the source is higher-educated women is also not consistent with the positive effects of fertility from low-education to high-education agents that we find.

Instead, we interpret the pattern as suggesting that the social forces are positive both within and across subgroups, but that the negative effects of competition and scale diseconomies are more important for low-education women. Although competition for promotion (and there the incentive to delay childbearing when peers are having children) can be important for both education groups, it is possible that sex segregation in tasks is more prevalent for lower-education women (occupational sex segregation is decreasing in education level, Cotter, Hermsen and Vanneman 2004), which makes female coworkers a more important group of workplace competitors than for higher-education women who are more likely to also be competing with men. A related, but distinct, explanation for the different signs of the within-group peer effects for higher-education and lower-education women is that lower education women also received less training from employers and acquired less firm-specific human capital, making them less costly to replace. If the costs to firms of keeping a position open increase for women in both subgroups when more women in the same subgroup take leave at the same time, then this difference in replacement costs across subgroups would lead to greater employment risk associated with fertility for low-education women (when more of their peers have children) and more negative peer effects. Indeed, it is well known that education lowers the risk of unemployment for women as well as men (e.g., Mincer 1991). This channel is also supported in our data. In our sample, we find that more educated women are substantially more likely to have positive earnings in 2005, and that their likelihood of having earnings in 2005 is less responsive to their own fertility, and to the interaction between their fertility and their coworkers' fertility during the sample period.<sup>15</sup>

Table 8 has the same structure as Table 6, but reports estimates for peer effects by age group. As in the previous table, there is evidence of important heterogeneity, and of some positive peer effects. However, the pattern in this table differs from the pattern by education in

---

<sup>15</sup> The rates of non-participation in 2005 are 8 percent for lower-education women and 5 percent for higher-education women. Having a child during the sample period predicts a significant 4 percent increase in non-participation for lower-education women but an insignificant 0.2 percent increase for higher-education women. Finally, the estimated effect of fertility on non-participation increases for low-education women by 1.6 percent (from a base of 1.9 percent) for each peer who has a child, but is unaffected by peer fertility for high-education women. These patterns are consistent with the hypothesized channel, but it is important to note that the estimates do not address the endogeneity of fertility and are thus not likely to capture the true causal effects of fertility on participation.

that here the within-group effects are always negative and the cross-group effects are always positive. As in the previous table, this pattern is most consistent with the presence of positive peer effects (from social norms or coordination of childcare or information sharing) that are offset within subgroups of more similar women who are more likely to be competing (for promotions or for job security). The fact that the overall within-group peer effects are negative for both age groups, even though the within-group effect is positive for high-education women, is consistent with higher-education women being a minority within both age groups. Hence, lower-education women are likely driving the overall within-group estimates. The positive cross-group effects seem to indicate that older and younger women are not competing as strongly against one another.

In both Tables 6 and 8, the presence of heterogeneous peer effects (and of some positive peer effects) raises the threat of multiple equilibria, even using our outcome measure defined at the peer group level. We compute the share of all workplaces in which the equilibrium outcome is non-uniquely determined and report these values in the tables. Multiplicity is common in our sample: over 40 percent of workplaces in Table 6 and over 50 percent in Table 7 have values of the observable controls (and unobservable errors) that would indicate more than one potential outcome. The frequency of multiple equilibria in the models with heterogeneous peer effects highlights the value of our estimation approach (that explicitly allows for these cases and uses them to infer bounds on the parameters). It also makes the discussion of marginal effects more complicated. Although we incorporated all of the potential equilibrium outcomes in estimation without selecting among them, we apply an equilibrium selection rule in computing marginal effects.

Tables 7 and 9 report average marginal effects for women in our sample using values from the highest fertility equilibrium. Following the structure of Table 5, which reports average marginal effects in the homogeneous peer effects model, the first panel shows marginal effects of covariates when peer effects have their estimated values (estimates in Table 6 are used for Table 7 and in Table 8 for Table 9) and the second panel shows marginal effects when the endogenous (strategic) peer effects are all set to zero. The incremental impact of peer effects on fertility rates for the average woman in the sample is computed by comparing the fertility rates with and without peer effects for the case of experience = 0 (when all of the women in the sample are assigned their observed values for the controls). In the model with two types of peer effects by

education in Table 7, the combination of peer effects experienced by the average women in the sample increases her fertility propensity by 25 percentage-points (more than doubling the baseline fertility rate with endogenous peer effects set to zero). In the model with two types by age in Table 9, the average effect of peer fertility has a similar impact of increasing fertility propensity by 24 percentage-points (a 93 percent increase over the baseline rate without endogenous peer effects).

## **V. Policy Simulations: Sorting of Women across Establishments**

This section reports results from simulation exercises that explore the importance of sorting of women across establishments on overall fertility rates. As discussed above, one implication of peer effects in fertility among coworkers is that the female labor force participation would then affect fertility, not just through the direct effects of working for pay on the opportunity costs of childbearing, but also through interactions at the workplace. In that case, *where* each woman works, and the peers *with whom* she works, can also affect fertility decisions.

In our policy experiment, we measure the implied effect of sorting on fertility rates using the parameter estimates from our structural models. We do this by creating a set of hypothetical, equally-sized work establishments, and assigning 7 women from our estimation sample to these establishments (thereby creating peer groups) according to each extreme of the potential degree of sorting. First, in what we call “perfect” sorting, we order all women according to the individual propensity to have a child in the sample period, excluding the endogenous and contextual peer effects, and then assign them to workplaces in order (the first 7 women are assigned to the first workplace, the next 7 to the next, etc.). Our second assignment rule, called “random”, involves filling each open slot in order with a woman drawn randomly (without replacement) from the estimation sample.

Table 10 summarizes the different predicted fertility rates for each of these samples using estimates from structural models with homogeneous and heterogeneous peer effects. In all cases of multiple equilibria, we use the equilibrium with the highest fertility rate. The baseline case presented in the first row is from the basic model with endogenous peer effects set to zero. Note, however, that contextual peer effects are still present and women are affected by their coworkers’ characteristics. These contextual effects may explain why fertility is higher (31 percent) in the random sorting sample than the sample with perfect sorting (28 percent).

As expected, fertility rates decline in both samples when the homogeneous peer effects are applied in the next row. The magnitude of the fertility decline (both in absolute terms and relative to the baseline) is larger for the case of perfect sorting. Under perfect sorting, women who are unlikely to have children (absent peer effects) are those who experience the *smallest* negative peer effects while those who are most likely to have children experience the *largest* peer effects because more of their coworkers have children. In the case of negative peer effects, the concentration of women with higher fertility preferences together leads to lower fertility rates than the rates that would result if those women were most dispersed across workplaces.

The impact of sorting is more complex in the case of heterogeneous peer effects. The results for the two-type case by age group are reported next in Table 10. As described in the previous section (and shown in Table 8), the within-type effects are negative for both types but the cross-type effects are both positive. This means that different sorting rules not only affect the likelihood that each individual woman has a peer with a strong taste for fertility but that the sorting rules also affect the chance that she has a peer of her same type (or opposite type) with such tastes. Under perfect sorting, women have mostly same-type peers, and experience mostly negative within-type peer effects. With random sorting, women face a mix of peers and can experience both positive and negative peer effects. The result is that sorting has a much larger impact on fertility in the case with heterogeneous peer effects and also a much larger effect on the incremental effect of workplace peer interactions. Instead of simply moderating the size of the peer effect, here, sorting even affects the direction of the overall peer effect, going from negative with perfect sorting (where the negative within-type effects dominate) to positive with random sorting (where more positive cross-type effects are present).

## **VI. Conclusions**

This paper develops and estimates a model of strategic peer effects in fertility decisions at the workplace. Using register-based data on the population of Denmark, and a sample of women working at medium-sized establishments in November 2002, we find evidence that interactions between female coworkers generate substantial peer effects in fertility outcomes over 2003-2005. The peer effects are negative overall, but they are also heterogeneous across worker types defined by age or education. Cross-type effects are positive in all cases, suggesting either positive social effects or scale economies in childcare. Within type effects are negative for low-

education women (about two-thirds of the sample) and for both older and younger women. The negative effects are likely due to career concerns related to having a child when several coworkers are doing the same – if employers face sufficiently large costs, they may not be able to retain all of the workers through their maternity leaves or to provide all returning mothers with the same opportunities for advancement. The pattern of these relationships suggests that economic interactions among coworkers affect individual fertility decisions.

## References

- Bandiera, O., I. Barankay, and I. Rasul (2010). “Social Incentives in the Workplace.” *Review of Economic Studies* 77 (2), 417-458.
- Becker, G. (1960). “An Economic Analysis of Fertility,” in Becker (ed.) *Demographic and Economic Change in Developed Countries*. Princeton, N.J.: Princeton University Press.
- Bernheim, B. D. (1994). “A Theory of Conformity.” *Journal of Political Economy* 102(5), 841-877.
- Blake, D. and L. Mayhew (2006). “On The Sustainability of the UK State Pension System in the Light of Population Ageing and Declining Fertility.” *Economic Journal* 116(512), F286-F305.
- Bloom, D., D. Canning, I. Gunther, and S. Linnemayr (2008). “Social Interactions and Fertility in Developing Countries.” Harvard School of Public Health Working Paper.
- Blume, L. and S. Durlauf (2005). *Identifying Social Interactions: A Review*. San Francisco: Jossey-Bass.
- Borsch-Supan, A. (2000). “A Model Under Siege: A Case Study of the German Retirement Insurance System.” *Economic Journal* 110(461), F24-F45.
- Brock, W. A. and S. N. Durlauf (2001). “Interactions-based Models,” in Heckman and Leamer (eds.) *Handbook of Econometrics*, Vol. 5, pp. 3297-3380. Elsevier.
- Brock, W. A. and S. N. Durlauf (2007). “Identification of Binary Choice Models with Social Interactions.” *Journal of Econometrics* 140 (1), 52-75.
- Card, D. and L. Giuliano (2011). “Peer Effects and Multiple Equilibria in the Risky Behavior of Friends.” NBER Working Paper 17088.
- Chernozhukov, V., H. Hong and E. Tamer (2007). “Estimation and Confidence Regions for Parameter Sets in Econometric Models.” *Econometrica*, 75, 1243–1284.
- Ciliberto, F. and E. Tamer (2009). “Market Structure and Multiple Equilibria in Airline Markets.” *Econometrica* 77(6), 1791-1828.
- Cohen, A., Freeborn, B., and McManus, B. (2011, forthcoming). “Competition and Crowding-Out in the Market for Outpatient Substance-Abuse Treatment.” *International Economic Review*.
- Cotter, D. A., Hermsen, J. M., and Vanneman, R. (2004). *Gender inequality at work*. Russell Sage Foundation.
- Crane, J. (1991). “The epidemic theory of ghettos and neighborhood effects on dropping out and teenage childbearing.” *American Journal of Sociology* 96, 1226–1259.
- Dahl, G. B., K. V. Løken, and M. Mogstad (2012). “Peer Effects in Program Participation.” NBER Working Paper No. 18198.

- Duflo, E. and E. Saez (2003). "The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence From a Randomized Experiment." *Quarterly Journal of Economics* 118 (3), 815-842.
- Galor, Oded (2005). "The Demographic Transition and the Emergence of Sustained Economic Growth." *Journal of the European Economic Association*, 3(2-3): 494-504.
- Graham, B. S. and J. Hahn (2005). "Identification and Estimation of the Linear-in-Means Model of Social Interactions." *Economics Letters* 88, 1-6.
- Grant, J., S. Hoorens, S. Sivadasan, M. van het Loo, J. DaVanzo, L. Hale, S. Gibson, and W. Butz (2004). "Low Fertility and Population Aging: Causes, Consequences and Policy Options." RAND Corporation Technical report.
- Hotz, J. V., J. Klerman, and R. Willis (1997). "The economics of fertility in developed countries," in Rosenzweig and Stark (eds.) *Handbook of Population and Family Economics*. Vol. 1, pp. 275-347. Elsevier.
- Jones, L., A. Schoonbroodt, and M. Tertilt (2011). "Fertility Theories: Can They Explain the Negative Fertility-Income Relationship?" in Shoven (ed.) *Demography and the Economy*. University of Chicago Press.
- Juul, S. W. Karmaus, J. Olsen and The European Infertility and Sub-fecundity Study Group (1999). "Regional Differences in Waiting Time to Pregnancy: Pregnancy-based Surveys from Denmark, France, Germany, Italy and Sweden." *Human Reproduction* 14 (5), 1250-1254.
- Kearney, M. S. (2004). "Is There an Effect of Incremental Welfare Benefits on Fertility Behavior? A Look at the Family Cap." *Journal of Human Resources* 39(2): 295-325.
- Kohler, H.-P. (2001). *Fertility and Social Interaction - An Economic Perspective*. Oxford: Oxford University Press.
- Krauth, B. V. (2006). "Simulation-based Estimation of Peer Effects." *Journal of Econometrics* 133(1), 243-271.
- Kravdal, O. (2002). "Education and Fertility in Sub-saharan Africa: Individual and Community Effects." *Demography* 39(2), 233-250.
- Kuziemko, I. (2006). "Is Having Babies Contagious? Estimating Fertility Peer Effects Between Siblings." Mimeo, Harvard University.
- Lazear, E. P. and S. Rosen (1981). "Rank-order Tournaments as Optimum Labor Contracts." *Journal of Political Economy* 89(5), 841-864.
- Lindh, T. and B. Malmberg (1999). "Age structure effects and growth in the OECD 1950-1990." *Journal of Population Economics* 12(3), 431-449.
- Manski, C. (1993). "Identification of Endogenous Social Effects: The Reflection Problem." *Review of Economic Studies* 60 (3), 531-542.
- Manski, C. (1995). *Identification Problems in the Social Sciences*. Harvard University Press.
- Manski, C. and J. Mayshar (2003). "Private incentives and social interactions: fertility puzzles in Israel." *Journal of the European Economic Association* 1(1), 181-211.
- Mas, A. and E. Moretti (2009). "Peers at Work." *American Economic Review* 99(1), 112-145.
- Miller, A. (2011). "The Effects of Motherhood Timing on Career Path." *Journal of Population Economics* 24(3), 1071-1100.
- Mincer, J. (1991). "Education and Unemployment of Women." NBER Working Paper 3837.
- Moffitt, R. (1998). "The Effect of Welfare on Marriage and Fertility: What Do We Know and What Do We Need to Know?" National Research Council.
- Montgomery, M.R. and J.B. Casterline (1998). "Social Networks and the Diffusion of Fertility

- Control.” Population Council Policy Research Division Working Paper No. 119.
- Montgomery, M.R. and J.B. Casterline (1996). “Social Learning, Social Influence, and New Models of Fertility.” *Population and Development Review* 22(Supplement: Fertility in the United States: New Patterns, New Theories): 151-175.
- Mumford, K. (2007). “The Optimal Tax Treatment of Families with Children.” SIEPR Discussion Paper No. 0620.
- Mumford, K. and M. F. Lovenheim (forthcoming). “Do Family Wealth Shocks Affect Fertility Choices? Evidence from the Housing Market Boom and Bust.” *Review of Economics and Statistics*.
- Murray, C. (1993). “Welfare and the Family: The U.S. Experience.” *Journal of Labor Economics* 11 (1), S244-S262.
- Nielsen, H. S., M. Simonsen, and M. Verner (2004). “Does the Gap in Family-friendly Policies Drive the Family Gap?” *Scandinavian Journal of Economics* 106(4), 721-744.
- Rangel, A. (2003). “Forward and Backward Intergenerational Goods: Why Is Social Security Good for the Environment?” *American Economic Review* 93(3), 813-834.
- Rennhoff, A. D., & Owens, M. F. (2012). “Competition and the Strategic Choices of Churches.” *American Economic Journal: Microeconomics*, 4(3), 152-170.
- Sacerdote, B. (2001). “Peer Effects with Random Assignment: Results for Dartmouth Roommates.” *Quarterly Journal of Economics* 116, 681-704.
- South, S. and E. Baumer (2000). “Deciphering community and race effects on adolescent premarital childbearing.” *Social Forces* 78(4): 1379–1408.
- Waldfogel, J. (1998). “Understanding the ‘Family Gap’ in Pay for Women with Children.” *Journal of Economic Perspectives* 12 (1), 137-156.
- Willis, R. (1973). “A New Approach to the Economic Theory of Fertility Behavior.” *Journal of Political Economy* 81 (2), S14-S64.

**Table 1: Illustration of Nash Equilibrium Outcomes with Two Agents**

<i>Index of possible outcomes</i>	<i>Women having children</i>	$v_{1e}$	$v_{2e}$
1	0	$\alpha_r X_{1e} + \epsilon_{1e}^{(s)} < 0$	$\alpha_r X_{1e} + \epsilon_{1e}^{(s)} < 0$
2	1	$\alpha_r X_{1e} + \epsilon_{1e}^{(s)} > 0$	$\alpha_r X_{2e} + \epsilon_{2e}^{(s)} + \delta_r^r < 0$
2	1	$\alpha_r X_{1e} + \epsilon_{1e}^{(s)} + \delta_r^r < 0$	$\alpha_r X_{2e} + \epsilon_{2e}^{(s)} > 0$
3	2	$\alpha_r X_{1e} + \delta_r^r + \epsilon_{1e}^{(s)} > 0$	$\alpha_r X_{2e} + \delta_r^r + \epsilon_{2e}^{(s)} > 0$

Notes: This table illustrates the case of a workplace with two agents and three possible equilibria. Each row shows the conditions on the net utility of each agent that would make that outcome a valid Nash Equilibrium. There are two sets of conditions that would each make the outcome with one child a valid equilibrium.

**Table 2: Descriptive Statistics*****Panel A -- Individuals***

	No Birth	Birth	Total
Birth 2003-2005	0	1	0.237
Age greater than 30 years	0.464	0.595	0.495
More than 12 years of education	0.269	0.401	0.300
Less than 6 years of experience	0.482	0.517	0.490
No children before 2003	0.507	0.514	0.509
One child born before 2003	0.124	0.344	0.176
Two children born before 2003	0.282	0.123	0.244
More than two children born before 2003	0.087	0.018	0.071
Any sister with birth in 2000-2002	0.118	0.141	0.123
Number of observations	115,541	35,953	151,494

***Panel B -- Establishments***

	Mean	Std. Dev.
Establishment size	20.46	10.11
- Share 20 employees or fewer	0.63	
- Share 21-30 employees	0.20	
- Share 31-40 employees	0.10	
- Share more than 40 employees	0.07	
Number of women aged 20-40	4.78	3.83
One woman aged 20-40	0.18	
Number of women aged 20-40 who have a child in 2003-2005	1.13	1.47
Private firm	0.72	
# Establishments		31,725

Source: Administrative register-based data on the population of Denmark. Sample of establishments is limited to those with 10 to 50 employees. Sample of individuals is limited to women aged 20 to 40 who worked at one of these establishments in November 2002. Peer groups are defined based on work establishment in November 2002.

**Table 3: Probit Estimates Relating Own Fertility to Peer Fertility, 2003-2005**

	# Peers Having Children	
	Marginal Effect	S.E.
<hr/>		
Exploratory Conditioning Sets		
None	0.0103***	0.0071
+ Individual characteristics	0.0033***	0.0007
+ Sister fertility	0.0032***	0.0007
+ Relationship status and partner characteristics	0.0032***	0.0007
+ Establishment characteristics	0.0030***	0.0008
+ Peer characteristics	0.0037***	0.0008
<hr/>		
Main Conditioning Sets		
Basic	0.0051***	0.0007
+ Contextual effects	0.0055***	0.0007

Notes: Robust standard errors clustered at the work establishment level. The first set of estimates is from separate Probit models that add an extensive set of covariates. See Appendix for the full list of exploratory conditioning variables. The second set of estimates uses the conditioning variable sets in the main models in Tables 4 to 10. The total number of observations is 151,494.

**Table 4: Fertility Game Estimates with Homogeneous Peer Effects**

Variable	(1)	(2)	(3)	(4)
Peer fertility	[0.044, 0.064]	[-0.307, -0.252]	[-0.278, -0.272]	[-0.275, -0.271]
<i>Individual controls:</i>				
Constant	[-1.701, -1.670]	[-2.204, -2.064]	[-2.405, -2.253]	[-2.164, -2.157]
Age > 30	[0.612, 0.702]	[1.014, 1.203]	[1.176, 1.332]	[1.303, 1.309]
College educated	[0.419, 0.458]	[0.889, 1.040]	[0.989, 1.042]	[0.878, 0.884]
Experience	[0.466, 0.582]	[0.852, 0.095]	[0.964, 0.994]	[0.902, 0.906]
One child	[0.728, 0.814]	[0.943, 1.130]	[0.979, 1.072]	[1.252, 1.261]
Two children	[-0.215, -0.137]	[-0.830, -0.657]	[-0.907, -0.706]	[-1.035, -1.024]
<i>Instrument:</i>				
Sister fertility			[0.190, 0.255]	[0.132, 0.145]
<i>Contextual effects:</i>				
Median age >30				[-0.231, -0.223]
Median educated				[0.011, 0.019]
Median experience				[0.034, 0.044]
Median one child				[-0.611, -0.599]
Median two children				[0.1010, 0.108]
Function value	1.57E+04	1.60E+04	1.65E+04	1.64E+04
Fit	0.1277	0.1245	0.1257	0.1265
Percent multiple	0	0	0	0

Notes: Each column reports 95-percent confidence bounds on parameter values for the effects of variables on the fertility decision in different models of the fertility game. Column (1) is from the basic model with only individual controls; column (2) adds firm-specific and establishment-specific random errors; column (3) adds the control for sister fertility; column (4) adds contextual effects summarizing coworker characteristics. The total number of observations is 31,725.

**Table 5: Marginal Effects in Homogeneous Peer Effects Model**

Variable	1	0	Marginal Effect
<i>Peer Effects On</i>			
Age > 30	0.2966	0.2112	0.0854
Education	0.2832	0.2264	0.0568
One child	0.3095	0.2197	0.0898
Two children	0.204	0.2671	-0.0631
Sister fertility	0.2456	0.2371	0.0085
Experience	0.2435	0.2381	0.0054
<i>Peer Effects Off</i>			
Age > 30	0.3542	0.2583	0.0959
Education	0.3369	0.2738	0.0631
One child	0.3679	0.2678	0.1001
Two children	0.2512	0.323	-0.0718
Sister fertility	0.2959	0.2863	0.0096
Experience	0.2936	0.2875	0.0061
Marginal effect of peer fertility			-0.0494

Notes: The values in this table are predicted population average fertility rates for different values of the explanatory variables in models with and without peer effects in fertility. The first column has fertility rates with the binary variables (for age, education, one child, two children, and sister fertility) set to one for each woman and the second column has the same variables set to zero. For the discrete variable measuring experience, the second column has the actual value and the first column increases the variable by one unit (corresponding to 10 years). The marginal effect in the third column is the difference in fertility with the variable set to one versus zero. The average impact of peer effects on fertility in the sample is shown by the difference in predicted fertility with peer effects on versus off in the case of experience.

**Table 6: Fertility Game Estimates by Education**

Variable	(1)	(2)	(3)	(4)
<i>Peer Effects by Education Level:</i>				
Low on low	[-0.791, -0.753]	[-0.803, -0.741]	[-0.823, -0.722]	[-1.140, -1.062]
Low on high	[1.7901, 1.812]	[1.838, 1.907]	[1.660, 1.741]	[1.953, 2.018]
High on low	[6.337, 6.651]	[5.998, 6.088]	[6.282, 10.574]	[10.460, 10.525]
High on high	[5.994, 6.619]	[6.602, 6.693]	[8.645, 9.906]	[9.176, 9.274]
<i>Individual controls:</i>				
Constant	[-2.512, -2.300]	[-2.824, -2.762]	[-2.719, -2.471]	[-2.500, -2.169]
Age > 30	[1.018, 1.086]	[1.219, 1.290]	[0.700, 0.746]	[0.852, 1.001]
Education	[-1.907, -1.744]	[-1.841, -1.748]	[-0.157, 0.151]	[-0.183, -0.105]
Experience	[1.005, 1.345]	[1.394, 1.476]	[0.301, 1.403]	[0.315, 0.482]
One Child	[0.796, 0.891]	[0.889, 0.952]	[1.259, 1.600]	[1.139, 1.322]
Two Children	[-0.327, -0.229]	[-0.157, -0.095]	[0.467, 1.071]	[-0.359, 0.180]
<i>Instrument:</i>				
Sister fertility		[0.068, 0.156]	[0.085, 0.202]	[0.083, 0.234]
<i>Contextual effects:</i>				
Median age >30			[0.367, 0.513]	[0.131, 0.512]
Median educated			[-2.196, -1.470]	[-3.971, -3.856]
Median experience			[-0.022, 0.615]	[0.554, 0.852]
Median one child			[-0.435, -0.302]	[-0.593, -0.293]
Median two children			[-0.967, -0.546]	[-0.495, -0.182]
Correlation				[0.372, 0.495]
Function value	1.47E+04	1.52E+04	1.50E+04	
Fit	0.1182	0.1188	0.1186	
Share multiple	0.4234	0.4264	0.4295	

Notes: The 95-percent confidence parameter bounds in this table are from expanded versions of the models in Table 4 that allow for different effects of peer fertility that depend on the education level of the agent and the coworker. All models include firm-specific and establishment-specific error terms. Column (1) has individual controls; column (2) adds the instrument based on sister's fertility; column (3) adds contextual effects; column (4) adds correlated error terms within work establishments. The total number of observations is 31,725.

**Table 7: Marginal Effects in Peer Effects Model with Two Types by Education**

Variable	1	0	Marginal Effect
<i>Peer Effects On</i>			
Age > 30	0.4533	0.4455	0.0078
Education	0.4848	0.4421	0.0427
One child	0.4602	0.4483	0.0119
Two children	0.4573	0.4492	0.0081
Sister fertility	0.4542	0.4500	0.0042
Experience	0.4519	0.4508	0.0011
<i>Peer Effects Off</i>			
Age > 30	0.2045	0.1865	0.0180
Education	0.2312	0.1858	0.0454
One child	0.2128	0.1916	0.0212
Two children	0.2048	0.1933	0.0115
Sister fertility	0.2039	0.1939	0.0100
Experience	0.1976	0.1961	0.0015
Marginal effect of peer fertility			0.2547

Notes: The values in this table are predicted population average fertility rates for different values of the explanatory variables in the models with peer effects by education group and without peer effects in fertility. In cases of multiple equilibria, we selected the equilibrium with the largest number of births. The first column has fertility rates with the binary variables (for age, education, one child, two children, and sister fertility) set to one for each woman and the second column has the same variables set to zero. For the discrete variable measuring experience, the second column has the actual value and the first column increases the variable by one unit (corresponding to 10 years). The marginal effect in the third column is the difference in fertility with the variable set to one versus zero. The average impact of peer effects on fertility in the sample is shown by the difference in predicted fertility with peer effects on versus off in the case of experience.

**Table 8: Fertility Game Estimates by Age**

Variable	(1)	(2)	(3)	(4)
<i>Peer Effects by Age:</i>				
Younger on younger	[-2.834, -2.768]	[-3.295, -3.248]	[-2.163, -2.122]	[-3.760, -3.702]
Younger on older	[3.846, 3.906]	[4.296, 4.339]	[3.361, 3.420]	[4.469, 4.542]
Older on younger	[4.088, 4.120]	[5.436, 5.507]	[5.638, 5.679]	[5.510, 5.575]
Older on older	[-3.962, -3.853]	[-5.272, -5.210]	[-5.698, -5.661]	[-6.417, -6.344]
<i>Individual controls:</i>				
Constant	[-2.013, -1.956]	[-2.110, -2.063]	[-2.265, -2.231]	[-2.100, -2.040]
Age > 30	[0.495, 0.558]	[0.570, 0.620]	[-0.107, -0.075]	[-0.123, -0.067]
Education	[0.392, 0.463]	[0.327, 0.376]	[0.288, 0.320]	[0.599, 0.645]
Experience	[0.523, 0.594]	[0.555, 0.599]	[0.077, 0.118]	[-0.169, -0.114]
One Child	[0.674, 0.729]	[0.698, 0.749]	[0.921, 0.961]	[1.064, 1.122]
Two Children	[-0.449, -0.384]	[-0.370, -0.305]	[-0.016, 0.045]	[0.405, 0.475]
<i>Instrument:</i>				
Sister fertility		[0.135, 0.183]	[0.098, 0.132]	[0.103, 0.202]
<i>Contextual effects:</i>				
Median age >30			[0.955, 0.997]	[0.991, 1.050]
Median educated			[0.216, 0.253]	[-0.119, -0.073]
Median experience			[0.534, 0.602]	[0.701, 0.779]
Median one child			[-0.122, -0.087]	[-0.400, -0.341]
Median two children			[-0.306, -0.244]	[-0.662, -0.602]
Correlation				[0.701, 0.763]
Function value	1.37E+04	1.41E+04	1.39E+04	
Fit	0.117	0.1171	0.1178	
Share multiple	0.5440	0.5540	0.5504	

Notes: The 95-percent confidence parameter bounds in this table are from expanded versions of the models in Table 4 that allow for different effects of peer fertility that depend on the age group of the agent (over or under 30 years of age) and the coworker. All models include firm-specific and establishment-specific error terms. Column (1) has individual controls; column (2) adds the instrument based on sister's fertility; column (3) adds contextual effects; column (4) adds correlated error terms within work establishments. The total number of observations is 31,725.

**Table 9: Marginal Effects in Peer Effects Model with Two Types by Age**

Variable	1	0	Marginal Effect
<i>Peer Effects On</i>			
Age > 30	0.5268	0.5005	0.0263
Education	0.5461	0.4958	0.0503
One child	0.5117	0.5040	0.0077
Two children	0.5088	0.5039	0.0049
Sister fertility	0.5075	0.5046	0.0029
Experience	0.5059	0.5050	0.0009
<i>Peer Effects Off</i>			
Age > 30	0.2833	0.2578	0.0255
Education	0.3143	0.2488	0.0655
One child	0.2874	0.2568	0.0306
Two children	0.2769	0.2553	0.0216
Sister fertility	0.2742	0.2593	0.0149
Experience	0.2632	0.2618	0.0014
Marginal effect of peer fertility			0.2432

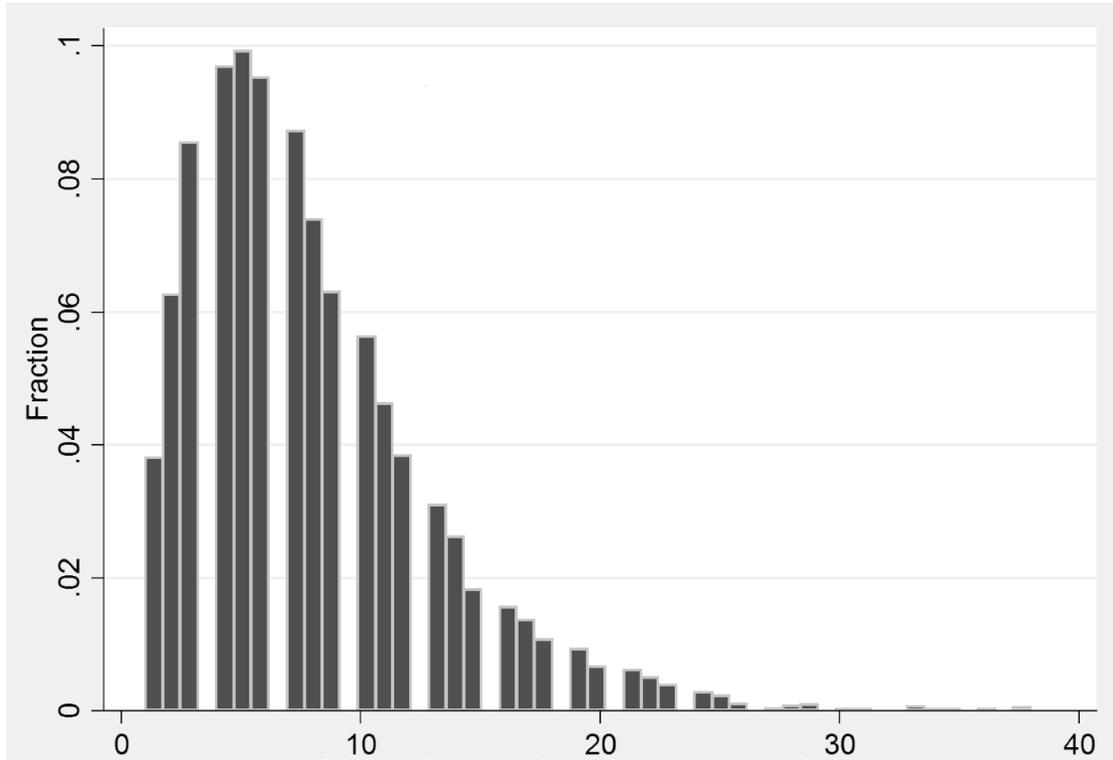
Notes: The values in this table are predicted population average fertility rates for different values of the explanatory variables in models with by peer effects by age group and without peer effects in fertility. In cases of multiple equilibria, we selected the equilibrium with the largest number of births. The first column has fertility rates with the binary variables (for age, education, one child, two children, and sister fertility) set to one for each woman and the second column has the same variables set to zero. For the discrete variable measuring experience, the second column has the actual value and the first column increases the variable by one unit (corresponding to 10 years). The marginal effect in the third column is the difference in fertility with the variable set to one versus zero. The average impact of peer effects on fertility in the sample is shown by the difference in predicted fertility with peer effects on versus off in the case of experience.

**Table 10: Impact of Alternative Rules for Assigning Women to Establishments**

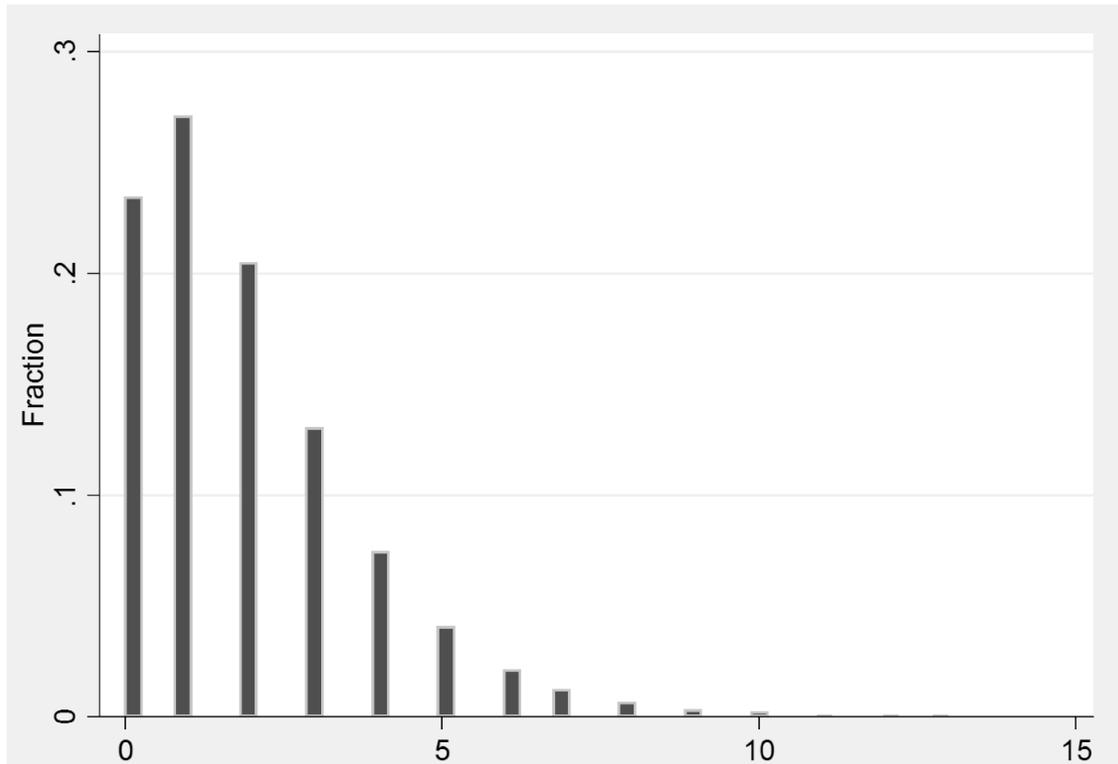
Sorting and Assignment Rule	Perfect	Random
Baseline: No (endogenous) peer effects	0.281	0.308
Homogeneous peer effects	0.192	0.228
Incremental peer effect	-0.089	-0.080
Relative to baseline fertility	-32%	-26%
Heterogeneous (by age) peer effects	0.064	0.738
Incremental peer effect	-0.217	0.430
Relative to baseline fertility	-77%	140%

Notes: The values in this table are predicted population average fertility rates using estimated parameters from the structural models on different simulated samples of peer groups. Each simulated establishment has 7 fertile-age women. In the first column, women are assigned to peers that are most similar to them (in terms of their predicted fertility propensity, based on individual covariates). In the second column, women are drawn and assigned to workplaces at random. In cases of multiple equilibria, we selected the equilibrium with the largest number of births. The first row reports predicted fertility using parameters from the homogeneous effects model (Table 4) but setting peer effects to zero. In the second row, the rates are again derived from the homogeneous effects model, but with the estimated peer effects. The next predicted fertility rates (in the 5th row) are from the heterogeneous effects model with two types by age.

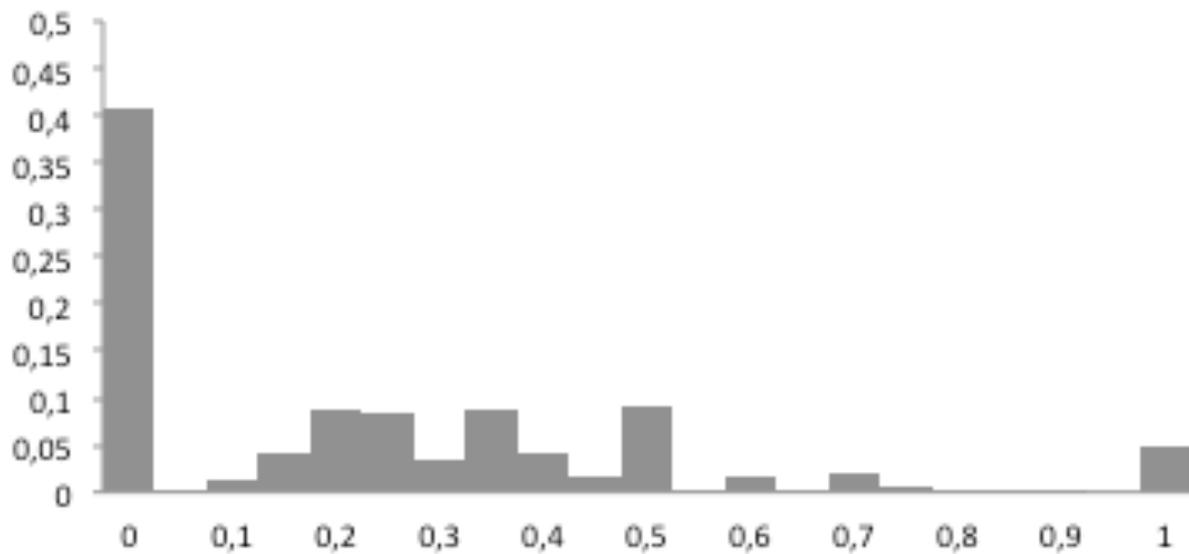
**Figure 1: Distribution of Women per Workplace, November 2002**



**Figure 2: Distribution of Number of Women with Births, Across Establishments, 2003-2005**



**Figure 3: Distribution of Share of Women with Births, Across Establishments, 2003-2005**



## **Appendix: Variables in Conditioning Set**

*Personal characteristics:* Indicator for being less than 25 years of age, indicator for being 25-29 years of age, indicator for having more than 12 years of education, indicator for professional occupation, indicator for tenure less than four years, experience, experience squared, indicator for living in a big city, indicator for living in a smaller city.

*Spouse characteristics:* Indicator for having a partner, indicator for high income, indicator for spouse being more than five years older, indicator for spouse having more than 12 years of education, indicator for spouse in professional occupation.

*Establishment characteristics:* Indicator for private company, indicator for large establishment (more than 20 employees).

*Peer characteristics:* Share of peers less than 25 years of age, share of peers aged 25-29, share of peers with more than 12 years of education, share of peers in professional occupation, share of peers with less than four years of tenure, mean experience among peers, mean experience squared among peers.

**Table A1: Fertility Game Estimates with Peer Effects Based on Shares**

Variable	(1)	(2)
Peer fertility	[0.247, 0.277]	[-1.517, -1.363]
Constant	[-1.680, -1.665]	[-2.474, -2.403]
Age > 30	[0.676, 0.688]	[1.281, 1.332]
College education	[0.478, 0.491]	[0.899, 1.006]
Experience	[0.572, 0.582]	[1.097, 1.157]
One child	[0.650, 0.676]	[1.013, 1.069]
Two children	[-0.273, -0.258]	[-0.719, -0.641]
Function value	1.56E+04	1.60E+04
Fit	0.1266	0.1245
Multiple	0	0

Notes: Each column reports bounds on parameter values for the effects of variables on the fertility decision in different models of the fertility game. Column (1) is from the basic model with only individual controls; column (2) adds firm-specific and establishment-specific random errors. These specifications correspond to those in the first two columns of Table 4, but with the peer fertility variable defined as the share of coworkers having a child in the period, rather than the number of coworkers having a child.