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The Family Peer Effect on Mothers' Labour Supply

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Abstract

The well documented rise in female labour force participation in the last century has flattened in recent decades, but the proportion of mothers working full-time has been steadily increasing. In this paper we provide the first empirical evidence that the increase in mothers' working hours can be amplified through the effect on her labour decisions from the decisions of her family peers. Using Norwegian administrative data covering the full population of women, we study the long-run influence of the family network on mothers' labour decisions up to seven years post birth by regressing the mothers' working hours on the average working hours across her sisters and female cousins. To identify the causal peer effect, we exploit and extend the partially overlapping peer group approach by considering for each mother both her family and her neighbourhood networks, therefore assuming that a mother interacts with her neighbours and family but she does not interact meaningfully with her family's neighbours. Moreover, we provide some empirical evidence on the potential mechanisms such as the importance of information transmission versus imitation in explaining the peer effect.

JEL Classification: D85, C21, C26

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1 Introduction

Over the last century and in almost all developed countries, female labour participation has been characterized by a steep increase, which has been driven mainly by mothers labour participation (Eckstein and Lifshitz 2011 and Fogli and Veldkamp 2011). Such changes in the mothers' labour supply may have been triggered by the increase in the availability of child care, cultural changes, the introduction of fertility control methods and other institutional and policy changes. However, what it is becoming more evident - for instance by the large variation in labour supply across subgroups of workers and across neighbourhoods - is that the influence of peers on individual labour decisions can amplify the effect of such triggering events, and may ultimately be the reason for the rapid increase in female labour participation over time (see Maurin and Moschion 2009, Fogli and Veldkamp 2011, Mota et al. 2016).

More recent decades have seen a flattening of the trend in mothers' labour participation rates, but a steady increase in the proportion of mothers working full-time. This is true in Norway (see Fig. 1) and other OECD countries (Blau and Kahn, 2013[1]), indicating that current changes in female labour supply is along the intensive margin. In this paper we provide the first empirical evidence on the causal influence of peers on the working hours of mothers in each of the first seven years post childbirth. In comparison previous papers that have estimated the causal peer effect on mothers' labour supply have focused exclusively on the extensive margin measured and at any point of the mother's life (see Maurin and Moschion 2009, Mota et al. 2016).

Mothers' labour decision can be affected by their peers' decisions because of information transmission and imitation. A mother's work decisions after childbirth can have long term effects on her human capital, earnings and employment prospects (Edin and Gustavsson 2008) and on her child's outcomes (Ermisch and Francesconi 2005; Bernal 2008; Liu et al. 2010; Bernal and Keane 2011; Del Boca et al. 2014). The peer transmission of information

[1] which shows the large (small) increase in female participation in OECD countries (US) is accompanied by no change (a fall) in part-time and therefore an increase in full-time work.

may be caused by the uncertainty of the effect of maternal employment on children, which leads mothers to look to peers for information (Fogli and Veldkamp 2011). The imitation mechanism can be explained by the fact that a mother's utility may increase by behaving similarly to her peers (see Akerlof and Kranton 2000).

By using Norwegian administrative data covering the full population identifying both where people are living each year, as well information on individuals' family relations over multiple generations, we are able to focus on naturally occurring peer groups from the complete network of family peers and neighbours. Furthermore, by allowing the family peer effect to differ by level of education and parity, we provide some empirical evidence on the potential mechanisms such as the importance of information transmission versus imitation in explaining the peer effect. Our focus is on the causal influence of the family network on long-run labour supply decisions of mothers post childbirth, in addition to the effect of neighbours as in existing studies. The mother is more likely to interact meaningfully with her family members and we may expect these interactions to be more important than interactions with peers outside the family, such as neighbours and therefore to have a stronger effect on womens' labour decisions. The causal effect of the family network has been studied in some recent papers that have focused on the spillover effect of siblings on various outcomes but not on female labour supply.[2] Contrary to these papers, we focus on a wider definition of family network that goes beyond the household members and includes cousins as well as siblings.

The identification and estimation of the effect of peers has proved to be challenging because of the issues of *reflection (simultaneity)*, *correlated omitted variables* and *endogenous peer membership* (Manski 1993, Moffitt 2001). To solve these identification issues we exploit and extend the partially overlapping peer groups approach (Bramoullé et al. 2009; Lee et al. 2010; De Giorgi et al. 2010).

[2] See Oettinger (2000), Monstad et al. (2011), Adermon (2013), Qureshi (2013), Joensen and Nielsen (2015), Altonji et al. (2013), Aparicio-Fenoll and Oppedisano (2016), Dahl et al. (2014), and Nicoletti and Rabe (2016).

We approach the issue of reflection by adopting an instrumental variable estimation of the effect of the average working hours of family peers on mothers' working hours. More precisely we rely on the fact that the neighbours of the family peers of a mother living in different areas do not affect her labour decision directly but only indirectly through the family peers' labour decisions, so that we can instrument the average working hours of family peers by considering the average of their neighbours characteristics. Assuming that neighbours of family living in different areas do not interact directly with the mother in question is less restrictive than the corresponding assumption imposed by previous papers on school and university peers effect (see Bramoullé et al. 2009; Calvó-Armengol et al. 2009; De Giorgi et al. 2010; Lin 2010; Patacchini and Zenou 2012; Mora and Gil 2013; Patacchini and Venanzoni 2014), which consider peers of peers within the same location, for example students and friends of their nominated school friends or college students taking different classes. Meaningful interaction between the student and their peers of peers is highly likely if they are in the same college or school and cohort and the list of nominated friends is not exhaustive. In our application the two peer groups of family and neighbourhood exist in different settings and the assumption of no relevant interactions between a person and her peers of peers is more credible. In any case we run a set of sensitivity checks to test the validity of this assumption.

We solve the issue of correlated omitted variables that would confound the effect of family peers by controlling for a set of mother, father and child characteristics as well as for the average of these characteristics across family peers, which can affect the labour decision of women after childbirth. Because our instruments are given by average characteristics of neighbours of the family peers, endogeneity caused by omitted variables can occur also if mothers sort into similar neighbourhoods. To control for these potential unobserved correlated factors we implement a neighbourhood (network) fixed effect estimation, which takes account of all observed and unobserved neighbourhood characteristics therefore solving the endogeneity issue. This is an improvement with respect to De Giorgi et al. (2010), who do not control for potential unobserved network characteristics which may be correlated with both the individual and the peers of peers' outcomes. A residual endogeneity bias could remain if there are contextual or environmental influences that change across time and that affect areas which are larger than a neighbourhood, potentially including both the mothers' and her family peers' neighbourhoods. In the specific case of working hours such a residual bias may be caused by area labour market shocks affecting both mothers and her family peers' neighbours, which we control for by including a set of labour market dummies interacted with year dummies.

Finally, an issue of endogenous peer membership may occur if the likelihood to interact with peers depends on unobserved characteristics which also affect the outcome variable. Peers are defined as people belonging to the same family or neighbourhood so the likelihood to form interactions depend on the selection into the family and into the neighbourhood. Our control for a neighbourhood fixed effect controls for the endogenous family and neighbourhood network by controlling for the selection into the neighbourhood but also for the fact that mothers might select into neighbourhoods with women who have unobserved genetic traits and background characteristics similar to the ones observed in the family. The neighbourhood fixed effect controls only for time invariant neighbourhood unobservables and to correct for the potential residual bias from a changing neighbourhood composition we chose as neighbours only those who have given birth between one and five years earlier than the family peers. This implies that recent changes in the composition of the neighbourhood that may explain the decision of family peers to move to a specific neighbourhood are not correlated with our instrumental variables, which are characteristics of mothers living in that neighbourhood who gave birth in the past. Notice also that because we consider only neighbours who have given birth in the past and family peers who have given birth at least one month before the mother, we also solve any potential reflection issues, i.e. any reverse causality going from the neighbours to the family peers and from the family peers to the mother in question. Finally to reassure ourselves that the unobserved common genetic and background characteristics of family peers do not lead to any residual bias, we estimate the family peer effect when defining peers as sisters-in-law and cousins-in-law rather than sisters and cousins.

Using the Norwegian administrative data covering the full population of mothers giving birth between 1997 and 2002 (see Section 4 for a description of the data) and an estimation approach that takes account of potential biases caused by the omission of neighbourhood characteristics, the reflection problem, and endogeneity and measurement error issues (see Section 3); we find that cousins and sisters have a statistically significant causal (endogenous) peer effect on the number of hours worked by mothers for children at preschool age (see Section 5). We show that these results are robust when we control for common macro shocks, genetics, general equilibrium effects, work place peer effects, when considering multiple sets of instrumental variables (see Section 6) as well as when considering different types of model specification (see Section 9). We also provide some suggestive empirical evidence that imitation plays a more relevant role than information in explaining the family peer effect (see Section 7).

Finally, to compare our results with previous papers on the effect of neighbours on women's labour supply (see Section 2), we use our identification strategy in reverse, i.e. by exchanging the roles of the neighbourhood and family networks, to identify the neighbours effect on mothers' hours worked. We do not find any significant effect of neighbours even if we consider only mothers living in the same zip code with the same level of education and with their first child born between 1 and 5 years earlier than the mother being studied (see Section 8). This seems to suggest that interactions between family peers matter more than interactions between neighbours.

2 Related literature

Looking at previous papers on peer effects on women's labour supply, there is empirical evidence of a positive effect of sister-in-law participation in Neumark and Postlewaite (1998), of mother-in-law participation in Fernandez et al. (2004), and of the mother and mother-in-law employment decisions in Del Boca et al. (2000). Nevertheless, there are only two papers that have attempted to estimate a causal (endogenous) peer effect on women's labour participation, which are Maurin and Moschion (2009) and Mota et al. (2016) and both papers focus on neighbours rather than family peer effects. Maurin and Moschion (2009) consider only mothers who have at least two children and evaluate the effect on their labour participation of the participation rate of their neighbours, which they instrument using the sex composition of the two eldest siblings of the neighbours and the proportion of neighbours with a second child born in the last quarter of the year.[3] Mota et al. (2016) relies on temporal variations in the characteristics of the neighbours and of the women being studied to identify the effect of the numbers of working peers, non-working peers, working non-peers and non-working non-peers living in the same neighbourhood (where peers and non-peers are neighbours with and without similar characteristics defined by gender, level of education, age of children and marital status). Both papers find evidence for a statistically significant effect of neighbours' labour decisions on womens' own decisions and this seems to suggest that the rapid increase in female labour participation over time can be explained in part by a social multiplier effect, i.e. by the fact that an increase in the labour participation rate of the woman's neighbours can lead to an increase of her participation.

There are several studies on peer effects on outcomes different from the labour supply, which have looked at the spillover effect of siblings as well as at the effect of other types of peers that go from work colleagues (Mas and Moretti 2009, and Dahl et al. 2014), to neighbours (Durlauf 2004) and school mates (Sacerdote 2011 and Lavy et al. 2012). Some

[3] Mothers with two eldest children with the same sex are more likely to have a third child and less likely to work. Children born during the last quarter of the year start school later and therefore may cause a reduction in their mother's labour supply.

of these studies have estimated a causal peer effect by using exogenous variation in the peers members caused by fieldwork experiments such as the MTO (Moving to Opportunity) experiment in U.S. or quasi-experiments such as the random allocation of students in to classes occurring in some schools. Other studies have instead exploited exogenous shocks, caused e.g. by policy interventions, which affected only a part of the population and have examined the spillover effect on people not directly affected by the shocks. It is only more recently that empirical studies have begun to estimate the effect of peers by exploiting the intransitivity of the network to identify a person's peers of peers that are not her direct peers and therefore can affect her only indirectly through her peers. This approach has borrowed from the spatial statistics (see Kelejian and Prucha 1998 and Lee 2003) and it is now been used in several empirical economic studies (see Bramoullé et al. 2009, Chen 2013, Mora and Gil 2013, and Patacchini and Venanzoni 2014). Generally these studies are based on surveys which collect details of a sample of individuals and their peers such as the U.S. National Longitudinal Survey of Adolescent Health (AddHealth), which provides details on school mates and their peers. Because there are not many of these surveys, some new empirical studies have begun to rely on administrative data with details on the universe of individuals and peers defined as neighbours, work colleagues or school mates. If individuals interact in groups and belong to two or more reference groups (e.g. the family and the neighbour groups) which are only partially overlapping, then it is possible to identify peers of peers who are not direct peers and exploit this intransitivity in the network to identify the effect of peers (see De Giorgi et al. 2009 and 2015 and Nicoletti and Rabe 2016).

3 Identification and estimation of within-family peer effects

We consider a mean regression model that allows for two different peer effects, one for the family members and another one for the neighbours. More specifically we consider the following equation

$$y_{ir} = \alpha + \bar{y}_{F,i}\rho_1 + \bar{y}_{N,i}\rho_2 + \mathbf{x}_{ir}\ \boldsymbol{\beta} \qquad (1)$$
$$+\bar{\mathbf{x}}_{F,i}\boldsymbol{\gamma}_1 + \bar{\mathbf{x}}_{N,i}\boldsymbol{\gamma}_2 + \mu_r + \epsilon_{ir},$$

where i denotes mothers in our sample where $i = 1, ..., n$; r denotes the neighbourhood and $r = 1, ..., R$; y_{ir} is the number of weekly hours worked by mother i in a specific year after childbirth; $\mathbf{x}_{ir}$ is a row vector with K individual maternal exogenous variables; $\bar{y}_{F,i} = \frac{\sum_{j\in P_{Fi}} y_{jr}}{n_{Fi}}$ and $\bar{y}_{N,i} = \frac{\sum_{j\in P_{Ni}} y_{jr}}{n_{Ni}}$ are respectively the family and neighbourhood averages of y, while $\bar{\mathbf{x}}_{F,i} = \frac{\sum_{j\in P_{Fi}} \mathbf{x}_j}{n_{Fi}}$ and $\bar{\mathbf{x}}_{N,i} = \frac{\sum_{j\in P_{Ni}} \mathbf{x}_j}{n_{Ni}}$ are the corresponding averages of the vector of variables $\mathbf{x}$, P_{Fi} and P_{Ni} are the sets of family and neighbour peers of mother i excluding herself, i.e. the subsample of mothers who belong to the same family (sisters or cousins) and/or who live in the same neighbourhood; n_{Fi} and n_{Ni} are the numbers of family and neighbour peers of mother i; μ_r is the neighbourhood effect capturing any other unobserved characteristics which do not change across mothers living in neighbourhood r; and ε_{ir} is an error term with $E(\varepsilon_{ri}|\mathbf{x}) = 0$. The scalar parameters ρ_1 and ρ_2 measure the endogenous family and neighbourhood peer effects, $\boldsymbol{\gamma}_1 = [\boldsymbol{\gamma}_{11}, ..., \boldsymbol{\gamma}_{1K}]'$ and $\boldsymbol{\gamma}_2 = [\boldsymbol{\gamma}_{21}, ..., \boldsymbol{\gamma}_{2K}]'$ are two $K \times 1$ vectors of exogenous family and neighbourhood effects, $\boldsymbol{\beta}_0 = [\boldsymbol{\beta}_{01}, ..., \boldsymbol{\beta}_{0K}]'$ is a $K \times 1$ vector of the effects of the corresponding K mothers' characteristics and finally the scalar parameter α is the intercept.

To solve the potential reflection issue we use an instrumental variable approach that can be viewed as an extension of the approach introduced by Kelejian and Prucha (1998) and Lee (2003).[4] The extension consists of considering interactions occurring between people within multiple rather than a single network. More specifically, we consider the family and neighbourhood networks, and assume that each mother interacts with her family members (cousins and sisters) and with her neighbours but that mothers do not interact with her

[4]See also Lee (2007), Bramoullé et al. (2009), Calvó-Armengol et al. (2009), Lee et al. (2010), and Lin (2010).

family members's neighbours. Note that we consider *homogenous neighbours* i.e. neighbours who have given birth shortly before the sister or cousin and with the same education, defined as having a degree or not. The approach to consider homogenous peers has become standard in recent papers on neighbours peer effects and it is justified by the fact that interactions between non-homogenous peers are not likely. Maurin and Moschion (2009) estimate the effect of neighbours on womens' labour supply selecting homogenous peers defined as neighbours who are mothers aged between 21 and 35, in 2 parent families and with at least 2 children. Mota et al. (2016) show that the non-homogeneous group of neighbours generally has no effect on female labour supply and that mothers with similar age children appear to be the most relevant peers.

Our identification strategy is similar to the approach used by De Giorgi et al. (2010) and it exploits the fact that different reference groups of a person are partially overlapping, but contrary to De Giorgi et al. (2010) we do not impose that the different reference groups (the family and neighbourhood in our case) have the same peer effect. Our identification approach is closer to the one adopted by Nicoletti and Rabe (2016) and De Giorgi et al. (2015), where the effect of different peer groups is allowed to be different. Nicoletti and Rabe (2016) consider the sibling spillover effect that goes from the older to the younger sibling and derive instrumental variables using average characteristics of the older sibling's school mates; De Giorgi et al. (2015) consider the peer effects on household consumption decisions of the wife's work colleagues and of the husband's work colleagues and derive instrumental variables using the average characteristics of the colleagues of the colleagues' spouses.

Our approach exploits the fact that neighbours characteristics of the mothers' family peers who do not live in her neighbourhood can affect the mothers' decision only through the decision of her family peers. Analytically this means that we can use the averages of the variables x for the neighbours of the mothers' family members, i.e. $\bar{\bar{\mathbf{x}}}_{NF,i} = \frac{\sum_{j \in P_{Fi}} \bar{\mathbf{x}}_{N,j}}{n_{Fi}}$ and the mean of the dependent variable y for the neighbours of the mothers' family members, i.e. $\bar{\bar{y}}_{NF,i} = \frac{\sum_{j \in P_{Fi}} \bar{y}_{N,j}}{n_{Fi}}$ as instrumental variables for $\bar{y}_{F,i}$. Both $\bar{\bar{\mathbf{x}}}_{NF,i}$ and $\bar{\bar{y}}_{NF,i}$ are averages of predetermined variables because we consider only mothers' family peers who gave birth at least one month earlier than the mother and neighbours of the mothers' family peers who gave birth between one and five years earlier than the family peers. For our main results we use as instrumental variable only $\bar{\bar{y}}_{NF,i}$, but in our sensitivity analysis we consider also a set of additional instruments, $\bar{\bar{\mathbf{x}}}_{NF,i}$, which are based on birth outcomes (low birth weight, very low birth weight, congenital malformation, severe deformity and multiple births) and combinations of mothers' and fathers' education and age at birth.

While we make sure that our instrumental variables are predetermined by considering the working hours of peers that have given birth in the past, De Giorgi et al. (2010) and Nicoletti and Rabe (2016) use the average for the peers of peers (excluded peers) of variables which are good predictors of the dependent variable and observed in the past (e.g. lagged test scores to predict current test scores and self-reported expectation on future decisions to predict current decisions).

As in any other type of application, to be valid our instrumental variables must be: (i) relevant, i.e. they must be important in explaining the average working hours after childbirth of family peers, our instrumented variable; and (ii) exogenous, i.e. they must be uncorrelated with unobserved variables explaining the mothers' work status after childbirth, which is our dependent variable. We discuss condition (i) in Section 5 and condition (ii) refers to the issue of correlated unobservables which we discuss now.

We can assure that our instruments are exogenous if there are no omitted neighbourhood characteristics and if neighbourhood peers of the mothers' family peers do not interact directly with the mother in question. We consider three potential deviations from these assumptions and our strategies solve for them.

The first issue for the validity of our instruments is caused by the fact that our instrumental variables are neighbourhood average characteristics and if mothers have family peers who tend to sort out in very similar neighbourhoods, then failing to control thoroughly for the neighbourhood characteristics of the mothers can lead to an overestimation bias of the family peer effect. We avoid this potential issue by considering neighbourhood fixed effects, which net out the potential bias caused by the sorting of family peers into similar neighbourhoods. In practice we do this transforming all the variables in equation (1) as deviations from their neighbourhood average, i.e. we consider the following model

$$\widetilde{y}_{ir} = \widetilde{\bar{y}}_{F,i}\rho_1 + \widetilde{\mathbf{x}}_{ir}\ \boldsymbol{\beta} + \widetilde{\bar{\mathbf{x}}}_{F,i}\ \boldsymbol{\gamma}_1 + \widetilde{\epsilon}_{ir}, \tag{2}$$

where $\widetilde{}$ indicates that a variable is expressed as deviation from the neighbourhood mean and where both endogenous and exogenous neighbourhood effects cancel out. We estimate model (2) using a two-stage least squares estimation with fixed effects (2SLS,FE). The first stage consists in the neighbourhood fixed effect estimation of the regression of $\bar{y}_{F,i}$ on $\mathbf{x}_{ir}$, $\bar{\mathbf{x}}_{F,i}$ and the instrumental variables $\bar{\bar{\mathbf{x}}}_{NF,i}$ and $\bar{\bar{y}}_{NF,i}$.[5] The second stage consists in the neighbourhood fixed effect estimation of (2) by replacing $\widetilde{\bar{y}}_{F,i}$ with its prediction from the first stage.

The second issue for the validity of our instruments is caused by potential interactions between a mother and the neighbours of her family peers. If such interactions exist then the family peers' neighbours could have a direct effect on the mother and therefore the average characteristics of the neighbours of her family peers, $\bar{\bar{\mathbf{x}}}_{NF,i}$ and $\bar{\bar{y}}_{NF,i}$, would be invalid instruments. These interactions between a mother and the neighbours of her family peers are likely to occur if some of her family peers live in her same neighbourhood but are less likely if they live in different neighbourhoods. Since we consider neighbourhood fixed effect estimation, our estimated coefficients are net of the mothers' neighbourhood effect and this implies also that they are net of the effect of the neighbours of the mothers' family peers living in the same neighbourhood as the mother.

However, even for mothers living in different neighbourhoods to her family our instru-

[5] Because we control for neighbourhood fixed effect also in this first stage, the estimated effect of the instrument is net of the effect of neighbours of family members living in the same neighbourhood as the mother in question. This is the reason why our instrumental variable approach is similar in spirit to De Giorgi et al. (2010), who use as instrumental variables the averages of $\mathbf{x}$ for the excluded peers.

ments could be invalid if there are unobserved factors explaining labour market decisions of both the peers of peers and the mother in question or if there are direct interactions between a mother and her family peers' neighbours. We consider potential threats to the validity of our instruments and perform sensitivity analyses to show that our estimation results are not affected by such threats. In particular we consider i) common macro shocks which affect individuals living in different neighbourhoods, ii) unobserved genetic traits, iii) general equilibrium and iv) work peer effects and finally we vary the set of instruments used for estimation and test for overidentification (see Section 6).

Another third concern is that labour supply decisions of family peers may affect the corresponding decisions of their neighbours because of the so called feedback or reverse causality effect. This implies that our instruments, which are average characteristics of the family peers' neighbours, may be endogenous i.e. correlated with the error term in our main equation. We avoid any potential bias caused by this endogeneity issue by considering only neighbours that had their first child between one and five years earlier than the family peers living in the same neighbourhood.

In addition to solving the potential issues of reflection and correlated unobservables, our identification strategy aims to control for the endogeneity of the peer membership (Manski 1993; Moffitt 2001). If the probability to interact with peers depends on unobserved characteristics which affect the outcome variable, then our estimation could be biased because of the endogenous peer membership. Such bias is unlikely in our estimation because we consider neighbourhood fixed effects to control for the selection into neighbourhood. This means that our instrumental variable estimation with neighbourhood fixed effects corrects for the potential bias caused by the fact that mothers might select into neighbourhoods with women who have unobserved genetic traits and background characteristics similar to the ones of their family. In addition we select as neighbours only those who gave birth between one and five years prior to the family peers to control for time varying compositional changes to the neighbourhood. Even after controlling for the fixed effect, some peer group endogeneity could remain and we test for this in Section 6 by estimating the family peer effect using sister and cousin - in laws who have no genetic link to the mother.

Finally, ordinary least square estimation (OLS) of the family peer effect on hours worked are prone to attenuation bias caused by measurement error in the variable used to construct labour hours.[6] Our instrumental variables method corrects for this bias and therefore when interpreting the difference in estimates from OLS and two-stage least squares we note that instrumenting for the family peer effect controls for both the reflection problem and measurement error.

4 Data

4.1 Data and sample selection

We use Norwegian administrative register data for the period 1960-2010, which are collected and maintained by Statistics Norway. The data provides unique linkage of the population of Norway across different registers and across time, providing information to enable identification of family members and neighbours living in the same zip code and information on labour market status, the month and year of birth, birth outcomes, earnings and demographic variables including age and education.

For all births since 1960 we extract identifiers of the new born's mother from census data. We then link on the sisters and cousins of this child's mother by the following method. To link the mothers with her sisters we define her mother's identifier (the maternal grandmother of the child). Mothers to children with a common maternal grandmother are siblings. In order to link the mother to her female cousins, we take her maternal and paternal grandmothers' identifiers and consider all mothers with either a shared maternal or paternal grandmother (the two maternal great-grandmothers of the child). Any mothers to children with a common maternal great-grandmother are defined as cousins. This creates a set of

[6] See Appendix A for full details.

maternal cousins (whose child's maternal grandmother has the same mother) and a set of paternal cousins (whose child's maternal grandfather has the same mother). We can identify the cousins as long as their grandmothers are alive in the first census year in 1960. Assuming an average gap of 30 years between generations and considering children born in 1997, their two maternal great-grandmothers would be born in 1907 and be 53 years old in 1960. This suggests that children born from 1997 onward are likely to have their two maternal great-grandmothers alive in 1960. Our main sample is selected from all births between 1997 and 2002. We cut off births before 1997 because we want to minimize the number of cases of children with maternal great-grandmothers who are not identifiable because they are not alive in 1960. Births after 2002 are not considered as we need to observe the labour supply of mothers up to 7 years after the childbirth year and information on labour supply are currently available up to 2010.

We construct a measure of weekly hours worked by the mother from the labour market register, which started in 1986. Hours is recorded as a discrete variable taking the values of 0, 1-19, 20-29 and 30+. We create a variable for hours by taking the mid-point of these categories, thereby recording hours as 0, 10, 24.5 and 40 as the final category which represents a full-time contract in Norway. Additionally we construct an indicator for working before childbirth which takes the value 1 if mothers worked in the year prior to childbirth and 0 otherwise.

The neighbourhood peer group is constructed by linking each mother to all other mothers living in her zip code and similarly to the family peer group, we select only those neighbours giving birth between one and five years earlier than the mother and family peers giving birth at least a month earlier. Restricting the neighbours and family peers to women who gave birth in the past, we avoid the fertility contagion from neighbours and family members (see Kuziemko 2006). Furthermore, to consider a more homogeneous definition of neighbourhood, we consider mothers who live in the same zip code and with the same level of education, defined by an indicator for having a degree. Our assumption here is that neighbours are much more likely to interact with other neighbours with their same level of education. In the empirical part we will perform a robustness check to control for labour market shocks which may affect individuals living in different neighbourhoods but within a common labour market (Section 6). For this analysis we use the 90 labour markets as defined by Geographers in Norway, which are similar to a travel-to-work area. The size of the labour market varies between 1,000 and 65,000 households.

We take from the administrative register the education level and age of both parents and use as additional controls the fathers' earnings and employment status in the year of birth.

We drop from our sample families where the mothers' siblings have different fathers. We select first births to each mother because the decision to work after having a child differs across the birth order of offspring. We therefore compare like-with-like when comparing the decision of the mother with that of her peers. The sample of births occurring between 1997 and 2002 consists of 46,614 first births to mothers with at least one sister or female cousin. Table 1 shows that the family peer group consists of on average 3.073 maternal cousins, 3.149 paternal cousins and 0.613 sisters. The second peer group - homogenous neighbours - is larger, with on average 50.273 neighbours living in the same zip code. The average size of a neighbourhood is of 3100 individuals and 1400 households in our period of observation, but the relevant group of neighbours (which is defined as the group of mothers living the same zip code, giving birth to their first child between 1 and 5 year earlier than the mother in question and with the same level of education) includes on average only 26.883 peers.

Looking at the labour participation of mothers in the year after childbirth we find that on average mothers work 18.6 hours a week with a variation within family which is only 12% of the total variance and variation within neighbours which is 90% of the total variance. The average number of hours worked by new mothers increases steadily from 18.6 in the year after childbirth to 23.3 hours 7 years after childbirth. Looking at other socio-demographic characteristics, we find that on average 77.5% of mothers work in the year prior to childbirth, mothers and fathers have on average 13.3 and 12.7 years of schooling. The majority of fathers

(98.2%) work in the birth year of their first child and the age of parents at the first births is on average 25.8 years for mothers and older at 29.3 years for fathers. We control for the month of birth and a set of controls relating to birth outcomes of the child, including an indicator for twins, low birth weight, congenital malformation and severe deformity which may drive the labour supply of a mother. These birth indicators are relatively rare events, with 4.8% and 0.6% of newborns having a low or very low birth weight child respectively, 4.1% and 2.4% of newborns having congenital disorders and severe deformity respectively and 1.8% of births being non-singletons, but they are potential determinants of maternal labour supply so important controls for labour market participation of new mothers.

All our estimations control for the list of variables reported in Table 1 as well as for a set of dummies for the year and month of birth. We include these dummies to control for the potential bias caused by the measurement error on the working hours (see Section 10 for details) as well as to take account of potential institutional and policy changes. In recent years in Norway there have been several reforms with potential consequences on the women labour supply: parental leave reforms which expanded the amount of leave taken by mothers and introduced a paternity leave (Cools et al. 2015, Dahl et al. 2013, Carneiro et al. 2015a); the lowering of school starting age from 7 to 6 (Finseraas et al. 2015) and universal preschool child care reforms (Havnes and Mogstad 2011a, Havnes and Mogstad 2011b, Andresen and Havnes 2014, Havens and Mogstad 2015). Nevertheless, the only policy which was actually introduced during our sample period and with some potential effects on mothers' labour supply is a child care reform which led to an increase in the percentage of children in child care aged between 1 and 2 (3-6) from about 40% to 80% (80% to almost 100%) from 2001 to 2012 (see Andresen and Havnes 2014). This policy may in part explain the positive trend in the proportion of mothers working full time (30 hours or more), which increased by almost 20 percentage points from 1986 to 2010 and by about 10 percentage points during our sample period (see Fig. 1).

In our additional analysis we will also use two extra samples to consider (i) second births to mothers, to evaluate the effect of family peers on labour supply after a second childbirth, (ii) family peers defined as sisters-in–law and female cousins-in-law, to evaluate the effect of the husband's relatives.

5 Estimation results

In Table 2 we report the results for the linear in mean model (see equation (1)). More precisely we report the estimated family (sisters and cousins) peer effect on mothers' weekly hours worked in each of the 7 years after the first childbirth, with each column representing the estimated family peer effect in a different post childbirth year. By row, we report three different estimates of the family peer effect: the OLS (ordinary least squares), the 2SLS (two-stage least squares) and the 2SLS with neighbourhood fixed effects (2SLS FE). In all regressions we control for the so called correlated effects (see Manski 1993 for a definition) by including individual characteristics that are likely to be similar between family members and relevant in explaining mothers' labour supply. In particular we consider the mothers' and fathers' years of education, an indicator for working in the year prior to childbirth, fathers' earnings and work status in the year post childbirth, fathers' and mothers' age at the birth of the child, child health conditions at birth (dummies for low birth weight, for very low birth weight, for congenital malformations and severe deformity) and an indicator for multiple births. Furthermore, we control also for potential cohort and seasonality effects by including 9 birth cohort year dummies and dummies for the month of birth. We control additionally for the contextual peer effect by including family peer means of the same set of covariates. Finally, we define the mothers' neighbourhood peers as all neighbours living in the same area, giving birth between 1 and 5 years prior to the mother and with the same level of education, which we call homogenous neighbours.

The OLS (ordinary least squares) estimates of the family peer effect are very similar across post birth years and suggest that a one hour increase in the mean family peers' hours supplied to the labour market is associated with an increase in mothers' labour supply by about half an hour. However this is not a causal peer effect for two reasons. Firstly, there is a potential upward bias caused by the reflection problem. Secondly the coefficient is prone to attenuation bias from measurement error (see Section 10 for details).

To correct for the reflection problem and measurement error inherent in OLS estimation, we report 2SLS (two-stage least squares) estimation results. We instrument the average hours worked by family peers by considering the average across their neighbours of mothers' working hours after childbirth. More precisely, we take for each cousin (sister) the mean of this variable defined across the set of her homogenous neighbours and then we average these means across the mothers' sisters and cousins who gave birth at least one month earlier than the mother in question. The 2SLS estimate of the family peer effect increases for all post birth years and seems to suggest that the OLS estimation is affected by an attenuation bias caused by measurement error, which is larger than the overestimation bias caused by the reflection problem. Nevertheless, this result could also be caused by a tendency of family peers to sort into similar neighbourhoods. Because our instrument is based on average characteristics of the neighbours of the family peers, the sorting into similar neighbourhoods would lead to a correlation between our instrument and potential unobserved neighbourhood characteristics and therefore to the invalidity of instrumental variables.

We control for this residual endogeneity issue by considering a 2SLS with neighbourhood fixed effects (2SLS FE in Table 2). The estimated family peer effects reduce considerably but are still statistically significantly higher than zero. These show long-run peer effects from the family on the hours worked after childbirth between 0.33-0.59. This implies that an increase in mean family working hours by 1 hour leads the mother to raise her hours by 20-35 minutes. The exception is the family peer effect at 7 years after childbirth which is not statistically significantly different to zero. Nevertheless because the family peer effects are not very precisely estimated we cannot conclude that there is a systematic difference of the peer effect on mothers' labour supply 7 years after childbirth.

The Hausman test does not reject the assumption of equality between the coefficients estimated using the 2SLS FE estimation and neighbourhood fixed effect estimation without instruments, which suggests that the attenuation bias caused by measurement error is of equal magnitude but opposite sign compared with the endogeneity bias. The F-test for the significance of the instrument reported at the bottom of Table 2 suggest that our instrumental variable is significant statistically different from zero.

These 2SLS FE estimation results reported in Table 2 are our preferred results and we will use them as benchmark against which we compare any other additional estimation. The full regression results for the 2SLS FE estimation are reported in Appendix B Table A1 (split in two parts, A1a and A1b) for the second stage estimation and in Appendix Table A2 for the first stage estimation.

Looking at the full results in Table A1 and in particular at the effects of the mother and father characteristics on the mothers' working hours after childbirth and focusing on the most statistically and substantially significant effects, we find that mothers with relatively high years of schooling, who worked in the year before the childbirth and who are older, work on average more hours in each of the 7 years after childbirth. The effects of the fathers' education and work have the same direction although smaller in size, while fathers' age is negatively related to the mothers' labour supply in each of the 7 years after childbirth. Multiple births have a negative effect on the number of working hours of mothers but only in the first two years after childbirth.

The exogenous peer effects reported in Table A1 measure the effects of the mean characteristics of family peers on mothers' hours of work after childbirth. We find that the averages across family peers' of mothers' years of schooling, working in the year prior to childbirth and age at birth seem to have a systematic effect of reducing mothers' labour supply and in a few instances the family peers' average of fathers' education has a negative effect also. Notably, these effects become statistically not significant 7 years after birth, by which time the child has entered school. Only a handful of other coefficients are statistically significant, suggesting that they are not relevant exogenous family peer effects.

Moving to the first stage results in Table A2 we see that the average of the father and mother characteristics across family peers are generally significant at 1% level in explaining the average of mothers' work hours across family peers (our dependent variable in the first stage equation), whereas the individual father and mother characteristics are less statistically significant except for mothers' years of schooling and the dummy for mothers who work in the year prior to childbirth, which are statistically significant at 1% level for each of the 7 years considered. We find also that our instrument has an individual statistically significant effect at the 1% level.

To summarize, an hour increase in the mean labour market participation of mothers' family peers is associated with an increase in hours worked by the mother of between 20-35 minutes once we control for measurement error, unobserved neighbourhood characteristics and the reflection issue.

6 Threats to the identification strategy

In this section we consider potential threats to the identification strategy used to estimate family peer effects and present robustness checks for the validity of the strategy. Our methodology relies on the identification assumption that a mother interacts with her family peers but not meaningfully with her family's neighbours. We consider violations of this assumption through i) common macro shocks which affect individuals living in different neighbourhoods, ii) unobserved genetic traits, iii) general equilibrium and iv) work peer effects and finally we vary the set of instruments used for estimation and test for overidentification.

The first threat to identification is the potential presence of unobserved characteristics at area level which change across time and therefore cannot be controlled by considering neighbourhood fixed effect. We are concerned in particular about the possibility that shocks in the local labour markets, which are generally larger than the neighbourhood, might affect the labour supply decisions of both the mothers and their peers. For this reason we estimate family peer effects using the same specification and estimation used for our benchmark results but adding among the explanatory variables a set of labour market dummies interacted with year dummies. The results of this estimation, which are presented in Table 3 panel (a), are not too dissimilar from our benchmark results in Table 2. Because there are 90 distinct labour markets in Norway and we consider children born between 1997 to 2002, we are effectively adding 450 new explanatory variables, which lead to an increase in the standard errors. Nevertheless, the 2SLS estimation with neighbourhood fixed effect still lead to statistically significant family peers effect on the mothers' worked hours from 2 to 6 years after childbirth with the exception of 4 years after childbirth.

The second threat to identification is the potential endogeneity of the network, through unobserved characteristics that drive the probability of interactions between peers and their neighbours as well as the mothers' outcome. In particular, the network will be endogenous if mothers form links with their neighbours depending on unobserved genetic traits or unobserved family background characteristics that are shared by family peers and that can affect the labour supply of women. We have chosen as neighbourhood peers only those who gave birth between one and five years before the family peers and in theory if mothers interact with all of her neighbours and we control for neighbourhood fixed effects, it is unlikely that such endogeneity issue occurs. However to check if this is the case we estimate the effect of family peers when considering sisters-in-law and cousins-in-law (with no genetic link to the mother) rather than sisters and cousins. Our expectation is to find a similar effect if there is no bias caused by unobserved genetic and family background characteristics which are shared between a mother and her sisters and cousins, but which are not shared (or are shared to a less extent) by a mother and her sisters-in-law and cousins-in-law. We show the results of this family-in-law effects in the first 7 years after childbirth in Table 3 panel (b) using again the same specification and estimation used for our benchmark results. We find very similar and comparable results to Table 3 at least for the first 5 years, therefore providing evidence that our estimation is not biased by unobserved genetic or family background characteristics.

A third threat to identification is that mothers' labour supply decisions might affect labour market outcomes of their family members and their neighbours through general equilibrium effects in the labour market, because, for example, when a mother (neighbour) gets a job this might be at the expenses of others, including their excluded peers. A fourth threat which we address simultaneously is that the neighbours of the mothers' family may be in a peer group with the mother other than the family or neighbourhood. As we are considering as an outcome hours of work, the most relevant additional peer group is the work peers. We control for potential general equilibrium and work peer effects by including a set of dummy variables for the mother occupation interacted with dummies for the mothers' level of education (see Table 3 panel (c)) or alternatively considering the triple interactions between education level, occupation type and labour market dummies (see Table 3 panel d). After adding these new variables the peer effects are less precisely estimated, but we still find evidence supporting the presence of a strong family peer effect on mothers' worked hours after childbirth in most of the cases.

Finally we run sensitivity analyses to check that the instrumental variable used for our benchmark estimation is valid. In our main specification we have used the neighbour's hours worked in the year after childbirth, averaged across family peers as an instrument. This instrument is predetermined as neighbours are included in the sister or cousin's peer group only if they gave birth between 1-5 years prior to the sister or cousin. The instrument is valid if the mother does not interact with her sister or cousin's neighbours. We are unable to directly test this assumption but we provide evidence on the validity of the instrument by including additional instruments and reporting the p-value for the Hansen overidentification test. The results are reported in Table 4, where we include 2SLS estimates controlling for the neighbourhood fixed effect. All the instruments are derived by computing the average across the mothers' family peers of their neighbourhood average of the chosen variable.

In all columns the set of derived instruments are based on hours worked and additionally panel a) adds all birth outcomes (indicators for low birth weight, very low birth, congenital malformation, severe deformity and multiple birth); panel b) adds father age at birth and father education; panel c) adds mother age at birth and education and d) adds both mother and father age at birth and education. In almost all regressions (24 out of 28), the p-value for the Hansen test is above or equal 0.05, suggesting that our instruments are valid. Note that the F-statistics for the first stage significance of the instruments are lower once we combine multiple instruments compared to using just one instrument and therefore the results of Table 2 are more precisely estimated. However, in most cases the magnitude of the estimated family peer effect is in line with Table 2.

7 Mechanisms

Two potential main mechanisms which explain the family peer effects on mothers labour supply decisions are the information transmission and imitation. Manski (1993) posits that peer effects are likely to be present in the context of decision making with uncertainty and typically new parents face a lot of uncertainty over the effect of decisions they make after childbirth and may look to peers' for information before taking their own decisions (see Fogli and Veldkamp 2011, Carneiro et al. 2015b). Specifically, new mothers might look to family peers who have already experienced a child birth for information about costs and benefits of choosing different amounts of working hours after childbirth and consequently they might take decisions that are similar to their family peers.

The second main reason why mothers might adopt decisions similar to their family peers is imitation, which is usually justified if a mother's utility increases by behaving similarly to their family peers. The imitation mechanism may play an important role in explaining the effect of peers especially when the group of peers share the same type of identity and therefore the same types of norms on how they should behave.[7] E.g. mothers might feel

[7]Examples of identities that are usually related with specific social norms are gender and ethnicity. In

more accepted by their family if they follow social norms that have been already followed by their family peers (see Akerlof and Kranton 2000, Bertrand 2010).

To assess the role of information transmission and imitation we compare the family peer effects estimated for subgroups of mothers which differ by level of uncertainty and of internalization of identity norms.

We begin by comparing the effect of family peers on mothers' labour supply decisions after their first and after their second childbirth. Uncertainty on the consequences of mothers' work decisions is larger for new mothers than for mothers who are at their second childbirth, therefore the role of information transmission in explaining the family peer effect will be larger for first than second births. On the contrary, we think that the potential internalization of social norms on how mothers should behave, and more in general on norms related to a woman's identity as mother within her family, may be stronger for women that already has a child than for new mothers especially in the first year after childbirth. The intuition is that for first birth mothers, the mothers' identity and social norms associated with this identity are new (unlike more typical types of identity such as gender and ethnicity that are defined since birth) and the adoption of these norms may not be instantaneous so that the role of imitation mechanism may be small for new mothers in the first year after childbirth.

In Table 5 we report the family peer effect on hours of work after the second childbirth in each of the 7 years post birth. The estimation method and model specification are identical to the ones adopted for our benchmark results in Table 2. The only difference is that we focus on mothers at the second childbirth and we change the definitions of family peers and neighbours to reflect that. A mothers' family peers include only sisters and cousins with a second child born at least one month earlier than her second child; whereas a mother's neighbours are given by all mothers who live in the same zip code, have the same education and with a second child born between 1 and 5 years earlier than hers.

We find that the family peer effect on mothers' working hours is statistically significantly

our case it is the identity associated with motherhood.

higher than zero in each of the first 6 years after the second childbirth but becomes statistically insignificant after 7 years. These estimated family peer effects do not seem much different in size than the corresponding effects for new mothers (see 2SLS FE in Table 2). If the information sharing were the key mechanism in explaining the family peer effect we would expect these effects to decrease when moving from first to second childbirths. The fact that they do not decrease may suggest that imitation mechanism is the dominating force. Furthermore, in the first year after childbirth the effect of family peers seems to be larger for the second child than for the first child. This suggests that the imitation mechanism may become more relevant because mothers tend to conform more and more to norms shared by other mothers as they spend more time as mothers and with the birth of a second child.

To assess the importance of the imitation mechanism further, we compare family peer effects between mothers with and without a university degree. We may expect heterogeneity in the family peer effect by the level of mothers' education for two reasons. On the one hand, more highly educated mothers may be less affected by norms related to their own identity as a mother within their family, therefore they feel less pressure and get less advantage in conforming to the behaviour of other mothers in their family. The intuition is that mothers with a degree are compelled by career concerns and more likely to have employment contracts, which would dilute the family peer influence. On the other hand, there may be a less relevant role of information sharing for highly educated mothers, who might be more informed on consequences of their labour supply decisions and therefore face less uncertainty. In this case the consequence of both channels would see a lower peer effect for highly educated mothers.

We modify the model (1) to allow the family peer effect to differ between mothers with and without a degree and we report the results in Table 6 adopting again the 2SLS FE estimation and the same explanatory variables and instrument used for the benchmark results. In line with our expectations we find that the family peer effects for mothers without a university degree are statistically significantly higher than the corresponding peer effects for mothers with a degree.

In order to distinguish between the two mechanisms, imitation and information transmission, Table 7 then reports the results of the analysis allowing for heterogeneity in the family peer effect by maternal education, but for second births. We expect the information channel to become weaker for second births especially for low educated mothers, while we expect the imitation mechanism to be stronger for second births for both low and high educated mothers. Looking at the results for second births in Table 7, we find that, in the first 5 years after birth, there is no statistically significant difference in the peer effect between low and high educated mothers. In this context, the reduced difference between low and high educated mothers is probably driven by a reduction of the role of the information mechanism for low educated mothers. This result suggests that the smaller family peer effect found for highly educated mothers after their first child birth is probably mainly caused by the fact that mothers highly educated do not look (or look to a lesser extent) to their family peers for information before deciding how much to work, whereas low educated mothers look for information after the birth of their first child but to a lesser extent after the birth of their second child.

In summary, we have provided suggestive evidence that there are two important mechanisms for the family peer effect - information and imitation. We have found evidence that on the whole (for the total sample), imitation is a stronger driving force for the family peer effect than information.

8 Neighbourhood peer effect

There are no studies that have estimated the causal effects of family peers on mothers' labour supply;[8] but, as noted in the introduction, there are two papers that have focused on causal neighbourhood effects on women's labour participation, which are Maurin and

[8] There are some studies who look at the association in labour participation decisions across family peers, but their results do not have a causal interpretation (see Neumark and Postlewaite, 1998, for the effect of sister-in-law's employment on a woman's own employment probability; Del Boca et al., 2000, for the effects of work status of the mother-in-law and of the mother on a woman's own employment; and Fernandez et al. ,2004, for the effect of having a mother-in-law who works on the probability of own (female) work).

Moschion (2009) and Mota et al. (2016).

The first stage equation in our 2SLS estimation regresses the average number of working hours across family peers on the corresponding average across neighbours of the family peers controlling for all explanatory variables. The effect of the average working hours across neighbours cannot be interpreted as an endogenous effect of neighbours. This is because this effect could capture contextual and environmental characteristics as e.g. employment opportunities in the neighbourhood. This is not a concern for the validity of our instruments as long as the neighbourhood average of the working hours is a relevant factor explaining the number of hours of the family peers (is a strong first stage predictor) and the variation in the neighbourhood average of family peers is not endogenous, i.e. the instrumental variable is not correlated with the error term in our main equation (1). We now adapt our identification strategy to estimate the neighbourhood peer effect on the mothers' working hours. These results will be comparable to the neighbourhood peer effect estimated by Maurin and Moschion (2009) and Mota et al. (2016). We still estimate equation (1), but we exchange the roles of the neighbours and family peers and consider an instrumental variable estimation with family fixed effect (2SLS FE) and with an instrument given by the average across the mothers' homogenous neighbours of the average hours worked by their family peers. Note that neighbourhood peers are defined as those giving birth between 1-5 years before the mother, with the same level of degree level education.

Results are presented in Table 8 where we report OLS and 2SLS with and without family fixed effect. For one hour growth in the average worked hours of the mothers' neighbours, the mother increases her hours by between 4 and 6 minutes when considering the OLS estimation and between 4 and 19 minutes when adopting the 2SLS estimation. Nevertheless, once controlled for family fixed effects, i.e. for unobserved family characteristics that might confound the results, we find that neighbours do not have any significant effect on mothers' worked hours. Notice that the instrument used is highly significant (see F-tests in the first stage equations reported in Table 8), which suggests that the absence of the neighbourhood effect is not caused by a weak instrument.

On the contrary, Maurin and Moschion (2009) find that a 10 percentage point increase in the percentage of close neighbours participating in the labour market raises individual participation by 6 percentage points. The magnitude of this neighbour effect seems in similar range or slightly higher than our family peer effects estimated using 2SLS FE. Mota et al. (2016) consider various definition of homogenous neighbours (which they call peers) and find the largest neighbourhood effects when defining homogenous neighbours as women living in the same neighbourhood, with children of similar age and with (or without) the same level of education. In their most robust estimation they find that one additional working homogeneous neighbours increases the probability of a woman working by about 4.5 percentage points, one additional non-working homogenous neighbours decreases her probability by about 9 percentage points, whereas the labour participation of non-homogenous neighbours do not have any significant effect. These effects seem smaller than in Maurin and Moschion (2009).

Our estimates seem to contradict previous empirical evidence on the existence of neighbourhood effects on women' labour participation, but this could be in part explained by the type of definition and size of the neighbourhood used. Maurin and Moschion (2009) consider as neighbours mothers with at least 2 children aged between 21 and 35 and living in 20 adjacent households. Mota et al. (2016) consider 10 nearest neighbours and define homogenous neighbours by considering women aged between 25 and 60 with similar characteristics (see definition provided above). We adopt a definition of homogenous neighbours similar to Mota et al. (2016), but our neighbourhood area is larger so that we end up with an average size for the group of homogenous neighbours of 27, which is considerably larger than the average size of 3.5 in Mota et al. (2016). Evidence that broader definitions of the neighbourhood lead to no significant effect of neighbours is provided also in Mota et al. (2016), who find that neighbours do not matter when using groups of neighbours who are less homogenous.

9 Sensitivity analysis: model specification

So far we have treated the number of working hours as if it were a continuous variable, but it is actually an interval variable. For this reason, we also consider a interval regression model and an ordered probit model for the 4 observed levels of working hours (0, between 1 and 19, 20 and 29 and 30 or more). In addition, because much of the literature of peer effects on labour supply consider extensive margins, we also estimate the family peer effect using linear probability models for the 7 labour participation dummies, one for each of the 7 year post childbirth.

In panel (a) of Table 9 we report the maximum likelihood estimation results of the interval regression model for the mothers' hours of work, which is estimated jointly with a linear regression (auxiliary model) for the average hours worked across family peers. The explanatory variables in the interval regression are the same as in our main regression model considered in Table 2 and we use dummy variables to control for neighbourhood effects. The auxiliary regression include exactly the same explanatory variables plus the instrumental variable, which is given by the average across family peers of the neighbourhood average of the mothers' hours worked in the specific post-childbirth year. Again each column reports the family peer effect on hours of work at different points in time, with column 1 representing hours worked 1 year after childbirth up to column 7 reporting hours worked 7 years after birth. The results are very similar to the preferred specification in Table 2, with the family peer effect between 0.367-0.56 for the first six years post birth but a statistically insignificant effect once the child has entered school. The instrument's coefficient is always significantly different from zero (see p-value reported in the second row of Table 9) except for the model for the hours of work 7 years after childbirth.

Panel (b) reports the joint maximum likelihood estimates for the ordered probit model for the mothers' hours of work, which is estimated again jointly with a linear model for the average across family peers of mothers' hours worked (auxiliary model). Again we use the same choice of explanatory variables. The ordered probit model has the same explanatory variables considered in our main regression plus dummy variables for the neighbourhoods, while the auxiliary model makes use of the same set of variables plus the instrument. We report marginal effects (at the mean) of the family peer hours of work on the conditional probabilities of observing a mother working 0 hours and 30 or more hours. One year after childbirth, a change in the family peer hours of work by 1 hour lowers the conditional probability of working 0 hours by 0.9 percentage points and raises the conditional probability of working 30 or more hours by 0.9 percentage points. To understand the magnitude of the coefficient we normalise by the conditional probability of observing a mother working 0 and 30 or more hours computed at the average of the covariates (0.345 and 0.371 respectively). A change in the mean peer hours by 1 hour lowers (raises) the relative conditional probability of a mother working 0 (30 or more) hours by 2.5% (2.4%) after 1 year. Similarly to the main results in Table 2, the relative marginal effect is fairly constant across the years after childbirth but insignificant 7 years after birth.

We next move our focus to the effect of family peers on the extensive margin, i.e. looking at how important peers are in the decision to return to work versus stay at home. We report in panel (c) the results of the 2SLS FE estimation for the linear probability model using again the same explanatory variables and the same instrumental variable as in our main estimation. The auxiliary equation, or the first stage equation in this case, is still the linear regression of the family average hours worked on all covariates and the instrument. The precision of the estimates has fallen, as shown by fewer coefficients with statistical significance. In terms of magnitude, the interpretation of the coefficient is now slightly different. Looking at column 1, an increase in the family peer mean labour market participation 1 year after childbirth by 10% raises the mothers' labour supply by 4% points. These magnitude increase to a 7% point at 5 years post childbirth but falls to 0.6% 7 years after birth.

In conclusion, we have tested the specification by explicitly modelling hours worked as an interval regression, an ordered probit and looking at the peer effect of labour market participation up to 7 years after birth. For all specifications, our main findings are confirmed and there is evidence for a strong long-run family peer effect which tends to be statistically significant up to 6 years after birth.

10 Conclusions

By estimating the causal family peer effect on a mother's labour supply decisions after childbirth, we show how the influence of a mother's peers is a relevant mechanism which can amplify the effect of changes affecting women's labour supply. We actually find that the long-run family peer effect on mothers' decisions to work after the first childbirth is large and statistically significant. An increase in the family peer hours worked by 1 hour raises the mothers' working hours by about half an hour in the first six years after birth. Such family peer effects would imply a social multiplier of about two, meaning that a policy change which causes a direct effect on mothers' labour supply of one working hour would be amplified by a factor of two through the indirect effect operating via the influence of family peers.

We find a similar peer effect for mothers' labour supply after the second childbirth. This seems to indicate that the family peer effect is not driven mainly by information transmission between family members. If the information transmission was the main mechanism explaining the family peer effect, we would have expected a sharp reduction in the peer effect because after their second childbirth mothers are presumably more informed about the consequences of their decision and much less affected by the information transmission at this stage. The family peer effect is larger for mothers without a university degree than with a university degree after the first childbirth, while they are comparable after the second childbirth. We interpret this result as suggestive of a bigger role of information transmission for mothers without a university degree after the first childbirth and a potential imitation mechanism that gets larger after the second childbirth.

Our estimation strategy takes account of the reflection problem and endogeneity issues. Nevertheless, to reassure ourselves that our results are not biased, we run a large set of robustness checks to assess (i) the size of the potential bias caused by unobserved shocks and characteristics of local labour markets, by unobserved family background characteristics, such as family norms and genetic endowments, by general equilibrium effects and work place peer effects; (ii) the validity of our instruments using extra instrumental variables; (iii) the consequences of model specification assumptions. These robustness checks suggest that there is no substantial bias in our estimates.

Finally, to compare our results with the effect of neighbours on women's labour supply found in previous empirical studies, we also use our strategy in reverse to identify the effect of neighbours living in the same post code with the same level of education and having giving birth between 1 and 5 years earlier than the mother in question. Even with such a refined definition of neighbours we do not find any significant effect. This indicates that interactions between neighbours are less relevant than between family peers.

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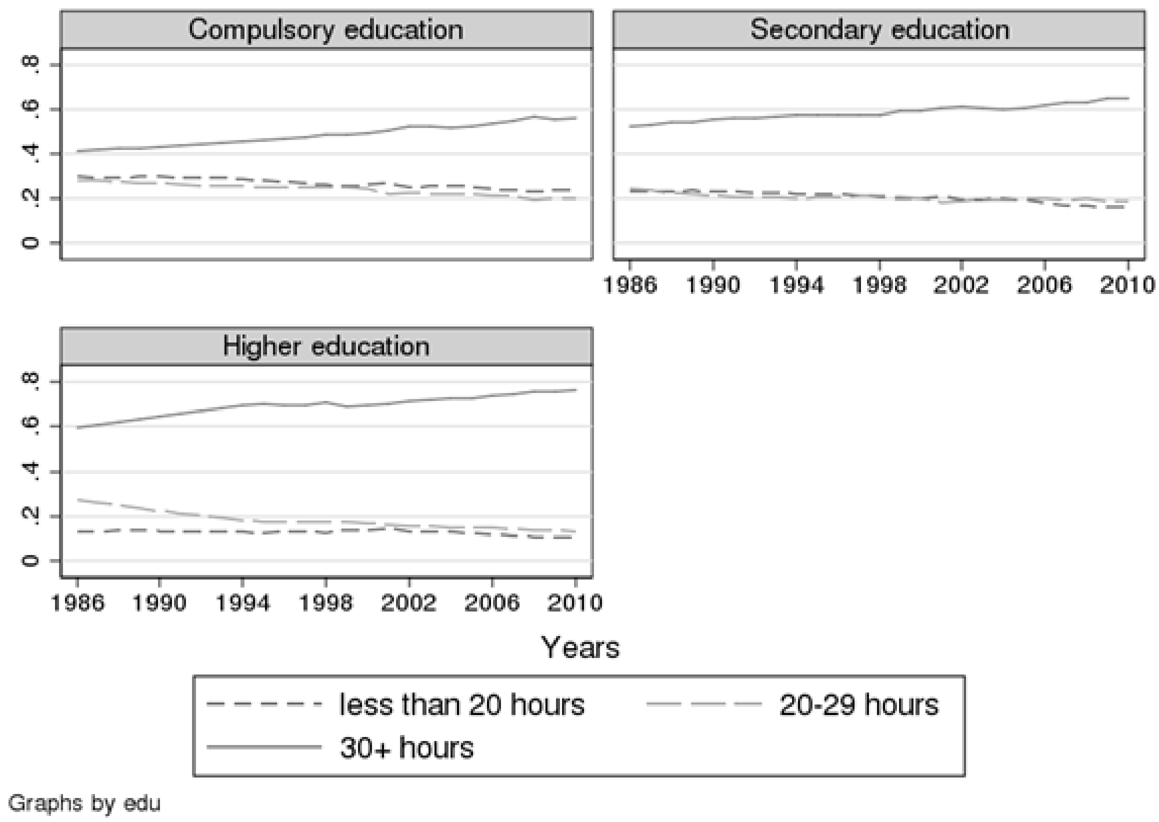
Figure1: Mothers Labour Supply



Notes: Norwegian register data.

Table 1: Descriptive Statistics

Peer Groups	Mean	Standard Deviation	Min	Max
Number of Maternal Cousins	3.073	2.698	0	32
Number of Paternal Cousins	3.149	2.728	0	32
Number of Sisters	0.613	0.748	0	7
Number of Neighbours	26.883	33.211	1	296
Individual Characteristics				
Mother Worked After 1 Year	0.601	0.490	0	1
Hours Worked After				
1 year	18.593	17.864	0	40
2 years	19.233	17.770	0	40
3 years	19.256	17.674	0	40
4 years	20.410	17.538	0	40
5 years	21.691	17.396	0	40
6 years	22.398	17.315	0	40
7 years	23.312	17.146	0	40
Mother Worked 1 yr before Birth	0.775	0.418	0	1
Mother's Education	13.254	2.284	9	21
Father's Education	12.661	2.314	9	21
Father's Earnings, K1,000	268.439	164.850	0	9975.1
Father's Work Status	0.982	0.133	0	1
Mother's Age at Birth	25.826	4.369	16	45
Father’s Age at Birth	29.325	5.265	16	62
Low Birth Weight Indicator	0.048	0.214	0	1
Very Low Birth Weight Indicator	0.006	0.078	0	1
Congenital Disorder at Birth	0.041	0.197	0	1
Severe Deformity at Birth	0.024	0.155	0	1
Twin Indicator	0.018	0.133	0	1
Child's Year of Birth	1999.592	1.703	1997	2002
Child's Month of Birth	6.457	3.413	1	12
Number of observations	46,614			

Table 2: Estimation Results of the Family Peer Effects. First Birth.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mothers' Working Hours						
Years Post Childbirth	1	2	3	4	5	6	7
OLS	0.546***	0.546***	0.543***	0.538***	0.532***	0.541***	0.534***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
2SLS	0.702***	0.827***	0.830***	0.841***	0.737***	0.811***	0.598***
	(0.123)	(0.114)	(0.122)	(0.151)	(0.133)	(0.157)	(0.153)
F statistic 1st Stage	58.37	70.53	62.14	40.34	51.21	36.55	36.79
Hausman Test p-value	0.20	0.01	0.02	0.04	0.12	0.08	0.68
2SLS FE	0.334*	0.524***	0.525***	0.456**	0.528***	0.593**	0.270
	(0.173)	(0.152)	(0.167)	(0.225)	(0.169)	(0.231)	(0.229)
F statistic 1st Stage	33.34	41.19	34.01	18.86	33.74	17.47	19.00
Hausman Test p-value	0.21	0.91	0.93	0.72	0.99	0.81	0.24
N	46,614	46,614	46,614	46,614	46,614	46,614	46,614

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. OLS Ordinary Least Squares; 2SLS two-stage least squares; 2SLS FE two-stage least squares with mothers' neighbourhood fixed effect. regressors include mothers' and fathers' years of education, an indicator for working during pregnancy, fathers' earnings and work status in the year post childbirth, father and mother age at birth, dummies for low birth weight, for very low birth weight, for congenital malformations and severe deformity an indicator for multiple births, birth cohort year and month of birth dummies, and family peer means of the same set of covariates. F-statistic is the F-test for H_0: instruments have zero coefficients.

Table 3: Threats to Identification: Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mothers' Working Hours						
Years Post Childbirth	1	2	3	4	5	6	7
	(a)						
	Including interactions of labour market and years dummies						
2SLS FE	0.188	0.432***	0.447***	0.316	0.451**	0.519**	0.104
	(0.194)	(0.162)	(0.167)	(0.252)	(0.184)	(0.255)	(0.288)
F statistic 1st Stage	28.90	37.28	34.32	15.84	28.86	14.34	13.25
Hausman Test p-value	0.05	0.49	0.58	0.38	0.67	0.94	0.11
N	45,990	45,990	45,990	45,990	45,990	45,990	45,990
	(b)						
	Evaluating peer effects of sister-in-law and cousins-in-law						
2SLS FE	0.317*	0.457**	0.518**	0.484**	0.456**	0.239	0.431*
	(0.162)	(0.195)	(0.224)	(0.220)	(0.191)	(0.270)	(0.260)
F statistic 1st Stage	36.94	23.81	18.12	18.86	24.82	13.20	13.22
Hausman Test p-value	0.12	0.58	0.85	0.72	0.62	0.22	0.65
N	37,734	37,734	37,734	37,734	37,734	37,734	37,734
	(c)						
	Including interactions between occupations and education						
2SLS FE	0.310	0.536***	0.534***	0.336	0.524***	0.470	0.255
	(0.211)	(0.180)	(0.190)	(0.271)	(0.200)	(0.286)	(0.256)
F statistic 1st Stage	23.04	29.99	26.60	13.55	24.39	11.63	15.31
Hausman Test p-value	0.26	0.96	0.98	0.45	0.96	0.81	0.26
N	40,039	40,039	40,039	40,039	40,039	40,039	40,039
	(d)						
	Including interactions between occupations, education and labour market						
2SLS FE	0.245	0.514***	0.551***	0.287	0.478**	0.468*	0.122
	(0.249)	(0.186)	(0.183)	(0.260)	(0.209)	(0.285)	(0.290)
F statistic 1st Stage	19.87	27.68	27.77	13.81	21.31	10.48	11.99
Hausman Test p-value							
N	39,479	39,479	39,479	39,479	39,479	39,479	39,479

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

2SLS FE two-stage least squares with mothers' neighbourhood fixed effect.

regressors include mothers' and fathers' years of education, an indicator for working during pregnancy, fathers' earnings and work status in the year post childbirth, father and mother age at birth, dummies for low birth weight, for very low birth weight, for congenital malformations and severe deformity an indicator for multiple births, birth cohort year and month of birth dummies, and family peer means of the same set of covariates. F-statistic is the F-test for H_0: instruments have zero coefficients.

Table 4: Using Multiple Instrumental Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Mothers' Working Hours				
Years Post Childbirth	1	2	3	4	5	6	7
			(a)				
IVs: hours, low birth weight, very low BW, congenital malformation, severe deformity, multiple birth							
2SLS FE	0.557***	0.625***	0.516***	0.494**	0.530***	0.510**	0.238
	(0.146)	(0.159)	(0.165)	(0.210)	(0.163)	(0.202)	(0.158)
F statistic 1st Stage	8.03	6.73	6.55	3.82	6.27	3.88	7.00
Hansen Test p-value	0.17	0.44	0.83	0.31	0.75	0.02	0.40
Hausman Test p-value	0.92	0.62	0.91	0.88	0.99	0.87	0.05
			(b)				
			IVs: hours, father age, father education				
2SLS FE	0.488***	0.524***	0.543***	0.215	0.473***	0.635***	0.255
	(0.153)	(0.154)	(0.165)	(0.227)	(0.170)	(0.214)	(0.217)
F statistic 1st Stage	15.02	14.28	12.75	7.22	11.61	7.10	7.33
Hansen Test p-value	0.23	0.94	0.32	0.28	0.44	0.30	0.34
Hausman Test p-value	0.70	0.91	0.97	0.16	0.74	0.67	0.19
			(c)				
			IVs: hours, mother age, mother education				
2SLS FE	0.378**	0.478***	0.425**	0.119	0.288*	0.291*	0.122
	(0.173)	(0.159)	(0.169)	(0.215)	(0.158)	(0.177)	(0.169)
F statistic 1st Stage	11.75	13.43	12.07	8.37	14.18	11.24	13.38
Hansen Test p-value	0.94	0.64	0.18	0.05	0.01	0.03	0.29
Hausman Test p-value	0.33	0.72	0.53	0.05	0.14	0.20	0.01
			(d)				
			IVs: hours, mother age, father age, mother education				
2SLS FE	0.501***	0.524***	0.362**	0.129	0.303*	0.345**	0.094
	(0.147)	(0.139)	(0.149)	(0.180)	(0.154)	(0.159)	(0.166)
F statistic 1st Stage	9.63	10.38	9.72	7.26	8.81	8.31	8.41
Hansen Test p-value	0.41	0.83	0.06	0.20	0.04	0.10	0.53
Hausman Test p-value	0.75	0.92	0.24	0.02	0.16	0.28	0.01
N	46,380	46,380	46,380	46,380	46,380	46,380	46,380

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

2SLS FE two-stage least squares with mothers' neighbourhood fixed effect.

regressors include mothers' and fathers' years of education, an indicator for working during pregnancy, fathers' earnings and work status in the year post childbirth, father and mother age at birth, dummies for low birth weight, for very low birth weight, for congenital malformations and severe deformity an indicator for multiple births, birth cohort year and month of birth dummies, and family peer means of the same set of covariates. F-statistic is the F-test for H_0: instruments have zero coefficients.

Table 5: Estimation Results of the Family Peer Effects. Second Birth.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mothers' Working Hours						
Years Post Childbirth	1	2	3	4	5	6	7
2SLS FE	0.593***	0.514***	0.671***	0.475***	0.427**	0.643***	0.155
	(0.117)	(0.176)	(0.190)	(0.156)	(0.208)	(0.196)	(0.262)
F statistic 1st Stage	57.37	25.57	21.44	32.95	20.19	20.50	15.02
Hausman Test p-value	0.47	0.35	0.98	0.20	0.24	0.89	0.03
N	35,194	35,194	35,194	35,194	35,194	35,194	35,194

Table 6: Estimation Results of the Family Peer Effects Allowing for Heterogeneity by Education. First Birth.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mothers' Working Hours						
Years Post Childbirth	1	2	3	4	5	6	7
2SLS FE							
Family Peer	0.439**	0.530***	0.599***	0.466**	0.536***	0.618***	0.258
	(0.180)	(0.143)	(0.156)	(0.227)	(0.165)	(0.234)	(0.225)
Family Peer * Degree	-0.267***	-0.157	-0.307***	-0.201*	-0.229**	-0.261***	-0.266**
	(0.090)	(0.098)	(0.117)	(0.105)	(0.101)	(0.097)	(0.112)
F statistic 1st Stage	16.70	18.41	14.25	9.31	15.68	8.87	9.71
Hausman Test p-value	0.17	0.56	0.59	0.46	0.54	0.85	0.07
N	46,614	46,614	46,614	46,614	46,614	46,614	46,614

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. 2SLS FE two-stage least squares with mothers' neighbourhood fixed effect. regressors include mothers' and fathers' years of education an indicator for working during pregnancy, fathers' earnings and work status in the year post childbirth, fathers' and mothers' age at birth, dummies for low birth weight, for very low birth weight, for congenital malformations and severe deformity an indicator for multiple births, birth cohort year and month of birth dummies, and family peer means of the same set of covariates. F-statistic is the F-test for H_0: instruments have zero coefficients.

Table 7: Estimation Results of the Family Peer Effects Allowing for Heterogeneity by Education. Second Birth.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mothers' Working Hours						
Years Post Childbirth	1	2	3	4	5	6	7
2SLS FE							
Family Peer	0.534***	0.390**	0.470**	0.388**	0.322	0.520***	0.102
	(0.134)	(0.187)	(0.185)	(0.154)	(0.214)	(0.193)	(0.280)
Family Peer * Degree	-0.078	-0.132	0.027	-0.121	-0.161	-0.224*	-0.488***
	(0.090)	(0.102)	(0.100)	(0.108)	(0.111)	(0.124)	(0.170)
F statistic 1st Stage	28.04	12.50	10.37	15.40	10.00	8.38	6.76
Hausman Test p-value	0.14	0.05	0.31	0.03	0.04	0.23	0.00
N	35,194	35,194	35,194	35,194	35,194	35,194	35,194

Table 8: Estimation Results of the Neighbourhood Effects. First Birth.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mothers' Working Hours						
Years Post Childbirth	1	2	3	4	5	6	7
OLS	0.081***	0.097***	0.095***	0.089***	0.074***	0.085***	0.088***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
2SLS	0.074***	0.091*	0.197***	0.202***	0.314***	0.179**	0.108
	(0.028)	(0.047)	(0.060)	(0.076)	(0.082)	(0.088)	(0.094)
F statistic 1st Stage	5462.00	1631.00	965.10	571.00	517.80	452.90	377.40
Hausman Test p-value	0.62	0.69	0.12	0.16	0.00	0.31	0.86
2SLS FE	0.054	-0.217	-0.080	-0.007	0.004	0.286	0.182
	(0.080)	(0.147)	(0.175)	(0.212)	(0.275)	(0.313)	(0.337)
F statistic 1st Stage	877.10	213.90	139.70	92.82	58.60	45.54	37.33
Hausman Test p-value	0.79	0.04	0.44	0.74	0.86	0.43	0.64
N	46,726	46,726	46,726	46,726	46,726	46,726	46,726

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. OLS Ordinary Least Squares; 2SLS two-stage least squares, 2SLS FE two-stage least squares with mothers' neighbourhood fixed effect; regressors include mothers' and fathers' years of education, an indicator for working during pregnancy, fathers' earnings and work status in the year post childbirth, father and mother age at birth, dummies for low birth weight, for very low birth weight, for congenital malformations and severe deformity an indicator for multiple births, birth cohort year and month of birth dummies, and family peer means of the same set of covariates. F-statistic is the F-test for H_0: instruments have zero coefficients.

Table 9: Estimation Results of the Family Peer Effects Using Discrete Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Mothers' Working Hours				
	1	2	3	4	5	6	7
a) Interval regression							
Family Peer Effect	0.332	0.541***	0.434***	0.328***	0.549***	1.081	2.658
	(0.211)	(0.173)	(0.184)	(0.137)	(0.161)	(0.670)	(5.176)
Auxiliary Equation p value	0.000	0.000	0.000	0.000	0.000	0.137	0.965
Hausman p-value	0.07	0.47	0.67	0.67	0.73	0.82	0.08
b) Ordered Probit. Dependent variable Mother Hour							
Predicted Probability Hours=0	-0.008***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.005
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)
Relative marginal effect (RME)	-2.5%	3.2%	3.3%	-3.9%	-4.0%	-4.2%	-2.7%
Predicted Probability Hours=40	0.008***	0.012***	0.012***	0.013***	0.013***	0.014***	0.007
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)
RME	2.4%	3.1%	3.2%	3.5%	3.1%	3.2%	1.9%
Auxiliary Equation p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hausman p-value	0.25	0.91	0.91	0.86	0.86	0.79	0.23
c) Linear Probablity							
2SLS FE0	0.344	0.519**	0.498	0.431	0.619	0.835	-0.193
	(0.215)	(0.240)	(0.360)	(0.390)	(0.464)	(1.235)	(0.617)
Auxiliary Equation p value	21.99	16.76	7.47	6.43	4.54	0.69	3.62
Hausman p-value	0.45	0.97	1.00	0.89	0.77	0.76	0.19
Observations	46,614	46,614	46,614	46,614	46,614	46,614	46,614

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Regressors include neighbourhood fixed effect, mother's and father's years of education, an indicator for working during pregnancy,father's earnings and work status in the year post childbirth, father and mother age at birth, dummies for low birth weight, for very low birth weight, for congenital malformations and severe deformity an indicator for multiple births, birth cohort year and month of birth dummies, family peer means of the same set of covariates and dummy variables for neighbourhoods. IV coefficient p value for H_0: instruments have zero coefficients in the auxiliary equation .

Appendix A: Estimation in presence of measurement errors

In our application we consider the dependent variable y_{ir} the number of weekly hours worked by a mother in each of the 7 years after childbirth. These variables are subject to measurement error. This is because for all mothers we observe their working hours in November of the considered year after their childbirth. This implies that the number of hours worked Δ years after childbirth by women who gave birth in January of the year t is observed in November of the year $(t+\Delta)$, i.e. $[12\ \Delta\ +10]$ months after childbirth, while for women giving birth in December of the year t we observe their labour supply only $[12\ \Delta\ -1]$ months after childbirth. Henceforth we define our outcome variable as the mother's working hours Δ years and 6 months after childbirth, where $\Delta = 1, ..., 7$. This implies that the working hours for women who give birth in June of the year t is correct, but the working hours for women who do not give birth in June will be subject to measurement error and will be probably overestimated for women giving birth before June and underestimated for women giving birth after June. This is especially true for the first years after childbirth where female labour supply is subject to more change than in later years.

Furthermore, we do not observe the exact number of hours worked, but we know whether the mother works 0, between 1 and 19, 20 and 29 or 30 or more hours per week. By rounding the working hours to 0 for non-working mothers and to 10, 24.5 and 40 for working mothers, we can use this "rounded" variable and quantify and compare differences between mothers in term of hours.

The measurement errors caused by the rounding and by the month of observation affect not only the dependent variables y_{ir}, but also the corresponding average of the peers (cousins and siblings), $\bar{y}_{F,i}$. We do not have any reason to believe that such measurement errors be correlated with any of observed and unobserved variables in our model. For this reason, in the following we assume that y_{ir} follows the model

$$y_{ir} = y_{ir}^T + \boldsymbol{d}_{ir}\boldsymbol{\eta} + e_{ir}, \tag{3}$$

where y_{ir}^T is the true working hours, d_{ir} is a row vector of 12 dummy variables indicating the month of birth of the child, η is the column vector of corresponding coefficients and e_{ir} is a classical measurement error which is independently and identically distributed across individuals, independent of the true value y_{ir}^T and independent of the explanatory variables and error term in our model of interest. Under this modified classical measurement error model, the error on y_{ir} does not cause any inconsistency as long as we control for the effect of month of birth.

Let us now consider the family peers average of the outcome variable

$$\bar{y}_{F,i} = \frac{\sum_{j \in P_{Fi}} y_{jr}}{n_{Fi}} = \overline{y}_r^{T(i)} + \overline{\boldsymbol{d}}_r^{(i)} \boldsymbol{\eta} + \overline{e}_r^{(i)}, \tag{4}$$

where $\overline{y}_r^{T(i)} = \frac{\sum_{j \in P_i} y_{jr}^T}{n_{Fi}}$, $\overline{\boldsymbol{d}}_r^{(i)} = \frac{\sum_{j \in P_i} \boldsymbol{d}_{ir}}{n_{Fi}}$ and $\overline{e}_r^{(i)} = \frac{\sum_{j \in P_i} e_{jr}}{n_{Fi}}$ are the averages across family peers excluding the mother i of the true working hours, of the vector of dummy variables for the month of birth and of the measurement error. $\overline{e}_r^{(i)}$ and e_{ir} are independent because e_{ir} is independently distributed across mothers and $\overline{e}_r^{(i)}$ is computed excluding the mother i herself. Under this modified classical measurement error model for $\bar{y}_{F,i}$ the consequence of the measurement error is simply an attenuation bias for the ordinary least square estimation of the main regression model (2) as long as we control for month of birth dummies averaged across the family peers. Furthermore, this attenuation bias tends to cancel when either the peer group size increases to infinity so that $\overline{e}_r^{(i)}$ will tend to zero, or when we use our instrumental variable estimation because our instruments are either free of measurement error or with a measurement error which is independent of the family average measurement error $\overline{e}_r^{(i)}$.

In conclusion, measurement errors for the hours worked do not cause any inconsistency for our two-stage least squares estimation with neighbourhood fixed effect, but it can cause some increase in the standard errors. We expect the measurement errors e_{ir} and $\overline{e}_r^{(i)}$ to be more relevant in the first years after childbirth when most of the mothers have not yet reverted back to their standard hours of work.

Appendix B: Additional Tables

Table A1a: Full Second Stage Results of Table 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mother's working hours						
Years Post Childbirth	1	2	3	4	5	6	7
	Endogenous Effect of Family Peers						
Average working hours of family peers	0.334*	0.524***	0.525***	0.456**	0.528***	0.593**	0.270
	(0.173)	(0.152)	(0.167)	(0.225)	(0.169)	(0.231)	(0.229)
Individual variable	Effect of individual covariates						
Mother years of schooling	0.553***	0.723***	0.654***	0.809***	0.915***	0.996***	1.203***
	(0.048)	(0.052)	(0.056)	(0.061)	(0.051)	(0.052)	(0.053)
Father years of schooling	0.160***	0.154***	0.116**	0.121**	0.143***	0.128**	0.044
	(0.045)	(0.046)	(0.049)	(0.055)	(0.048)	(0.053)	(0.047)
Mother works year prior to birth	10.001***	7.642***	6.435***	5.996***	5.360***	4.936***	5.025***
	(0.256)	(0.247)	(0.255)	(0.263)	(0.252)	(0.258)	(0.301)
Father Earnings	0.000***	0.000**	0.000	0.000	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Father works year post childbirth	2.407***	3.382***	2.534***	2.030***	1.967***	2.860***	2.560***
	(0.600)	(0.598)	(0.629)	(0.655)	(0.644)	(0.672)	(0.640)
Father Age at Birth	-0.044*	-0.087***	-0.043*	-0.058**	-0.074***	-0.052**	-0.051**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)	(0.023)
Mother Age at Birth	0.648***	0.665***	0.592***	0.526***	0.491***	0.433***	0.402***
	(0.033)	(0.033)	(0.033)	(0.034)	(0.033)	(0.032)	(0.031)
Low Birth Weight	-0.276	0.072	-0.058	0.442	0.371	0.132	0.125
	(0.442)	(0.453)	(0.450)	(0.441)	(0.450)	(0.446)	(0.427)
Very Low Birth Weight	-1.693	-0.777	0.217	-1.466	-0.687	-0.679	0.527
	(1.183)	(1.128)	(1.145)	(1.183)	(1.193)	(1.180)	(1.161)
Congenital Problems	0.188	-1.089	0.175	-0.000	-0.739	-0.524	-0.169
	(0.723)	(0.725)	(0.727)	(0.741)	(0.737)	(0.735)	(0.719)
Severe Deformity	-0.260	0.547	-0.542	-0.983	0.211	0.730	-0.044
	(0.912)	(0.917)	(0.920)	(0.925)	(0.920)	(0.959)	(0.883)
Multiple Births	-3.995***	-3.139***	-0.368	0.453	0.260	0.112	0.374
	(0.720)	(0.701)	(0.723)	(0.715)	(0.740)	(0.740)	(0.749)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Results are for the two-stage least squares with mothers' neighbourhood fixed effects.

Year and month of birth dummies and their averages across family peers are included.

Table A1b: Full Second Stage Results of Table 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Mother's working hours				
Years Post Childbirth	1	2	3	4	5	6	7
Family peers average			Exogenous Peer Effect				
Mother years of schooling	-0.074	-0.297***	-0.242**	-0.261	-0.413***	-0.563**	-0.226
	(0.091)	(0.101)	(0.097)	(0.165)	(0.153)	(0.223)	(0.248)
Father years of schooling	-0.079	-0.098*	-0.054	-0.128**	-0.117**	-0.085	-0.075
	(0.053)	(0.052)	(0.056)	(0.055)	(0.055)	(0.065)	(0.051)
Mother works year prior to birth	-2.616	-3.127**	-2.743**	-2.226	-2.260**	-2.497**	-0.781
	(1.713)	(1.257)	(1.144)	(1.383)	(0.944)	(1.198)	(1.116)
Father Earnings	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Father works year post childbirth	0.461	0.001	-0.128	-0.020	0.011	-1.050	0.123
	(0.682)	(0.709)	(0.666)	(0.715)	(0.756)	(1.018)	(0.889)
Father Age at Birth	-0.039	0.020	0.021	0.030	0.029	0.055	0.007
	(0.030)	(0.031)	(0.028)	(0.035)	(0.035)	(0.034)	(0.039)
Mother Age at Birth	-0.194	-0.351***	-0.363***	-0.252*	-0.269**	-0.292**	-0.130
	(0.139)	(0.126)	(0.119)	(0.152)	(0.114)	(0.125)	(0.116)
Low Birth Weight	-0.362	-0.507	0.287	-0.004	-0.438	-0.382	-0.298
	(0.511)	(0.517)	(0.539)	(0.549)	(0.528)	(0.577)	(0.532)
Very Low Birth Weight	2.148	-0.019	-1.893	0.135	0.218	-0.570	-2.273
	(1.407)	(1.380)	(1.442)	(1.539)	(1.434)	(1.544)	(1.480)
Congenital Problems	-1.369	0.726	-1.077	0.361	0.611	-0.585	-1.539*
	(0.869)	(0.863)	(0.864)	(0.902)	(0.906)	(0.939)	(0.898)
Severe Deformity	1.066	-0.235	0.922	-0.193	-0.156	0.551	1.870*
	(1.069)	(1.090)	(1.083)	(1.109)	(1.106)	(1.120)	(1.089)
Multiple Births	1.094	2.424**	0.741	-0.274	0.403	0.234	0.122
	(1.097)	(1.015)	(0.893)	(0.867)	(0.852)	(0.848)	(0.868)
Observations	46,614	46,614	46,614	46,614	46,614	46,614	46,614
R-squared	0.29	0.30	0.28	0.27	0.27	0.27	0.23
F statistic 1st Stage	33.34	41.19	34.01	18.86	33.74	17.47	19.00
Hausman Test p-value	0.21	0.91	0.93	0.72	0.99	0.81	0.24

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Results are for the two-stage least squares with mothers' neighbourhood fixed effects.

Year and month of birth dummies and their averages across family peers are included.

Table A2: Full First Stage Results of Table 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Family peers average working hours			
Years Post Childbirth							
Individual variable				Effect of individual covariates			
Mother Education	0.078**	0.139***	0.168***	0.169***	0.116***	0.090**	0.118***
	(0.037)	(0.038)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Father Education	-0.003	0.017	-0.092**	-0.132***	-0.087**	-0.109***	-0.069*
	(0.037)	(0.037)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Mother Work year Prior to Birth	0.912***	0.838***	0.860***	0.688***	0.758***	0.593***	0.938***
	(0.173)	(0.175)	(0.179)	(0.181)	(0.181)	(0.183)	(0.183)
Father Earnings	-0.000	-0.000	-0.000*	-0.000	-0.000*	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Father Work Status	0.350	0.057	0.057	0.675	0.330	-0.898	-0.505
	(0.510)	(0.526)	(0.532)	(0.532)	(0.545)	(0.554)	(0.561)
Father Age at Birth	0.015	-0.001	-0.008	0.012	-0.006	-0.023	0.010
	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Mother Age at Birth	-0.061**	-0.055**	-0.015	-0.056**	-0.040	-0.000	-0.026
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Low Birth Weight	-0.151	0.665*	0.092	-0.074	-0.241	-0.220	-0.120
	(0.361)	(0.369)	(0.372)	(0.365)	(0.367)	(0.375)	(0.376)
Very Low Birth Weight	-0.046	-0.269	0.110	0.433	0.302	0.435	0.218
	(0.951)	(0.950)	(0.968)	(0.979)	(0.975)	(0.986)	(0.977)
Congential Problems	0.206	0.447	0.337	0.285	0.029	0.318	-0.841
	(0.576)	(0.583)	(0.602)	(0.600)	(0.600)	(0.590)	(0.590)
Severe Deformity	-0.419	-0.243	0.033	-0.160	-0.240	-1.161	0.683
	(0.727)	(0.735)	(0.758)	(0.756)	(0.758)	(0.748)	(0.746)
Multiple Births	0.125	-0.116	1.008*	0.575	1.382**	0.968*	1.291**
	(0.562)	(0.574)	(0.579)	(0.565)	(0.548)	(0.582)	(0.574)
Family peers average				Exogenous Peer Effect			
Mother Education	0.393***	0.514***	0.445***	0.660***	0.805***	0.905***	1.023***
	(0.045)	(0.046)	(0.046)	(0.047)	(0.047)	(0.047)	(0.047)
Father Education	0.107**	0.075	0.128***	0.096**	0.120**	0.169***	0.041
	(0.046)	(0.047)	(0.047)	(0.048)	(0.047)	(0.048)	(0.047)
Mother Work year Prior to Birth	9.763***	8.074***	6.652***	6.032***	5.376***	5.052***	4.756***
	(0.198)	(0.204)	(0.207)	(0.209)	(0.210)	(0.211)	(0.211)
Father Earnings	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Father Work Status	1.878***	2.256***	1.216**	1.429**	2.317***	3.354***	2.753***
	(0.484)	(0.522)	(0.550)	(0.562)	(0.563)	(0.565)	(0.591)
Father Age at Birth	-0.081***	-0.106***	-0.053**	-0.098***	-0.131***	-0.088***	-0.124***
	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Mother Age at Birth	0.769***	0.782***	0.668***	0.649***	0.633***	0.511***	0.479***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.034)	(0.033)
Low Birth Weight	-0.004	-0.373	-0.880*	-0.791*	-0.603	-1.042**	-0.756
	(0.451)	(0.463)	(0.463)	(0.467)	(0.468)	(0.478)	(0.479)
Very Low Birth Weight	-0.391	0.185	1.456	2.728**	0.929	2.192	1.074
	(1.312)	(1.299)	(1.324)	(1.367)	(1.348)	(1.372)	(1.369)
Congential Problems	0.868	0.239	-0.039	0.069	0.813	0.816	0.521
	(0.796)	(0.819)	(0.852)	(0.855)	(0.830)	(0.821)	(0.839)
Severe Deformity	-0.355	-0.811	-0.923	-0.724	-0.919	-0.550	-0.576
	(0.987)	(1.005)	(1.042)	(1.043)	(1.021)	(1.011)	(1.033)
Multiple Births	-4.002***	-3.602***	-1.823**	-0.086	-0.503	-0.295	-0.658
	(0.827)	(0.819)	(0.807)	(0.798)	(0.782)	(0.819)	(0.825)
Instrumental Variables				Effect of the neighbours of family peers characteristics			
Hours	0.068***	0.076***	0.070***	0.052***	0.069***	0.050***	0.051***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Results are for the first-stage of the 2SLS with mothers' neighbourhood fixed effects.

Year and month of birth dummies and their averages across family peers are included.