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The Family Peer Effect on Mothers' Labour Supply

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Abstract

The historical rise in female labour force participation has flattened in recent decades, but the proportion of mothers working full-time has increased. We provide the first empirical evidence that the increase in mothers' working hours is amplified through the influence of family peers. For identification, we exploit partially overlapping peer groups. Using Norwegian administrative data, we find positive and statistically significant family peer effects but only on the intensive margin of women's labour supply. These are in part driven by concerns about time allocation from early childhood and concerns about earnings from age 5.

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, 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 (see Maurin and Moschion 2009, Mota et al. 2016).[2]

A mother's work decisions after childbirth may 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). There are two main channels through which mothers' labour decisions can be affected by their peers' decisions. One is transmission of information which may be caused

[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.

[2] A possible exception is Olivetti et al. (2016), who look at the intensive margin on women's labour supply and estimate the causal peer effect of a woman's school mates' mothers while controlling also for the mother's working hours.

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 other is imitation, where a mother's utility may increase by behaving similarly to her peers (see Akerlof and Kranton 2000).

We use Norwegian administrative data covering the full population and identify individuals' family relations over multiple generations as well as identifying where people are living each year. This means that we focus on naturally occurring peer groups from the complete network of family peers and neighbours. We identify 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 than with peers outside the family such as neighbours, leading to a stronger peer effect on women's labour decisions from her family. 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.[3] 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). The empirical strategy to solve the potential reflection and endogeneity issues is based on instrumental variable estimation, exploiting partially overlapping peer groups (Bramoullé et al. 2009; Lee et al. 2010; De Giorgi et al. 2010). More precisely we instrument the hours of work for family peers - sisters and female cousins - with hours worked for recent mothers in their neighbourhood, relying on the fact that the neighbours of a mother's family peers do not affect her labour decisions directly but only indirectly through the family peers' labour decisions. Moreover, we measure the effect only for those neighbours

[3] See Oettinger (2000), Monstad et al. (2011), Adermon (2013), Qureshi (2013), Joensen and Nielsen (2015), Aparicio-Fenoll and Oppedisano (2016), Dahl et al. (2014), Nicoletti and Rabe (2016), Altonji et al. (2017).

who gave birth before the mothers' relatives to solve any reverse causality issues between family and their neighbours. We can therefore instrument the average decisions of the family peers with average characteristics of the family's neighbours. We mainly use the working hours of the family's neighbours as the instrumental variable. An illustration of the strategy would be a situation where my sister was weighing up the advantages and disadvantages of working particular hours and looked to her neighbours. This interaction affected the labour supply of my sister, and I either took information from my sister about working hours or I imitated her behaviour.

The endogenous peer membership may occur if the likelihood to interact with peers depends on unobserved characteristics which also affect the outcome variable. Relating to our paper, the likelihood to form interactions may depend on the selection into the neighbourhood only, as individuals cannot select their family. To control for the potential unobserved common genetic traits and covariates between the labour supply of the mother's neighbours and of her family peers neighbours we include as control variable the average worked hours of the mother's neighbours. This is similar to a neighbourhood fixed effect, excluding the mother.[4] In addition, we control for an extensive 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.

A residual endogeneity bias could remain if there are contextual or environmental influences that affect areas which are larger than a neighbourhood, potentially including both the mothers' and her family peers' neighbourhoods. Examples of these scenarios include i) general equilibrium effects where my family's neighbour took a job which I would have applied for; ii) the mother working with her family's neighbour; iii) the mother having grown up with her family's neighbours. Our results are robust to specifications which control for these potential biases. Lastly, we conduct a set of falsification or placebo

[4]Controlling for the IV (hours worked) defined at the mother's neighbourhood level (what we call the individual IV) controls additionally for the exclusion bias, described in Cayers and Fafchamps (2016) and Section 3.

tests, by for instance matching mothers with fictitious relatives with similar characteristics as the actual relatives (see Section 7).

Our sample consists of mothers giving birth in Norway between 1997 and 2002 (see Section 4 for a description of the data) and uses 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 of preschool aged children (see Section 5). We also provide some suggestive empirical evidence of what explains the family peer effect (see Section 6). We find that the family peer effects seem driven by mothers' concerns about time investment in the child, while they seem driven also by concerns about earnings only when the child is 5 and 6 years old.

Finally we provide some evidence of the magnitude the family peer effect with a back of the envelope computation of the social multiplier effect. Any change in public policies or events, which lead to an increase in labour supply, will affect mothers' worked hours both directly and indirectly through the influence of peers. Based on our results the social multiplier factor is equal to 1.5, which means that, if the direct effect is an increase in the labour supply by Δ hours, the total effect will be given by Δ multiplied by 1.5.

2 Previous literature

Looking at previous papers on peer effects on women's labour supply, there are only three papers that have attempted to estimate a causal (endogenous) peer effect on women's labour participation. Maurin and Moschion (2009) and Mota et al. (2016) focus on neighbourhood rather than family peer effects, finding evidence of a statistically significant effect of neighbours' labour decisions on womens' own decisions. Olivetti et al. (2016) focus on the peer effect of mothers and of school mates' mothers and find that there are statistically significant effects on a woman's hours worked from both her mother's hours and of the average hours across school mates' mothers.

Several studies on peer effects have explored outcomes other than labour supply, which have looked at peer groups defined as work colleagues (Mas and Moretti 2009, and Dahl et al. 2014), neighbours (Durlauf 2004) and school mates (Sacerdote 2011 and Lavy et al. 2012). 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, who 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 population of individuals and peers defined as neighbours, work colleagues or school mates (see De Giorgi et al. 2010 and 2016 and Nicoletti and Rabe 2016).

3 Identification and estimation of within-family peer effects

We consider the following mean regression model

$$y_i = \alpha + \bar{y}_{-i}\rho + \mathbf{x}_i\ \boldsymbol{\beta} + \bar{\mathbf{x}}_{-i}\boldsymbol{\gamma} + \epsilon_i, \tag{1}$$

where the subscript i denotes mothers in our sample and $i = 1, ..., n$; y_i is the number of weekly hours worked by mother i in a specific year after childbirth; $\mathbf{x}_i$ is a row vector with K individual maternal exogenous variables; $\bar{y}_{-i} = \frac{\sum_{j \in P_{Fi}} y_j}{n_{Fi}}$ is the family average of y excluding individual i; $\bar{\mathbf{x}}_{-i} = \frac{\sum_{j \in P_{Fi}} \mathbf{x}_j}{n_{Fi}}$ are the corresponding averages of the vector of variables $\mathbf{x}$, P_{Fi} is the set of family peers of mother i excluding herself, i.e. the subsample of mothers who belong to the same family (sisters or cousins); n_{Fi} is the number of family peers of mother i; and ε_i is an error term with $E(\varepsilon_i|\mathbf{x}) = 0$. The scalar parameter ρ measures the endogenous family peer effects, $\boldsymbol{\gamma} = [\boldsymbol{\gamma}_1, ..., \boldsymbol{\gamma}_K]'$ is a $K \times 1$ vector of exogenous family effects, $\boldsymbol{\beta} = [\boldsymbol{\beta}_1, ..., \boldsymbol{\beta}_K]'$ is a $K \times 1$ vector of the effects of the corresponding K mothers' characteristics $\mathbf{x}_i$, and finally the scalar parameter α is the intercept.

To solve the potential reflection and endogeneity issues we use an instrumental variables approach that can be viewed as an extension of the approach introduced by Kelejian and Prucha (1998) and Lee (2003).[5] The extension consists of considering interactions occurring between people within multiple rather than a single network.[6] 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 family's neighbours. In practice you may imagine a scenario where my sister was weighing up the advantages and disadvantages of working particular hours and looked to her neighbours. This interaction affected the labour supply of my sister and I either took information from my sister about working hours or I imitated her behaviour.

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 neighbourhood peer effects and it is justified by the fact that interactions between non-homogenous peers are not likely.[7]

We can use the averages of the variables $\mathbf{x}$ and the dependent variable y for the neighbours of the mothers' family members as instrumental variables for $\bar{y}_{-i}$. Let $\bar{\mathbf{x}}_{N,-i} = \frac{\sum_{j \in P_{Ni}} \mathbf{x}_j}{n_{Ni}}$ and $\bar{y}_{N,-i} = \frac{\sum_{j \in P_{Ni}} \mathbf{y}_j}{n_{Ni}}$ be the neighbourhood average of $\mathbf{x}$ and y excluding the mother i, where P_{Ni} are the sets of neighbour peers of

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

[6]Nicoletti and Rabe (2016) and De Giorgi et al. (2015) also identify peers considering multiple networks.

[7]See Mota et al. (2016).

mother i excluding herself and n_{Ni} is the number of neighbour peers of mother i; then our instrumental variables can be defined as $\bar{\mathbf{x}}_{NF,-i} = \frac{\sum_{j \in P_{Fi}} \bar{\mathbf{x}}_{N,-j}}{n_{Fi}}$ and $\bar{y}_{NF,-i} = \frac{\sum_{j \in P_{Fi}} \bar{y}_{N,-,j}}{n_{Fi}}$. For our main results we use the instrumental variable $\bar{y}_{NF,-i}$, but in our sensitivity analysis we consider also a set of additional instruments, $\bar{\mathbf{x}}_{NF,-i}$, which are based on birth outcomes (low birth weight, very low birth weight, congenital malformation, severe deformity and multiple births).

We make sure that the instrumental variable $\bar{y}_{NF,-i}$ is predetermined by considering the working hours of peers that have given birth in the past.[8]

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. We discuss condition (i) in Section 5 where we measure the statistical significance of our instrumental variable 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.

Firstly our instrumental variables are defined at the neighbourhood level. If mothers and their family peers tend to sort into similar neighbourhoods, then failing to control thoroughly for the mothers' neighbourhood traits can lead to an overestimation bias of the family peer effect. For example, I and my family peers may choose to live in areas with good childcare coverage, making it easier for us to return to work. Any correlation between our decisions after

[8]Similarly De Giorgi et al. (2010) and Nicoletti and Rabe (2016) use the average for the peers of 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).

having children may reflect common local childcare provision and not a peer effect. We are concerned that the hours worked by neighbours of family peers, $\bar{y}_{NF,-i}$, can be correlated with the hours worked by the mother's neighbours, $\bar{y}_{N,-i}$, and similarly that the neighbourhood average of the covariates for the family peers, $\bar{\mathbf{x}}_{NF,-i}$ can be correlated with the average covariates across the mother's neighbours, $\bar{\mathbf{x}}_{N,-i}$. We avoid this potential bias by controlling for the average worked hours of the mothers' neighbours excluding herself, which we call "individual IVs" and average covariates across the mother's neighbours. This means that we include among the explanatory variables in equation (1) $\bar{y}_{N,-i}$ ($\bar{\mathbf{x}}_{N,-i}$) whenever we use as instrumental variable $\bar{y}_{NF,-i}$ ($\bar{\mathbf{x}}_{NF,-i}$).

$$y_i = \alpha + \bar{y}_{-i}\rho + \mathbf{x}_i\ \boldsymbol{\beta} + \bar{\mathbf{x}}_{-i}\boldsymbol{\gamma} + \bar{y}_{N,-i}\delta + \epsilon_i, \tag{2}$$

Controlling for the individual IVs corrects not only for the bias caused by unobserved characteristics of neighbours but also for the exclusion bias (see Guryan et al. 2009, Caeyers and Fafchamps 2016). We estimate equation (2) using a two-stage least squares estimation. Because we control for the individual IV, $\bar{y}_{N,-i}$ in both first and second stages, the estimated effect of the instrument $\bar{y}_{NF,-i}$ is net of the effect of neighbours of family members living in the same neighbourhood as the mother in question.

Secondly, we worry about 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, $\bar{\mathbf{x}}_{NF,-i}$ and $\bar{y}_{NF,-i}$, would be invalid instruments. As mentioned above, equation (2) controls for any interactions between mothers living in the same neighbourhood as her family. However, even for mothers living in different neighbourhoods as her family, our instruments could be invalid if there are unobserved factors explaining labour market decisions of both the peers of peers and the mother in question. Examples of these scenarios include general equilibrium effects where my family's neighbour took a job which I would have applied for, if I work with or grew up with my family's neighbour 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. Finally, we use multiple instruments and test the over-identifying restrictions to assess the validity of our instruments (see Section 7).

Thirdly, 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 correlated with the error term in our main equation. We avoid this potential bias by considering only neighbours that had their first child between one and five years earlier than the family living in the same neighbourhood.

To support that there is no residual endogeneity bias, we also consider the estimation of the family peer effect using sister and cousin - in laws who have no genetic link to the mother and we consider some placebo tests in Section 7. In particular, we consider the estimation of the family peer effect when replacing the family members with randomly chosen family peers with similar characteristics of the mother (placebo test 1), with the same date of birth of the mother (placebo test 2) and with cousins who give birth in the future (placebo test 3).

A remaining threat to our strategy which we cannot test, is where a mother's behaviour is affected by her family's neighbours, but the family's behaviour is not. An illustration of this threat would be situation where I just had a baby and my cousin tells me that her neighbour was very happy to go back to work soon after giving birth and I got influenced by this bit of information and decided to go back to work early, even if my cousin was not influenced by her neighbour experience and did not go back to work early. In this situation there is a potential direct effect from my cousin's neighbour to me. However, we think the likelihood of a mother changing her behaviour in response to information which her sister or cousins did not react to is small.

Finally, the estimation of the family peer effect on hours worked is prone to attenuation bias caused by measurement error in the variable used to construct labour hours. Our instrumental variable estimation corrects for such bias under the assumption that the labour hours of the family peers and of their neighbours have uncorrelated measurement errors, which is credible.[9]

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 newborn'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 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

[9] See Appendix A for full details.

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. So that future decisions of family cannot affect contemporaneous decisions of the mother, the family peer group of a mother when she gives birth is constructed as all cousins who have given birth in the past, which is defined as at least one month prior to the mother.

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.

The neighbourhood peer group is constructed by linking each mother to all other mothers living in her zip code and we select only those neighbours giving birth between one and five years earlier than the mother. Restricting the neighbours and family peers to women who gave birth in the past, we avoid the fertility contagion or peer effects 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 the same level of education.

Next we take from the administrative register variables which control for the timing of the mothers' birth. We also consider the level of education of the mothers[10] and a quadratic in the age at birth which together proxy for years

[10] We treat this variable as predetermined, as only 8% of mothers increase their education during the sample period.

of experience in the labour market. 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.[11]

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 45,985 first births to mothers with at least one sister or female cousin.

Table 1 shows that the family peer group consists of on average 3.074 maternal cousins, 3.149 paternal cousins and 0.614 sisters. The second peer group - homogenous neighbours - is larger, with on average 26.924 neighbours living in the same zip code. To give a little information on the size of a zip code, there are on average 3,100 individuals and 1,400 households within this neighbourhood, 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) is evidently smaller. It is not very common for a mother to live in the same zip code as her family peers (1% of mothers) but much more likely to live in the same municipality (23%).

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. This compares to 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 23.5 hours 7 years after childbirth. On average 77.6% of mothers work in the year prior to childbirth, mothers have on average 13.3 years of schooling. Nearly all fathers (97.7%) work in the birth year of their first child and the age of mothers and fathers at the first births is on average 25.8 and

[11] To assure that our results are not confounded by later fertility decisions, we interact the family peer effect with a dummy for not having another child within the sample window and with the exception of one year, find no significant interaction.

29.3 years respectively. 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 2.5% 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 8 for details) as well as to take account of potential institutional and policy changes.

5 Estimation results

In Table 2 we report the results for the linear in mean model (see equations (1) and (2)). 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 control for the IV at individual level (2SLS Individual IV).[12] We use the same instrumental variable across the 7 columns, which is the average across the neighbours of mothers' family peers of the working hours one year after childbirth. More precisely, we take for each cousin (sister) the mean of this variable defined across the set of her homogenous neighbours (i.e. neighbours living in the same postal code area, giving birth between 1 and 5 years prior to the family member and with the

[12] The OLS and 2SLS estiamtions are applied to model (1); whereas the 2SLS Individual IV is applied to model (2).

same level of education) and then we average these means across the mothers' sisters and cousins who gave birth before the mother. The corresponding IV at individual level is defined by taking the average of the worked hours one year after childbirth across the mother's neighbours who gave birth between 1 and 5 years earlier than the mother. In all regressions we control for the correlated effects 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' years of education in level and squared, an indicator for working in the year prior to childbirth, fathers' earnings and work status in the year of childbirth, fathers' and mothers' age at the birth of the child and their squares, 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. We control 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. We allow for correlation in the error terms within municipalities in all regressions and correct the standard errors to take account of this.

The OLS 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 and other potential endogeneity issues caused by omission of variables which could explain both the mother's and her family peers hours worked. Secondly the coefficient is prone to attenuation bias from measurement error (see Section Appendix A1 for details) and a negative bias caused by the exclusion of the mother from her family group peers (see Caeyers and Fafchamps 2016).

To correct for the biases caused by endogeneity issues and measurement error inherent in OLS estimation, we report 2SLS estimation results. 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 and other potential endogeneity issues. The 2SLS estimation is still potentially biased because of the exclusion issue and of the potential sorting of family peers into similar neighbourhoods. Caeyers and Fafchamps (2016) show that the exclusion bias is negative and converges to zero when the sample size tends to infinity if the peer group size remains small. Because in our sample the largest family group has size 32 while the sample size is 45,985, we expect a very small and negligible exclusion bias. On the contrary, we expect the omission of neighbourhood characteristics which are similar between the mother and her family peers to lead to an over-estimation bias, which can be substantial if mother's neighbours and family peers' neighbours have very similar worked hours. Controlling for the average worked hours of the mother's neighbours, i.e. the individual IV, allows us to eliminate both the biases (see the 2SLS individual IV in Table 2). Because the estimated family peer effects reduce considerably, we infer that the over-esitmation bias caused by the sorting of family peers into similar neighbourhoods is much larger than the potential negative exclusion bias.

We find no statistically significant peer effect in the year after birth, but strong and significant peer effects for the following years ranging between 0.30-0.45. The effect is strongest at 2 years after childbirth, whereafter statistical significance along with magnitude declines across the years. This implies that an increase in mean working hours of the mother's family peers by 1 hour leads the mother to raise her hours by 18-27 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.

We compute Hausman tests to check the assumption of equality between the coefficients estimated using the 2SLS individual IV estimation and OLS estimation controlling for the individual IV, and we do not reject the equality assumption at standard levels of significance (see p-values in Table 2). If we assume that the exclusion bias be insignificant because of our large sample size, then differences between the two estimations are caused by the fact that the OLS estimation is biased by measurement error and endogeneity issues (in particular by the reflection and omitted variables issues). Therefore the Hausman test results suggest that the attenuation bias caused by measurement error is of equal magnitude but opposite sign compared with endogeneity biases. The F-tests for the significance of the instrument reported at the bottom of Table 2 suggest that our instrumental variable is strong and statistically significant.

We apply the 2SLS Individual IV estimation for all our further regression analysis because the measurement error and endogeneity biases do not necessarily always cancel each other. We consider the 2SLS Individual IV estimation results reported in Table 2 as our preferred results and the benchmark against which we compare any further estimation. The full regression results for the 2SLS Individual IV estimation are reported in Appendix Table A1 (split in two parts, A1a and A1b) for the second stage estimation and in Appendix Table A2 for the first stage estimation.

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 18-27 minutes once we control for measurement error, unobserved neighbourhood characteristics, the reflection issue and a potential exclusion bias.

6 What explains the family peer effect

In this section we assess the importance of different channels which drive the family peer effect on mother's labour decisions. In Section 6.1 we examine whether the family peer effect on mothers' worked hours is driven mainly by a peer effect on mother's earnings power. In Section 6.2 we compare the family peer effect at intensive and extensive margins. For this, we assess whether the effect of the family peers on the mothers labour market decisions come mostly through her participation decisions rather than through her decision about how many hours to work. In Section 6.3 we estimate the neighbourhood peer effect in order to compare our estimates to the literature on the influence of peers on mothers' labour supply decisions. In Section 6.4 we give some magnitude to the family peer effect by calculating the social multiplier effect.

6.1 Time and money investments

When a mother with young children makes a decision about whether to work or stay at home, she faces a trade-off. On the one hand increasing hours worked may be a concern for a mother because of the potential constraints imposed on the time a mother can spend with their child. On the other hand, reducing hours worked can also be a concern because of the related reduction in earnings and increased constraints imposed on family consumption and monetary investments in the child.[13] The literature has found that time investments of parents are highest in early childhood and falling across age (Del Boca et al. 2012, Guryan et al. 2008, Zick and Bryant 1996) whilst financial investments tend to increase as children age (Kornrich and Furstenberg 2013 show that expenditure in child education is flat between years 0-2 but increasing thereafter). For this reason mothers may be influenced by their family peers through time spent with their child and through increased earnings and this influence may vary across child age.

We explore these two channels by analysing how the mothers' hours worked respond to the mean earnings of her family peers. In Table 3 we report the effect of the average *earnings* across family peers on mothers' hours worked, estimated using a 2SLS with individual IV. We find that this earnings effect is not statistically different from zero in the first three years after childbirth, while it becomes significant in the fourth, fifth and sixth year after childbirth. To give some idea of magnitude, family earnings, deflated to 2000, have been standardised to have a mean of zero and a standard deviation of one. The results show that a standard deviation increase in the family's earnings four years after birth (which equates to approximately 18,000 Norwegian Krone or 2000 US dollars) leads the mother to increase her hours worked by 3.6 hours.

[13] Models of parents making investment decisions which drive child human capital include Bernal (2008), Cunha and Heckman (2007), Cunha et al. (2010) and Carneiro et al. (2015b).

Five years and six years after birth a standard deviation change in the family peer's earnings raises the mother's hours by 2.9 and 2.3 hours respectively.

The lack of statistically significant peer effect in earnings in the early years suggest that women with very young children are not concerned with the financial investments of their family peers but with time investments of mothers in their children. On the contrary, once the child is in its fourth year, the earning consequences become relevant for mothers and they begin to be influenced by the earnings of their peers. This finding is in line with the literature which suggests that time investments are more important for very young children and financial investments begin to matter more later in life.

6.2 Intensive and extensive margins

We show in Fig. (1) that in recent years, a substantial shift in female labour supply has come through a change in hours worked. We aim now to provide evidence that the family peer group influences the mothers' decisions through the intensive margin, rather than through a participation decision. In Table 4 we analyse how important peers are in the decision to return to work versus stay at home. We report the results of the 2SLS Individual IV estimation of the linear probability model for mothers' labour participation using the same explanatory variables and instruments as in our main estimation. While in Table 2 we find that an increase in the mother's family peers average hours worked leads to an increase in the mother's worked hours, in Table 4 we find no statistically significant effect on the mother's labour participation. Therefore we conclude that the relevant effect of family peers is at the intensive, rather than the extensive margin of mothers' labour supply.[14]

[14] We also regressed the family peers' participation on the mothers' labour participation. With the exception of two years after childbirth, there was no significant family peer effect of participation. Note that between 3-7 years after birth the F-statistic falls to below 10 which again suggests that peers do not influence the participation decision of mothers in this period.

6.3 Neighbourhood peer effect

There are no studies that have estimated the causal effects of family peers on mothers' labour supply[15] 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 Moschion (2009) and Mota et al. (2016).

To compare to these papers, we now adapt our identification strategy to estimate the neighbourhood peer effect on the mothers' working hours. We still estimate equation (2), but we exchange the roles of the neighbours and family peers and consider an instrumental variable estimation. The instrument therefore is the average hours worked of the (homogenous) neighbours' family peers.[16] Again we control for the individual IV, which in this case is the mean hours worked by the mother's family, excluding the mother (2SLS Individual IV).

Results are presented in Table 5 where we report the 2SLS Individual IV. For one hour increase in the average worked hours of the mothers' neighbours, the mother increases her hours by between 2 and 17 minutes. Nevertheless, the peer effect is statistically significant at 5% level only between 3-5 years after childbirth. The instrument is highly significant (see F-tests 1st stage reported in Table 5), which suggests that the absence of a significant neighbourhood effect for some of the years is not caused by a weak instrument. This seems to suggest the family peers have a stronger effect than neighbourhood peers.

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 larger than our neighbourhood peer effect and more similar in magnitude to our family peer effects estimated using 2SLS Individual IV.

[15] 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).

[16] Neighbourhood peers are defined as those giving birth between 1-5 years before the mother, with the same level education.

In their most robust estimation Mota et al. (2016) find that one additional working homogeneous neighbour 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) and perhaps more in line with our estimates.

6.4 How important is the family peer effect

Whether the labour supply decisions of a mother affect those of her family members is interesting from a policy perspective, because the direct effect of any policy aiming at raising labour hours of mothers, such as the US Family and Medical Leave Act, is likely to be amplified through the indirect effect of peers influence. We now provide a calculation of the multiplier effect using the results in Table 2. If the family peer effect is a source of social interaction, we expect to find a multiplier greater than one. Imagine a policy which leads to a one weekly hour increase for the targeted mother. Through the family peer effect, the policy would increase also hours worked by her sisters and cousins. We calculate the multiplier effect as $\frac{1}{1-\hat{\rho}}$, where $\hat{\rho}$ is an estimate of ρ defined in equation 2 and take the mean multiplier across the seven estimates. The mean multiplier effect is 1.5, which means that if the direct effect of the policy is to increase hours worked in a week by 1, the total effect including the social multiplier is 1.5 hours.

The dramatic rise in female labour force participation which took place from the 1960s onwards has been explained in the literature by factors including the expansion of female education (Ekstein and Lifshitz 2011) and a reduction in the cost of children (Attanasio et al. 2008, Ekstein and Lifshitz 2011). Any triggering events which raise female labour supply will have an amplified effect through the family peer effect. We extend our calculation of the multiplier effect to examine how a policy to raise the compulsory schooling level of education from 10 years to 11 (or from age 16 to 17) raises the hours worked by women. Note that we use this example as an illustration of how the social multiplier works to spread the effect of a policy targeting mothers' labour supply. The true social multiplier effect would be applied to a causal estimate of education on mothers' hours worked. In our model, mothers hours worked are affected by her own education (Table A1a) and that of her family peers (Table A1b) although as only the former are generally statistically significant we focus on these coefficients to estimate the total effect on hours worked from the policy change. The direct effect of an increase in mothers' education by 1 year, assuming she had the compulsory 10 years of schooling is to raise her hours by 1.5 hours.[17] Adding in the multiplier through the family peer effect (multiplying the direct effect of education by the mean multiplier of 1.5), the total effect of the education expansion policy is to raise hours by between 1.8 hours, which is 48% of the direct effect.

Another metric of the importance of the family peer effect in explaining labour supply decisions of the mother, is the proportion of the variation in hours explained by the family peer effect, at each of the 1-7 years after birth. The family peer effect two years after birth explains 14.7% of the variation in hours after two years and this proportion falls steadily across the years so that 11.9%, 10.9%, 7%, 9% and 4.2% of the variation in hours 3-7 years after birth is explained by the family peer effect respectively.[18]

In summary, the family peer effect is an important source of social interaction for the hours worked by new mothers. With a multiplier effect larger than one, the family peer effect magnifies the effect of a policy targeting labour market hours of new mothers or raising the years of compulsory schooling. It explains a large proportion of the variation in hours worked, especially between 2 and 4 years after birth.

[17] This is calculated for each year after birth as the sum of the coefficient on mother education and the coefficient on mother education squared multiplied by 20. Then we calculate the mean.

[18] This was calculated as the ratio between the variance of the average worked hours multiplied by ρ^2 and the variance in the dependent variable.

7 Robustness and placebo checks

In our main specification we have used the neighbour's hours worked in the year after childbirth, averaged across family peers as an instrument. 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 2SLS individual IV estimation results are reported in the panel a) of Table 6. The IVs are the average across the mothers' family peers of their neighbourhood average of hours worked, dummy variables for low birth weight, very low birth weight, congenital malformation, severe deformity, and multiple birth. The p-value for the Hansen test is above or equal 0.32, 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 6 are less precisely estimated than in Table 2. However, the magnitude of the estimated family peer effect is in line with Table 2.

In the following we provide further empirical evidence on the validity of our estimation method by considering some robustness and placebo checks.

We start by considering two potential threats to our identification strategy. Firstly, mothers' labour supply decisions might affect labour market outcomes of their family members and their neighbours through general equilibrium effects in the labour market. For example, when a mother (neighbour) gets a job this might be at the expenses of others, including their excluded peers. Secondly, the mother may work with her family's neighbours, existing in the same work peer group. We control for these threats by including a set of dummy variables for the mother occupation interacted with dummies for the mothers' level of education (see Table 6 panel b). After adding these new dummy variables the peer effects are less precisely estimated, but we still find evidence supporting the presence of a positive family peer effect on mothers' worked hours after childbirth in all years but statistically significant only in the second and third year after childbirth.

Next, we consider an additional violation of our identification strategy which is that the mother may have grown up with her family members' neighbours. Imagine a situation where the mother moved away from her childhood neighbourhood but her sister did not. Then there may be a direct effect of the family's neighbours on the mother. In panel c) of Table 6, we include an additional control which is the average hours worked one year after birth at the municipality level where we exclude the mother, similar to controlling for a municipality fixed effect. In Norway there are approximately 450 municipalities of a much larger geographical area then neighbourhoods. We think that the mother is more likely to meaningfully interact with the neighbours she grew up with if they live currently in the same municipality. Also to the extent that mothers live in the same municipality when they have their child as when growing up, our estimates will be net of the effect of early life neighbours on the mother's labour supply decisions after birth. The estimates are less precise and slightly lower magnitude to our preferred specification but not statistically different.[19]

Our instrument is constructed at the level of the neighbourhood and there may be unobserved heterogeneity through similarities in characteristics of the mothers and of her family's neighbours. To test for this, we run two placebo tests. Firstly we randomly assign to each mother a fictitious set of relatives with similar characteristics as the true relatives (placebo test 1 in panel d). We divide the sample of mothers into cells, or subgroups, defined by level of the family's education (below and above the average of 12 years), age at birth (below and above the mean age at birth) and employment status before giving birth (working and non-working one year before the first childbirth). Each family peer of a mother is replaced with the family peer of a woman randomly selected from the subgroup of mothers within the same cell. We then apply the 2SLS estimation with individual IV to produce an estimate of the family peer

[19] Note that a potential worry is the presence of a macroeconomic shock which is common to mothers living in different neighbourhoods but the same wider area of a municipality. However, in our main estimation we control for time varying shocks to the neighbourhood and therefore also for any common shock to the wider geographical area.

effect using the observed average worked hours for these fictitious relatives and instrumenting it using the neighbours of these fictitious relatives. We repeat this random allocation of relatives to mothers re-shuffling the mothers within cells 1000 times and producing 1000 estimates of the family peer effects. Table 6 (see panel c, placebo 1) reports the percentage of cases out of the 1000 replications in which the family peer effect is found to be statistically significant at the 5% level. For each of the 7 years after childbirth, the family peer effect is statistically significant in less than 5% of replications when using fictitious relatives. Therefore, we conclude that the significant family peer effect found in the paper is not spuriously explained by similarities in the family peers characteristics.

It may be that the family peer effect we estimate is purely picking up a year effect or time trends in hours worked. Similarly to the implementation of the first placebo test we divide the sample of mothers into cells by the year of birth of their child and we randomly reassigned fictitious relatives to mothers by randomly choosing women form the subgroups of mothers with the same year of birth of their child. Again, we use these fictitious relative to estimate the family peer effect using 2SLS estimation with individual IV and repeating this random assignment of family peers within cells 1000 times. As above in over 95% of cases the estimated peer effect using fictitious family peers is not different to zero at 5% level of significance and we conclude that our estimation results are not driven by year or time trends effects (see placebo 2 in panel e) Table 6).[20]

We perform also a third placebo test where the family peers of a mother are defined considering sisters and female cousins who will have a child later rather than earlier than the mother. We take sisters and cousins who give birth in the future, and estimate the effect of the average hours worked by these family peers between 1-7 years after childbirth. This should break the causal link and give null effects if there is no influence from family peers who have not yet had a child. As instruments we still use the average of hours worked for the family

[20] The percentage of repetitions for which the F-statistic in the first stage is greater than 10 is 100% in all cases, for the two placebo tests.

peers' neighbours who gave birth to their first child between 1 and 5 years earlier. The results seem a little erratic but suggest that there is no clear statistically significant positive family peer effect on mothers' hours worked (see placebo 3 panel f) Table 6).

We check whether the family peer effect is driven by (i) sisters rather than cousins and (ii) by unobserved shared genetic and family background characteristics. By estimating the peer effect separately for sisters and female cousins, we find a positive and significant peer effects for using both definitions of the family peer group (panels a and b in Appendix Table A3 respectively). By considering the peer effect of the mother's sisters-in-law and female cousins-in-law, who are not genetically related and who do not share any grand-parent with the mother, we find that the peer effects are still positive and significantly different from zero (see panel c of Appendix Table A3).

In recent years in Norway there have been several reforms with potential consequences for female 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, Havnes and Mogstad 2015). Nevertheless, the only policy which was actually introduced during our sample period is a child care reform which was passed in 2002. Andresen and Havnes (2014) describe that the reform which affected mainly 1-2 year old, which lowered the cost of childcare for parents through subsidies and cheaper fees and invested in pre-school infrastructure. Of our sample children, those born in 2000-2002 may have potentially been affected by this policy as their children would be aged 1-2 during the post-reform period. To see if our results are driven by the policy, we firstly repeated our analysis selecting only the cohorts not affected by the reform and find our results are robust. Secondly we included the municipality level childcare coverage (measured as the number of childcare spaces as a proportion of the number of pre-school children in the municipality) and its interaction with the family peer effect. We found no significant interaction, suggesting that our results are not confounded by the policy.[21]

Finally we have estimated a Tobit model to allow working hours to have probability mass at zero and the corresponding average partial effect of family peers are reported in Appendix B Table A4. These effects are similar to our main estimation results, although slightly less precisely estimated in some regressions.

8 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 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 between 18 and 27 minutes. Such family peer effects would imply a social multiplier of 1.5, meaning that a policy change which causes a direct effect on mothers' labour supply of one working hour would be amplified by an additional 0.5 through the indirect effect operating via the influence of family peers. In addition to the pure multiplier effect, the family peer effect will amplify the effect of other policies which affect female labour supply and we illustrate an example of how this would work with a back of the envelope estimate showing that a reform raising the compulsory schooling age in Norway from 16 to 17 has a social multiplier effect which is 48% of the direct effect of the policy.

While a mother's working hours is influenced significantly by family peers her labour participation decision is not significantly affected by the average working hours of her family peers. In keeping with the literature on parental investments into child human capital, we show that the influence of family peers on mother's hours worked is explained by concerns about time allocation

[21] Results are available on request. Note that childcare availability data exists up to 2004 only.

between family and work from the second year after birth onwards; but as the child ages, concerns about financial investments also become important.

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. We find some significant effects but smaller than the family peer effects. This indicates that interactions between neighbours are less relevant than between family peers. This may be because mothers are less influenced by their neighbours, or because defining neighbourhood peers by mothers living in the same neighbourhood with the same education cannot guarantee that the mothers actually interact with other mothers in her postcode.

Finally, 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 for specific occupations and levels of education (such as general equilibrium effects or workplace peer effects) or unobserved shocks to a wider area than the neighbourhood; (ii) the validity of our instruments using extra instrumental variables; and iii) implementing some placebo test where real family peers are replaced with fictitious peers with similar characteristics or with cousins who give birth in the future. These robustness checks suggest that there is no substantial bias in our estimates.

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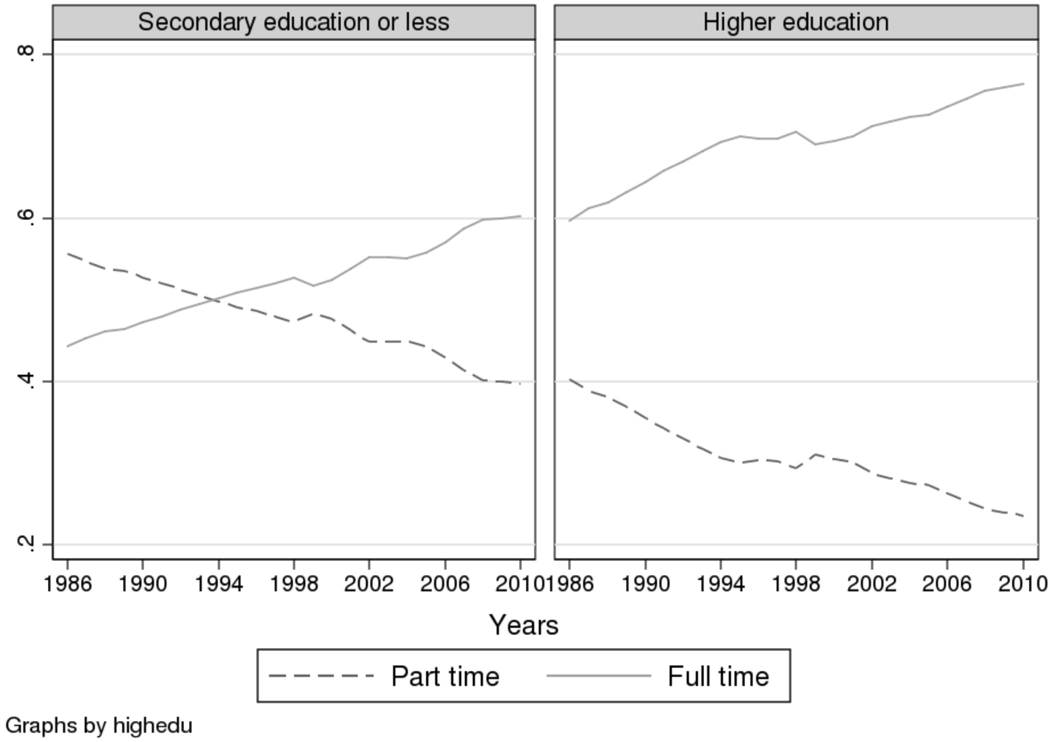
Figure 1: Mothers Labour Supply



Notes: Norwegian register data.

Table 1: Descriptive Statistics

Peer Groups	Mean	Standard Deviation	Min	Max
Number of Maternal Cousins	3.074	2.698	0	32
Number of Paternal Cousins	3.149	2.727	0	32
Number of Sisters	0.614	0.748	0	7
Number of Neighbours	26.924	33.256	1	296
Individual Characteristics				
Mother Worked After 1 Year	0.602	0.489	0	1
Hours Worked After				
1 year	18.640	17.855	0	40
2 years	19.313	17.759	0	40
3 years	19.340	17.660	0	40
4 years	20.523	17.515	0	40
5 years	21.841	17.357	0	40
6 years	22.544	17.274	0	40
7 years	23.463	17.095	0	40
Mother Worked 1 yr before Birth	0.776	0.417	0	1
Mother's Education	13.251	2.280	9	21
Father's Earnings, K1,000	243.333	173.089	0	17520.5
Father's Work Status	0.977	0.150	0	1
Mother's Age at Birth	25.818	4.364	16	45
Father’s Age at Birth	29.322	5.266	17	62
Low Birth Weight Indicator	0.048	0.213	0	1
Very Low Birth Weight Indicator	0.006	0.078	0	1
Congenital Disorder at Birth	0.041	0.198	0	1
Severe Deformity at Birth	0.025	0.155	0	1
Twin Indicator	0.018	0.133	0	1
Child's Year of Birth	1999.594	1.703	1997	2002
Child's Month of Birth	6.450	3.414	1	12
Number of observations	45,985			

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

	Mothers' Working Hours						
Years Post Childbirth	1	2	3	4	5	6	7
OLS	0.540***	0.542***	0.540***	0.534***	0.527***	0.537***	0.529***
	(0.015)	(0.013)	(0.014)	(0.011)	(0.012)	(0.011)	(0.011)
2SLS	0.639***	0.786***	0.825***	0.846***	0.697***	0.741***	0.557***
	(0.143)	(0.131)	(0.129)	(0.145)	(0.131)	(0.162)	(0.155)
F statistic 1st Stage	47.23	58.43	62.41	31.02	40.31	35.89	39.27
Hausman Test p-value	0.49	0.07	0.03	0.03	0.20	0.21	0.86
2SLS Individual IV	0.152	0.446***	0.400**	0.383*	0.304*	0.344*	0.235
	(0.196)	(0.160)	(0.180)	(0.196)	(0.167)	(0.197)	(0.201)
F statistic 1st Stage	37.07	48.48	52.05	37.52	38.79	27.69	32.57
Hausman Test p-value	0.10	0.56	0.48	0.46	0.22	0.35	0.18
N	45,985	45,985	45,985	45,985	45,985	45,985	45,985

Notes: Standard errors in parentheses clustered by municipality. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. OLS Ordinary Least Squares; 2SLS two-stage least squares; 2SLS Individual IV two-stage least squares controls for the IV at individual level. Regressors include mothers' and fathers' years of education and their squared values, dummies for working during pregnancy, fathers' earnings and work status in the year post childbirth, father and mother age and age squared 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: Effect of the average earnings of family peers on mothers' hours worked

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mothers' Working Hours						
Years Post Childbirth	1	2	3	4	5	6	7
2SLS Individual IV	0.950	2.252	2.089	3.567**	2.864**	2.339**	1.500
	(1.885)	(1.863)	(1.441)	(1.443)	(1.144)	(1.083)	(1.141)
F statistic 1st Stage	229.50	168.10	195.30	178.80	190.50	156.70	177.10
Hausman Test p-value	0.11	0.21	0.09	0.43	0.16	0.05	0.01
N	45,984	45,984	45,984	45,984	45,984	45,984	45,984

Notes: Standard errors in parentheses clustered by municipality. *** p<0.01, ** p<0.05, * p<0.1.

Earnings are measured standardized to have mean zero and variance one.

2SLS Individual IV is the two-stage least squares which controls for the individual IV.

The regressors are the same as in Table 3.

F-statistic is the F-test for H_0: instruments have zero coefficients.

Table 4: Family Peer Effect on Mother's Labour Participation

	Mothers' Participation						
Years Post Childbirth	1	2	3	4	5	6	7
Family peers hours	-0.003	0.005	0.007	0.004	0.002	-0.002	-0.003
	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
F statistic 1st Stage	37.07	48.48	52.05	37.52	38.79	27.69	32.57
Hausman Test p-value	0.03	0.12	0.26	0.22	0.09	0.02	0.03
N	45,985	45,985	45,985	45,985	45,985	45,985	45,985

Notes: Standard errors in parentheses clustered by municipality. *** p<0.01, ** p<0.05, * p<0.1.

2SLS Individual IV is the two-stage least squares which controls for the individual IV.

The regressors are the same as in Table 3.

F-statistic is the F-test for H_0: instruments have zero coefficients.

Table 5: Neighbourhood peer effects

	Mothers' Working Hours						
Years Post Childbirth	1	2	3	4	5	6	7
	2SLS Individual IV						
Neighbours effect	0.032	0.058	0.167***	0.177**	0.288***	0.134	0.070
	(0.023)	(0.050)	(0.055)	(0.077)	(0.079)	(0.084)	(0.104)
F statistic 1st Stage	711.60	1229.00	583.40	295.40	325.60	284.20	272.30
Hausman Test p-value	0.23	0.40	0.18	0.22	0.01	0.54	0.89
N	45,526	45,526	45,526	45,526	45,526	45,526	45,526

Notes: Standard errors in parentheses clustered by municipality. *** p<0.01, ** p<0.05, * p<0.1. 2SLS Individual IV is the two-stage least squares which controls for the individual IV. Regressors are the same as in Table 3. F-statistic is the F-test for H_0: instruments have zero coefficients.

Table 6: Robustness and Placebo Checks

	Mothers' Working Hours						
Years Post Childbirth	1	2	3	4	5	6	7
Panel a) Estimation using multiple IVs							
2SLS Individual IV	0.348**	0.549***	0.418***	0.403**	0.339**	0.309*	0.170
	(0.139)	(0.136)	(0.156)	(0.162)	(0.156)	(0.178)	(0.159)
F statistic 1st Stage	9.387	11.790	11.910	7.341	9.558	7.711	9.223
Hansen Test p-value	0.515	0.459	0.522	0.365	0.735	0.318	0.672
Hausman test p-value	0.558	0.627	0.464	0.277	0.174	0.229	0.052
Panel b) Estimation controlling for interactions between occupations and education							
2SLS Individual IV	0.165	0.387**	0.375**	0.232	0.202	0.164	0.134
	(0.208)	(0.164)	(0.178)	(0.213)	(0.183)	(0.225)	(0.206)
F statistic 1st Stage	30.17	39.38	41.43	31.54	29.23	24.58	31.37
Hausman test p-value	0.12	0.35	0.39	0.17	0.10	0.11	0.07
N	39,517	39,517	39,517	39,517	39,517	39,517	39,517
Panel c) Controlling for Municipality Level							
2SLS Individual IV	0.014	0.371**	0.328*	0.311	0.258	0.291	0.165
	(0.207)	(0.167)	(0.188)	(0.207)	(0.172)	(0.206)	(0.212)
F statistic 1st Stage	33.04	44.43	48.82	34.51	35.65	24.81	29.23
Hausman test p-value	0.04	0.33	0.32	0.30	0.16	0.26	0.12
N	39,517	39,517	39,517	39,517	39,517	39,517	39,517
Panel d) Placebo 1: Random assignment of peers by education, age at birth, working status one year before birth							
% of significant family peer effect	3.8%	3.9%	4.6%	4.0%	4.0%	3.7%	3.9%
Panel e) Placebo 2: Random assignment of peers by year of the child birth							
% of significant family peer effect	4.7%	3.7%	4.4%	3.5%	4.8%	3.4%	3.2%
Panel f) Placebo 3: Effect considering family peers who will become mothers in the future							
2SLS Individual IV	0.253**	-3.002	-0.358*	-0.054	-0.094	-0.022	-0.080
	(0.117)	(3.313)	(0.202)	(0.101)	(0.095)	(0.084)	(0.109)
F statistic 1st Stage	70.38	0.95	21.56	41.18	81.56	81.15	74.81
Hausman test p-value	0.08	0.00	0.00	0.00	0.00	0.00	0.00
N	51,833	51,833	51,833	51,833	51,833	51,833	51,833

Notes: Standard errors in parentheses clustered by municipality. *** p<0.01, ** p<0.05, * p<0.1. Peer effects are estimated using the two-stage least squares (2SLS Individual IV). The regressors are the same as Table 3. F-statistic 1st stage is the F-test for H_0: instruments have zero coefficients. % of significant family peer effect is percentage of cases out of 1000 with estimated peer effects which are statistically significant at 5% level. Panel c) and d) randomly assign fictitious family peers with 1,000 replications.

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, 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

	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	0.152	0.446***	0.400**	0.383*	0.304*	0.344*	0.235
	(0.196)	(0.160)	(0.180)	(0.196)	(0.167)	(0.197)	(0.201)
	Effect of individual covariates						
Neighbourhood Mean Hours	0.073***	0.060***	0.072***	0.064***	0.060***	0.052***	0.041***
	(0.016)	(0.016)	(0.016)	(0.013)	(0.013)	(0.013)	(0.013)
Mother years of schooling	2.104***	1.846***	1.724***	1.492***	2.384***	3.006***	3.673***
	(0.453)	(0.403)	(0.457)	(0.424)	(0.461)	(0.529)	(0.471)
Mother schooling squared	-0.061***	-0.044***	-0.043**	-0.028*	-0.055***	-0.075***	-0.093***
	(0.016)	(0.015)	(0.017)	(0.015)	(0.017)	(0.019)	(0.017)
Mother works year prior to birth	9.462***	7.023***	6.052***	5.620***	5.049***	4.576***	4.704***
	(0.336)	(0.284)	(0.287)	(0.286)	(0.275)	(0.255)	(0.274)
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	0.479	2.276***	1.321***	2.177***	2.220***	2.112***	1.661***
	(0.443)	(0.469)	(0.464)	(0.473)	(0.509)	(0.536)	(0.537)
Mother Age at Birth	2.857***	2.550***	2.141***	2.104***	2.090***	1.630***	1.399***
	(0.228)	(0.211)	(0.231)	(0.191)	(0.204)	(0.219)	(0.217)
Mother Age at Birth Squared	-0.041***	-0.035***	-0.028***	-0.029***	-0.029***	-0.021***	-0.018***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Father Age at Birth	0.727***	0.483**	0.260*	-0.038	-0.052	0.153	0.109
	(0.154)	(0.204)	(0.135)	(0.135)	(0.154)	(0.156)	(0.127)
Father Age at Birth Squared	-0.012***	-0.009***	-0.005**	-0.000	-0.000	-0.003	-0.003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Low Birth Weight	-0.247	-0.126	-0.153	0.459	0.334	0.055	0.150
	(0.446)	(0.463)	(0.392)	(0.404)	(0.404)	(0.417)	(0.417)
Very Low Birth Weight	-2.167*	-0.570	0.165	-1.272	-0.527	-0.579	0.463
	(1.152)	(1.167)	(1.101)	(1.217)	(1.116)	(1.109)	(1.185)
Congenital Problems	0.707	-0.993	0.507	0.248	-0.260	-0.140	-0.052
	(0.835)	(0.776)	(0.703)	(0.669)	(0.639)	(0.650)	(0.679)
Severe Deformity	-0.922	0.383	-0.647	-0.982	-0.410	0.020	-0.239
	(0.972)	(0.817)	(0.733)	(0.766)	(0.788)	(0.816)	(0.871)
Multiple Births	-4.306***	-3.241***	-0.389	0.314	0.339	0.313	0.503
	(0.635)	(0.608)	(0.822)	(0.693)	(0.680)	(0.671)	(0.702)

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

Results are for the two-stage least squares estimation which controls for the individual IV.

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

Table A1b: Full Second Stage Results of Table 2

	Mother's working hours						
Years Post Childbirth	1	2	3	4	5	6	7
Family peers average	Exogenous Peer Effect						
Mother years of schooling	-0.128	0.165	-0.214	-0.448	-0.084	-0.218	0.226
	(0.430)	(0.368)	(0.389)	(0.389)	(0.364)	(0.477)	(0.412)
Mother schooling squared	0.005	-0.015	0.002	0.008	-0.005	-0.004	-0.015
	(0.016)	(0.014)	(0.015)	(0.016)	(0.014)	(0.017)	(0.015)
Mother works year prior to birth	-0.914	-2.437**	-1.817	-1.764	-1.146	-1.361	-0.784
	(1.849)	(1.241)	(1.147)	(1.120)	(0.853)	(0.983)	(0.933)
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	0.194	-0.776	0.564	0.133	-0.445	-1.067	0.594
	(0.679)	(0.566)	(0.502)	(0.533)	(0.617)	(0.703)	(0.690)
Mother Age at Birth	-0.039	-0.732*	-0.678*	-0.647	-0.459	-0.201	-0.243
	(0.426)	(0.374)	(0.411)	(0.443)	(0.349)	(0.383)	(0.355)
Mother Age at Birth Squared	-0.000	0.009	0.008	0.008	0.006	0.001	0.003
	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)
Father Age at Birth	-0.211	-0.140	-0.053	0.180	0.276*	0.145	0.022
	(0.161)	(0.186)	(0.148)	(0.167)	(0.148)	(0.151)	(0.154)
Father Age at Birth Squared	0.003	0.003	0.001	-0.002	-0.004*	-0.002	-0.000
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Low Birth Weight	-0.324	-0.270	0.221	-0.330	-0.668	-0.538	-0.489
	(0.525)	(0.466)	(0.452)	(0.482)	(0.482)	(0.622)	(0.537)
Very Low Birth Weight	2.131*	-0.093	-1.383	0.370	0.583	0.242	-1.894
	(1.269)	(1.522)	(1.314)	(1.417)	(1.264)	(1.489)	(1.452)
Congenital Problems	-1.765*	0.793	-1.011	0.401	0.459	-0.615	-1.506*
	(0.932)	(0.970)	(0.783)	(0.710)	(0.743)	(0.873)	(0.826)
Severe Deformity	1.714*	-0.145	0.577	-0.335	-0.051	0.691	2.102**
	(0.982)	(1.048)	(1.007)	(0.978)	(0.987)	(1.104)	(1.009)
Multiple Births	0.341	1.554	0.190	-0.357	0.106	0.023	-0.131
	(1.111)	(1.020)	(1.000)	(0.805)	(0.753)	(0.739)	(0.896)
Observations	45,985	45,985	45,985	45,985	45,985	45,985	45,985
F statistic 1st Stage	37.07	48.48	52.05	37.52	38.79	27.69	32.57
Hausman Test p-value	0.10	0.56	0.48	0.46	0.22	0.35	0.18

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

Results are for the two-stage least squares estimation which controls for the individual IV.

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

Table A2: Full First Stage Results of Table 2

	Family peers average working hours						
Years Post Childbirth	1	2	3	4	5	6	7
Individual variable				Effect of individual covariates			
Neighbourhood hours	0.010	0.012	0.013	0.004	0.002	0.004	0.005
	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)	(0.011)	(0.009)
Mother schooling	1.196***	1.175***	0.612**	0.272	1.433***	1.180***	1.186***
	(0.356)	(0.350)	(0.308)	(0.329)	(0.344)	(0.296)	(0.332)
Mother schooling squared	-0.044***	-0.040***	-0.019	-0.007	-0.051***	-0.042***	-0.041***
	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.011)	(0.012)
Mother work year prior to birth	0.619***	0.645***	0.716***	0.594***	0.666***	0.385**	0.704***
	(0.161)	(0.164)	(0.164)	(0.162)	(0.165)	(0.168)	(0.170)
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	-0.107	0.761**	0.511	0.223	0.171	-0.026	0.606
	(0.412)	(0.383)	(0.484)	(0.448)	(0.430)	(0.513)	(0.461)
Mother age at birth	0.629***	0.465***	0.403***	0.260	0.148	0.337**	0.295*
	(0.153)	(0.168)	(0.155)	(0.166)	(0.163)	(0.155)	(0.167)
Mother age squared	-0.012***	-0.009***	-0.007***	-0.006*	-0.003	-0.006**	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Father age at birth	0.178	0.277***	0.101	0.135	0.190**	0.201*	0.008
	(0.109)	(0.103)	(0.099)	(0.099)	(0.092)	(0.111)	(0.108)
Father age squared	-0.002	-0.004***	-0.002	-0.002	-0.003**	-0.003*	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Low birth weight	-0.130	0.728**	0.255	-0.148	-0.127	-0.107	-0.163
	(0.312)	(0.334)	(0.364)	(0.367)	(0.347)	(0.367)	(0.375)
Very low birth weight	-0.660	-0.628	-0.348	0.402	-0.250	-0.141	0.055
	(1.055)	(0.994)	(0.818)	(0.883)	(0.829)	(0.873)	(0.963)
Congential problems	0.451	0.443	0.483	0.291	0.207	0.439	-0.687
	(0.530)	(0.716)	(0.629)	(0.511)	(0.591)	(0.635)	(0.712)
Severe deformity	-0.635	-0.320	-0.264	-0.348	-0.417	-1.169	0.714
	(0.632)	(0.831)	(0.734)	(0.614)	(0.793)	(0.841)	(0.872)
Multiple births	0.157	-0.139	1.106**	0.517	1.212**	0.826	1.221**
	(0.582)	(0.479)	(0.497)	(0.520)	(0.530)	(0.503)	(0.524)
Family peers average				Exogenous peer effect			
Mother schooling	-0.307	0.116	-0.092	-0.194	-0.056	0.949**	0.916***
	(0.514)	(0.501)	(0.425)	(0.394)	(0.377)	(0.407)	(0.344)
Mother schooling squared	0.026	0.013	0.019	0.032**	0.033**	-0.001	0.004
	(0.019)	(0.019)	(0.016)	(0.015)	(0.014)	(0.015)	(0.013)
Mother work year prior to birth	9.392***	7.623***	6.231***	5.726***	5.037***	4.730***	4.451***
	(0.232)	(0.221)	(0.234)	(0.226)	(0.257)	(0.234)	(0.248)
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	0.209	0.996**	0.862**	0.847*	1.564***	2.349***	2.322***
	(0.471)	(0.436)	(0.393)	(0.469)	(0.529)	(0.603)	(0.617)
Father age at birth	2.105***	2.128***	1.904***	1.806***	1.837***	1.345***	1.186***
	(0.200)	(0.213)	(0.196)	(0.196)	(0.215)	(0.206)	(0.197)
Mother age at birth	-0.026***	-0.026***	-0.024***	-0.022***	-0.023***	-0.016***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Mother age squared	0.224	0.159	0.109	-0.103	-0.212	-0.189	-0.101
	(0.139)	(0.161)	(0.146)	(0.128)	(0.140)	(0.161)	(0.141)
Father age squared	-0.005**	-0.005*	-0.003	-0.000	0.001	0.002	-0.000
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Low birth weight	0.199	-0.403	-0.849*	-0.805*	-0.686	-1.083**	-0.787
	(0.461)	(0.468)	(0.495)	(0.485)	(0.477)	(0.525)	(0.528)
Very low birth weight	0.120	0.876	1.879	2.714*	1.420	2.792**	1.201
	(1.181)	(1.419)	(1.642)	(1.494)	(1.340)	(1.395)	(1.264)
Congential problems	0.574	-0.045	-0.412	-0.374	0.488	0.550	0.529
	(0.713)	(0.848)	(0.816)	(0.834)	(0.784)	(0.815)	(0.854)
Severe deformity	-0.039	-0.450	-0.232	0.179	-0.398	-0.192	-0.409
	(0.896)	(0.988)	(0.978)	(0.989)	(0.983)	(1.031)	(0.996)
Multiple births	-4.256***	-3.870***	-1.824**	-0.323	-0.554	-0.333	-0.639
	(0.733)	(0.812)	(0.787)	(0.740)	(0.779)	(0.925)	(0.841)
Instrumental Variables				Effect of the neighbours of family peers characteristics			
Hours	0.074***	0.087***	0.082***	0.071***	0.080***	0.067***	0.065***
	(0.012)	(0.012)	(0.011)	(0.012)	(0.013)	(0.013)	(0.011)

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

Results are for the first-stage of the 2SLS estimation which controls for the individual IV.

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

Table A3: Peer Effects Using Different Definitions of Peers Groups

	Mothers' Working Hours						
Years Post Childbirth	1	2	3	4	5	6	7
Panel a) Peer effect considering only female cousins							
2SLS Individual IV	0.170	0.427**	0.409**	0.552***	0.391**	0.259	0.189
	(0.250)	(0.203)	(0.192)	(0.207)	(0.168)	(0.228)	(0.226)
F statistic 1st Stage	25.60	32.70	45.96	32.01	37.23	24.22	26.43
Hausman Test p-value	0.38	0.96	0.93	0.51	0.90	0.47	0.35
N	42,825	42,825	42,825	42,825	42,825	42,825	42,825
Panel b) Peer effect considering only sisters							
2SLS Individual IV	1.130*	0.733*	0.710**	0.197	0.434	0.642**	0.404*
	(0.586)	(0.395)	(0.353)	(0.223)	(0.307)	(0.321)	(0.220)
F statistic 1st Stage	6.03	15.26	13.37	23.38	7.80	8.50	16.35
Hausman Test p-value	0.02	0.07	0.03	0.52	0.27	0.05	0.16
N	45,985	45,985	45,985	45,985	45,985	45,985	45,985
Panel c) Peer effect considering sisters-in-law and cousins-in-law							
2SLS Individual IV	0.377*	0.606***	0.491**	0.587***	0.425**	0.424*	0.377*
	(0.208)	(0.227)	(0.191)	(0.199)	(0.216)	(0.242)	(0.208)
F statistic 1st Stage	36.99	24.93	32.61	31.05	22.01	20.01	36.99
Hausman Test p-value	0.42	0.86	0.71	0.91	0.55	0.59	0.42
N	37,373	37,373	37,373	37,373	37,373	37,373	37,373

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

Results are for the two-stage least squares estimation which controls for the individual IV.

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

Table A4: Tobit Instrumental Variables Estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mothers' Working Hours						
Years Post Childbirth	1	2	3	4	5	6	7
2SLS Individual IV	-0.019	0.492**	0.482*	0.426	0.305	0.255	0.141
	(0.213)	(0.244)	(0.268)	(0.294)	(0.234)	(0.265)	(0.264)
F statistic 1st Stage	37.09	52.56	55.57	35.01	37.87	25.56	34.92
N	45,985	45,985	45,985	45,985	45,985	45,985	45,985

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

Results are for the two-stage least squares estimation which controls for the individual IV.

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

Marginal effects reported.