Skills Beget Skills:

Addressing the Role of Mothers' Occupation-Specific Skills on Children's Developmental Process

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ABSTRACT

This paper examines how mothers' occupation-specific skills affect the process of children's skills formation. Whereas the impact of parental education on children's development has been widely studied in the literature, this has not been the case for parents' occupations. I exploit variations in mothers' occupation-specific skills that occur when mothers change their jobs and combine longitudinal family data from the NLSY79-CYA with the O*NET dataset. Using two-way fixed effects, inverse probability weighting techniques and asymmetric fixed effects models, results show that when mothers transition to a job in which more mathematical skills are required, their children's mathematical skills get boosted. The findings are similar for the literacy skills dimension although are less robust to the implementation of more demanding model specifications. Further results show that (i) the more time the mother spends on the job the larger the effect of these skills on children's development, (ii) the effect is dimension-specific, i.e., changes in mothers' occupation-specific mathematical skills affect children's mathematics but not literacy skills (and the other way around), (iii) this effect is mainly driven by skills upgrading but not skills downgrading, (iv) these results are robust to account for alternative pathways in which job changes can affect children's skills, (v) children with high-SES mothers benefit more from skills increases than those with low-SES ones. Overall, this study suggests that the transmission of occupation-specific skills might be a channel through which social reproduction operates.

1. INTRODUCTION

This paper examines the impact that mothers' occupation-specific skills have on children's skills formation. A wide literature on human capital formation has focused on the effect of parental education on child development (Anger & Heineck, 2010; Breinholt & Holm, 2020; Guryan et al., 2008; Rowe et al., 2016). However, the role of parental occupation in fostering children's skills has been mostly overlooked. Mothers' occupations are relevant for children's development for two reasons. First, mothers are still the main caring agents and are responsible for a large part of children's developmental outcomes (Huston & Rosenkrantz Aronson, 2005). Second, given the expansion of women's labour market participation in the last decades, mothers' occupations play a crucial role in mothers' lives, and consequently, home dynamics (Ruhm, 2004).

Occupation-specific skills are the skills that the workers learn effectively on the job and have been noted to affect labour market trajectories and outcomes (Kwon & Meyersson Milgrom, 2014; Lagoa & Suleman, 2016), as well as political preferences and attitudes formation (Emmenegger, 2009; Ortega & Polavieja, 2012). Therefore, following Jonsson et al. (2009) and Barg & Klein (2023), and considering that occupation-specific skills are a crucial component of individuals' skills sets, I suggest that they might also wield significant influence in the intergenerational transmission of skills, and contribute to the process of social reproduction.

I combine data from the US National Longitudinal Survey and the Children's Supplement with the O*NET dataset. The first datasets follow mothers and their children across several decades and provide valuable information on the occupation history of the mothers (with biannual observations) as well as assessments of the child's skills across different dimensions. The second dataset, O*NET, provides information about the specific skill levels needed to carry out each job. I measure mothers' occupation-specific skills with two indexes capturing (i) mathematical skills and (ii) literacy skills. Children's skills are measured through the age-specific Peabody Individual Achievement tests, implemented by external assessors, in the same two dimensions, mathematical and literacy. The children in the sample are between 5 and 15 years old.

The analytical strategy of this paper exploits mothers' occupational changes during their labour market trajectories that bring fluctuations in the level of required occupation-specific skills. This way, I estimate the effect of variations in mothers' occupation-specific skills at time t-1 on children's skills at time t. I employ a series of two-way fixed effects models in combination with inverse probability weighting, as well as asymmetric fixed effects models.

The main finding of this paper is that an increase in maternal occupation-specific mathematical skills at time t-1 has a positive effect on her child's mathematical skills at time t. The effect size is approximately one-ninth of a standard deviation. This result is robust to the inclusion of inverse probability weighting techniques. In the case of literacy skills, however, the results show a less consistent pattern, with positive and significant effects in some of the models that disappear after accounting for potential selection with the inverse weighting.

Moreover, the findings also shed light on the potential mechanism behind this effect. First, the positive effect of mothers' skills changes increases with the time the mother spends on the job. Second, the transmission of skills is produced in a dimension-specific way, which means that changes in mothers' mathematical skills do not impact children's literacy skills but only the mathematical ones (and the other way around). Finally, and thanks to the implementation of the asymmetric two-way fixed effects models, I disentangle the direction of the main causal effect. I find that children's skills vary as a response to mothers' skills upgrading, whereas mothers' skills downgrading does not show any effect on children's skills.

Additionally, I account for several alternative pathways through which mothers' job changes could impact children's skills formation. In the case of mathematical ability, the effect of occupation-specific skills remains constant despite considering several child-, family-, and job-specific factors. However, for the literacy skills example, the main effect disappears when accounting for the working hours of the mother and other occupation-related factors. Finally, after rerunning the models in stratified samples for high- and low-SES children, the results show that children from high-SES families benefit more from the skills changes than those from low-SES backgrounds.

This paper makes four key contributions to the literature. First, it represents, to the best of my knowledge, the first empirical test on whether changes in maternal occupation-specific skills impact the process of offspring's skills formation. Two previous papers have studied this issue theoretically (Jonsson et al., 2009) and in a descriptive setting (Barg & Klein, 2023). Second,

this study advances the existing research by disentangling the asymmetric causal effect and distinguishing between skills upgrading and downgrading, as well as by indirectly examining the potential mechanism behind this effect. Third, it investigates the stratified nature of intergenerational transmission of occupation-specific skills, which has significant implications for understanding the process of social reproduction. Finally, this paper explores the US case, which has been previously overlooked despite the rich available data.

2. THEORETICAL FRAME

2.1. Intergenerational transmission of skills

Several mechanisms have been noted as potential channels through which inequality persists across generations, such as the transmission of education, cultural inputs, wealth, genes, or even health (Bowles & Gintis, 2002). Among all of them, the transmission of skills has been considered especially relevant to understand how parents pass their socioeconomic status to their children (Blanden et al., 2007). Skills are generally highly rewarded in the educational system and the labour market (Gronqvist et al., 2010), and therefore, if parents with certain skills manage to pass them on to their offspring, these children will experience an advantage in the developmental process as compared to those children who do not receive certain inputs from their parents (Anger, 2012).

Most of the literature on the intergenerational transmission of skills has found evidence of skills persistence across generations (Anger & Heineck, 2010; Attanasio et al., 2020; Bowles et al., 2009; Campos-Vazquez, 2018; Gronqvist et al., 2010; Hsin & Xie, 2017; Lundborg et al., 2014). However, there are some variations based on the type of skills and the measure employed, as well as the stage of the child's lifecycle and the country studied.

Regarding the type of skills, there are two main groups of studies. The first and most developed branch of literature examines the intergenerational transmission of cognitive abilities (Agee & Crocker, 2002; Anger & Heineck, 2010; Hanushek et al., 2021). Among these, some studies use a very specific measure of cognitive abilities, namely IQ (Anger & Heineck, 2010; Bjorklund et al., 2009; Black et al., 2009), whereas others use test scores (Blanden et al., 2007; Duncan et al., 2009) or total measures of educational attainment (Lundborg et al., 2014;

Sacerdote, 2002). In all instances, there is consensus in the literature about the positive and persistent effect that parental cognitive skills have on children's cognitive skills.

The second type of skills examined, mainly from the psychological and developmental literature, has been non-cognitive ones. In general, the correlations between parents and children's non-cognitive skills are lower than the ones found for cognitive abilities (Attanasio et al., 2020; Mayer et al., 2004). Hsin & Xie (2017) suggest that the effect of parental socio-behavioural skills on their children is one-third of the cognitive skills effect. However, as Gronqvist et al. (2010) notice, measurement error is more present when measuring non-cognitive skills, and this can be biasing the results obtained in the previous studies.

The magnitude of these effects varies by country: whereas in Germany, an increase of one point in the cognitive ability scale of the mother implies 0.5 points increase in the children's abilities; in Scandinavian contexts (Sweden and Norway) the average increase is of around one-third of a point (Bjorklund et al., 2009; Black et al., 2009). Hanushek et al. (2021) use Dutch data to identify the causal connection between the cognitive skills of parents and their children. They use a within-family between-subjects estimation strategy and get that an increase in one standard deviation in the parents' abilities increases in 0.1 standard deviation in children's skills. In the US, Duncan et al. (2009) show that without further controls, mothers' math test scores have an average positive impact of 0.23 points on daughters' mathematical ability and 0.15 on sons' scores.

The process of intergenerational transmission of skills has been also noted to vary according to the stage of the life course. The most accepted position suggests that parental influence on children's skills is the largest during early childhood (Bijou, 1976; Datar et al., 2010; Durham et al., 2007; Farkas & Beron, 2004; Heckman, 2006; Rowe & Goldin-Meadow, 2009). However, some pieces of evidence suggest that the older the children get the strongest the intensity of transmission of skills (Anger, 2012), putting special emphasis on the teenage period (Campos-Vazquez, 2018; Lundborg et al., 2014).

2.2. A multidimensional approach to skills

The traditional literature on skills has relied on the assumption that skills are either innate, and therefore they can be captured through an IQ measure (Black et al., 2009), or acquired during

the educational trajectories, and thus the total level of education is a good proxy for the level of skills (Chevalier, 2004; Lundborg et al., 2014).

A caveat of these approaches is that they fail to integrate the role that occupations play in fostering certain skills. This is particularly relevant in the context of the third industrial revolution, which has brought with it a very high level of labour-market specialization (Autor & Dorn, 2013). In this line, Liu & Grusky (2013) suggest that the unidimensional approach to skills (well reflected in the division between skilled and unskilled workers) is insufficient to understand how skills operate in the new scenario of skills-biased technical change. Consequently, an emerging literature has started to investigate the role that occupation-specific skills play. These are specific types of skills that are effectively learned in the job (Polavieja, 2012), and have been noted to affect labour market trajectories and outcomes (Kwon & Meyersson Milgrom, 2014; Lagoa & Suleman, 2016), as well as political preferences and attitudes formation (Emmenegger, 2009; Ortega & Polavieja, 2012).

2.3. Intergenerational transmission of occupation-specific skills

If occupations are a pivotal part of individuals' skill sets, it would not be surprising that they also play an important part in the process of intergenerational transmission of skills that are responsible for social reproduction. This is especially relevant given the expansion of women's participation in the labour force during the last decades and the fact that mothers keep being the primary care source for children. In the US, for instance, the percentage of mothers with children younger than 6 years old who were in the labour market increased from 47% to 65% between the 80s and 90s (Ruhm, 2004).

Two conditions need to hold for this transmission of occupation-specific skills between parents and offspring to take place. First, there must be an association between what mothers do as part of their jobs (usually known as job tasks) and the skills they develop. As explained by Pankhurst (2010), on-the-job learning comes from the repetition of tasks, the self-reflection on mistakes, and the formal and informal evaluations of performance that take place at the workplace. On average, there is a linear relationship between the complexity of the job and the cognitive stimulation that is derived from performing that job (Pouliakas & Russo, 2015). Therefore, previous literature has concluded that there is a direct relationship between skills utilization in the job and skills development (Russo, 2016).

The second condition is that parents' occupation-specific skills must have spillovers into their child rearing practices or home environment, which eventually will impact children's lives (Augustine, 2014; Verropoulou & Joshi, 2009). A good example of this type of mechanism has been shown by Burghardt et al. (2020) and Mues et al. (2021) when examining how the mathematical component of the job of the parents influence the home numeracy environment, which has a direct impact on children's mathematical skills. These authors define the home numeracy environment "as all of the aspects in the family that support children's early mathematical learning, such as the frequency and quality of mathematical parent–child interactions, mathematical resources at home (e.g., books with numbers), and parental attitudes towards mathematics and teaching mathematics at home" (Mues et al., 2021: 4). This home environment comprises both formal activities such as doing homework together or having specialized books at home, but also other informal ones such as day-to-day application of mathematical knowledge or topic-relevant conversations held in the family (LeFevre et al., 2009). Similarly, in the case of literacy skills, parental jobs' skills can instill certain formal (i.e., reading books) and informal (i.e., introducing new words to everyday conversations) activities in the home environment (Martini & Sénéchal, 2012), which will impact children's literacy skills (Carroll et al., 2019; Griffin & Morrison, 1997).

On top of the influence on the home environment, the literature has noted that parental jobs impact some parental values and behaviours that are relevant to parenting. For instance, Parcel & Menaghan (1994) show that mothers who work in complex occupations build home environments that are more cognitively stimulating, and Downey & Moen (1987) sustain that parental attention to children, as well as levels of stimulation, will be affected by parental job arrangements. Yetis-Bayraktar et al. (2013) find that when mothers have jobs in which problem-solving skills are needed, they are likely to transfer these to their children so that higher occupational complexity during the first three years of the life of the children has a positive long-lasting effect on children's mathematical and literacy abilities. The underlying mechanism for Herman & Perry-Jenkins (2020) is that, when parents experience more autonomy and challenges in their work, they acquire cognitive resources that then they apply to their interactions with their children.

Consistently with these two arguments, Jonsson et al. (2009) suggest that one of the channels through which occupations or micro-classes are socially reproduced is through the transmission

of occupation-specific skills. Barg and Klein (2023) go a step further and test the associations between maternal occupation-specific skills and children's cognitive development in the UK. The authors use data from the Millennium Cohort Study and the British Skills Survey and find that mothers' literacy skills are positively associated with children's literacy ability (net of parental human, financial and social capital). Moreover, the children of mothers whose jobs require physical skills show lower literacy abilities. They, however, do not find associations between mothers' and children's non-literacy abilities. Some tangential works have explored how the skills associated with self-employment jobs are more commonly transmitted across generations (Colombier & Masclet, 2006) or how skills related to care-related occupations are more commonly passed from parents to children (Charles et al., 2015). Based on this literature, I suggest that (*hypothesis 1*) increases in mothers' occupation-specific skills will positively impact children's skills.

The mechanism behind this hypothesis is that parents learn certain skills as part of their jobs, and these directly impact the children's skills formation (i.e., they get "passed on" to the children). However, it could also be the case that getting a job is the reflection of a previous latent increase in skills that has been happening for some time, and therefore, the job changes are merely a proxy to capture the skills level of the mother. I account for this possibility by indirectly examining the underlying mechanism in three different ways.

First, I account for the time the mother has been in the job since changing occupations. Given that the process of learning is a cumulative and progressive one, mothers who spend more time in a job will get better at these skills, and therefore, their children will get larger returns from these new jobs than those mothers who quit a job earlier. Following this, if the mechanism suggested is true, I would expect (*hypothesis 2*) the effect of mothers' occupation-specific skills on children's skills to be larger the more time the mother has been on the job.

Second, given the multidimensional character of skills noted in the existing literature (Liu & Grusky, 2013), I propose that if the mechanism here suggested is true, the intergenerational transmission of skills will be subject-specific. This is, I expect (*hypothesis 3a*) increases in mothers' mathematical occupation-specific skills to impact children's mathematical skills, and (*hypothesis 3b*) increases in mothers' literacy occupation-specific skills to impact children's literacy skills. Otherwise, it could simply be the case that children generally benefit from their mothers' skills changes, but I could not claim that these skills get transmitted.

Finally, because of the cumulative aspect of skills, it is unlikely that mothers totally lose the skills that they have acquired even if they change their jobs. Therefore, if skills truly got passed across generations, I would expect children to respond differently to their mothers' skills changes when these imply an increase and a decrease in skills. I frame this as the asymmetric effect of occupation-specific skills and suggest that (*hypothesis 4*) children's skills will be positively influenced by mothers' occupation-specific skills increases, whereas they will not be affected by mothers' occupation-specific skills decreases.

2.4. Alternative pathways

When looking at the transmission of occupation-specific skills it is important to notice that there are several competing pathways through which parents' occupations can impact children's skills formation that do not necessarily imply the transmission of occupation-specific skills.

For instance, that is the case of the timing of maternal employment. Some studies suggest that child development is particularly vulnerable to maternal labour market participation during the first six months of life (Huerta et al., 2011), whereas others suggest that the first 18 months are the crucial period (Gregg et al., 2005), or even the first 3 to 4 years (Ruhm, 2004). Brooks-Gunn et al. (2010) examine the comprehensive childhood period and find that the short-term negative effect of maternal employment is neutralized in the medium term by a positive effect.

Another factor explored in the previous literature has been the number of working hours of the mother. The most common finding in this sense is that mothers find a way of compensating for the time they spend working, especially by reducing their housework, sleeping, and leisure time (Bianchi et al., 2006), by engaging in more positive interaction with their children (Bass et al., 2009) or by increasing their quality time with their children (Hsin & Felfe, 2014).

Finally, a competing channel that has been noted to connect parents' occupations with children's skills is job conditions. Children of mothers who experience psychological stress and physical hazards have been noted to show more developmental problems (Felfe & Hsin, 2012). Similarly, children of parents with non-standard work schedules show lower well-being and development levels (Li et al., 2014).

Despite the relevance of these factors to understanding how parental occupation impacts children's lives, I suggest that mothers' occupation-specific skills represent a substantively different phenomenon, and therefore, I expect the effect of mothers' occupation-specific skills on children's skills to exist independently of these job-related characteristics (*hypothesis 5*).

2.5. Heterogeneous transmission by SES

Previous literature has suggested that parents from different socioeconomic backgrounds present information asymmetries as well as different abilities and resources that condition the effectiveness of their skills transmission to their children (Heckman & Kautz, 2012; Rowe, 2008). Based on this, it might be the case that high-SES mothers are more able to transmit their occupation-specific skills, and therefore, their children would benefit more from increases in their mothers' occupation-specific skills than children with low-SES mothers (*hypothesis 6a*).

A competing possibility, however, is that since children and mothers in low-SES contexts present a lower baseline level of skills, a marginal improvement in the mothers' occupation-specific skills has a greater impact on them than on those children with high-SES mothers, who start with a higher level of skills, and thus, might suffer from a ceiling effect. If this is the case, I would expect low-SES mothers to benefit more from mothers' occupation-specific skills than those with high-SES ones (*hypothesis 6b*).

3. METHODOLOGY

3.1. Data

This paper combines two datasets. First, the National Longitudinal Survey and Children's Supplement data (NLSY79-CYA), which is a nationally representative US cohort-based data set that follows the children of those women who were part of the original NLSY79 survey (American women born between 1957-1964). The children born to these women from 1970 onward have been interviewed biannually from 1986 to 2018. The interviews with these children consisted of a set of assessments to evaluate the physical, cognitive, and socio-emotional development of the child.

The sample for this paper is restricted to children over 5 years old, given that the relevant cognitive assessments are only implemented and measured after this age. I also exclude the years in which the mothers were unemployed since it will be difficult to assess their initial level of skills when they are not associated with a particular job, as well as those who never change jobs since there is no variation to be exploited in those cases and the analytical strategy of this paper relies on it. The final analytical sample comprises approximately 17,000 units of observation (the final number varies depending on the model specification), for a total of 7,559 individuals and an average of 2.26 observations per individual over time. The minimum number of observations per individual is 2. These children are born from 4,941 mothers of the NLS79 original sample. There are no relevant patterns of attrition in the sample that are connected to either mothers' or children's skills or to the family's socioeconomic background.

Several aspects make this database suitable for this study. First, the long period available allows me to follow the mother and children's trajectories over decades. Second, the high frequency of the data makes it possible to capture changes in mothers' occupations with high precision. Third, given that the measures of children's skills are the product of interviewers' assessments, this circumvents the problem of mothers misreporting their children's abilities.

The second database employed is the O*NET dataset, which provides detailed information about the work characteristics and skills requirements of each job position. This database is produced by the U.S. Department of Labor and has been widely used in the literature on labour economics (Peri & Sparber, 2009; Tippins & Hilton, 2010). It provides information on almost 1,000 different occupations. The process of collecting the information is two-fold: first, a sample of businesses is selected from each type of occupation; and second, a sample of employees from each type of occupation is chosen to complete a survey. Businesses are selected with a proportional probability to the number of workers in the company to account for the distribution of the workforce (Burrus et al., 2013). These employees are asked to complete several surveys on the title, definition, and job zone of the occupation, the tasks that are part of the job, the knowledge required, the specific work activities, and the work context.

In the final stage, a group of occupational analysts, following a standardized process, rate the information on each of the above dimensions and assign a final number on the level of skills associated with each occupation[1].

I merge the NLSY79-CYA with the O*NET dataset through the six-digit occupational level of the mother (Standard Occupational Classification). Since some occupations have likely changed the level of skills required for that job over time, I use three different O*NET taxonomies: 2000, 2010, and 2019. This way, for each of the occupations held by the mother throughout her labour market trajectory, I have detailed information on the skills required according to the closest-in-time O*NET taxonomy.

3.2. Variables

The **dependent variable** of this study is **children's skills,** operationalized through the child's mathematical and literacy skills at time *t*. Both measures are part of the Peabody Individual Achievement Test (PIAT), which is a standardized measure of child development and achievement. This index is age-specific (i.e., measures the ability of the children for a given age) and relative (i.e., the children in the representative NLS sample are ranked based on their abilities compared to the other children in the sample). Therefore, if a child scores 100 points at age 5 but 50 points at 7 does not mean that the child's skills have decreased over time (i.e., it does not mean that the child reads worse at age 7 than she used to read at age 5). However, what it means is that the child who at age 5 was in the top percentile of the ability distribution for that age, is now in the medium part of the ability distribution when she turns 7 years old. The variables have been standardized with a mean of 0 and a standard deviation of 1.

The **independent variable** is the mother's occupation-specific skills at time *t-1*. I use two different operationalizations: mathematical and literacy skills. The O*NET dataset provides information about the degree to which a specific skill is needed to perform an occupation. The question in the O*NET original survey is worded in the following terms: "What level of [SKILL] is needed to perform your current job?". The respondent can choose from 1 to 7, but the O*NET data construction team assigns a zero score when respondents have reported in the

[1] All the information about the rating criteria and the whole process of data collection can be found in Fleisher & Tsacoumis' (2018) report titled "O*NET Analyst Occupational Skills Ratings: Procedures Update"

previous question (Importance Scale) that the skill in question is not important at all for their jobs. Therefore, the final measure ranges from 0 to 7, with higher values measuring higher levels of skills. To increase the consistency in the ratings, the respondents are given three specific examples or benchmarks of what could be considered that level of skill in different jobs (Handel, 2016).

The mathematical skills variable is constructed as a mean composite of several skills that belong to the scientific and mathematical areas of knowledge: science, mathematics, programming, system and operations analysis, system evaluations, and technology design. A description of each of these dimensions is given in **Table A1** in the Appendix. The high internal consistency of this index is shown by the 0.9 Cronbach alpha. Some examples of occupations that require a very high level of these skills are web developers, all types of engineers, physicists, statisticians, and finance-related jobs. The literacy skills variable is a mean composite of reading comprehension, speaking, writing, and active listening. The Cronbach alpha of this composite is 0.98. Occupations such as counselors, social workers, judges, magistrates, writers, or English teachers are associated with high levels of literacy skills. A change in an occupation usually implies a change in both dimensions, literacy, and mathematics, although not necessarily to the same extent. The correlation between the increases in mathematical and literacy skills is of 0.61, and of 0.5 in the case of skills decreases.

3.3. Analytical strategy

The analytical strategy of this paper combines several steps aimed at (i) identifying the changes in occupations experienced by the mothers, which will be considered a proxy in the saliency of skills at time *t-1*, and (ii) estimating their effect on the variation in children's skills at time *t.*

In the first stage of the analysis, I run a series of baseline OLS models for the two outcomes of interest (mathematical and literacy skills) including the usual sociodemographic controls. In the second stage, I introduce the main models of this analysis, the two-way fixed effects (TWFE) models that account for time-invariant unobservable confounders, which reduces the potential omitted variable biases in the obtained estimates. Since TWFE models control for both individual-specific and time-specific characteristics, this model specification is more appropriate for this study than exclusively individual or time-fixed effects. The TWFE model is specified in *Equation (1)* below:

$$S_{i,t} = \beta_o + \beta_1 MS_{i,t-1} + \beta_2 C_{i,t} + \alpha_i + \tau_t + \varepsilon_{i,t} \quad (1)$$

where $S_{i,t}$ is the children's specific skills at time *t*; β_1 is the coefficient for the variable maternal occupation-specific skills at time *t-1* ($MS_{i,t-1}$); β_2 is the coefficient for the control variables; α_i is the individual fixed effects for individual *i*; τ_t is the time fixed effect for time *t*; and $\varepsilon_{i,t}$ is the error term for individual *i* at time *t*. Standard errors are clustered at the family level.

The second stage of the analytical strategy aims to account for the selection into changing occupations by using inverse probability weighting (IPW). If the mothers who already have more skills (for instance, higher educational levels) are more prone to select themselves into changing occupations, there would be a positive selection (selection on unobservables) and the estimates would be upwardly biased. I implement IPW following Breinholt & Holm's (2020) steps: (i) I predict through a logit model the probability of mothers' changing occupations, (ii) I construct the inverse probability weights from those predictions so that the mothers who are less likely to change jobs have higher weights, (iii) I rerun the fixed effects model accounting for these weights. This allows me to identify which families benefit more from the mothers' occupational changes.

I use two types of predictors to construct the weights. First, cross-sectional predictors that do not vary together with the jobs held by the mother, such as the mother's level of education, race, job sector, long-term health problems, family size, the marital status of the mother, the gender of the child, the age of the mother at the moment of birth of the child and the anxious-personality scale. Second, I use job-related time-varying predictors such as household income, job quality, working hours of the mother and her partner, residential changes, reasons to leave the previous job, and flexible work arrangements. This second group of predictors accounts for the possibility of the weights varying within the same individual across time. I perform the IPW-TWFE with the *R* package *WeightIt*.

In the third stage, I implement three different specifications of the model that allow me to indirectly examine the mechanism underlying the effect previously described. First, I introduce an interaction term between the changes in mothers' occupation-specific skills and the years that have passed since she transitioned into a new job, as stated in *Equation (2)* below:

$$S_{i,t} = \beta_o + \beta_1 MS_{i,t-1} * Years\ in\ the\ job + \beta_2 C_{i,t} + \alpha_i + \tau_t + \varepsilon_{i,t} \quad (2)$$

Second, I introduce the alternative dimension of skills (i.e., literacy or mathematical) within the control variables ($C_{i,t}$ component in *Equation 1*) to test whether the transmission of skills is dimension specific.

Third, I implement a series of asymmetric two-way fixed effects models (ASYM-TWFE). The reason for this is that the default TWFE model assumes that the estimated causal effect is reversible, i.e., that the positive effect of an increase in the predictor variable will be of the same magnitude as the negative effect of a decrease. However, as Lieberson (1985) sustained, social processes are rarely reversible. In this specific case, given the cumulative character of skills (Cunha & Heckman, 2007; DiPrete & Eirich, 2006), I theoretically assume that once mothers have reached a certain level of skills it is unlikely that they lose those skills. That is why, I expect the average effect of changes in occupation-specific skills on children's development to be driven by increases in skills instead of decreases. To examine this, I implement the following model, which is an adaptation of Allison's (2019) work on asymmetric fixed effects:

$$S_{i,t} = \beta_o + \beta_1 MS^{+}_{i,t-1} + \beta_2 MS^{-}_{i,t-1} + \beta_3 C_{i,t} + \alpha_i + \tau_t + \varepsilon_{i,t} \quad (3)$$

where the effect of changes in maternal occupation-specific skills is disaggregated into two estimates: β_1 will account for the increases in skills and β_2 for the decreases in skills. To estimate this equation I use York & Light's (2017) method to (i) compute first differences and (ii) decompose the varying predictors in positive and negative components. This way, thanks to the first differences calculations and the use of a generalized least squares (GLS) estimator, the model will produce unbiased and efficient estimates for the positive and negative components of the predictor. The estimation is done with the *R* package *panelr*.

In the fifth stage of the main analysis, further tests are implemented to account for the possibility that a job change affects children's skills through other channels different from occupation-specific skills (i.e., competing pathways). That is the case of (i) child-related controls: gender, age, health problems, and cognitive delays; (ii) job-related controls:

household income, working hours, working hours of the partner, supervisory responsibilities, job quality, firm size, and the years that the mother has been in the new occupation; and (iii) family-related controls: whether the mother has been enrolled in continuing education, changes in the mother's marital status and the family size, whether there is a newborn at home, and whether the family has moved regions in the last period.

In the sixth step, I re-run the model in *Equation (1)* in a stratified sample by SES, to investigate the possibility that the effect of occupation-specific skills on children's development varies by the socioeconomic background of the parents.

Finally, I address some reverse causality concerns in the robustness checks section.

4. RESULTS

4.1. Descriptives

How common is it for mothers to change their occupations? Given that this is the source of variation that this study relies on, it is important to make sure that a sufficient proportion of mothers in the sample change their jobs with some regularity. **Figure 1** shows the percentage of women who change their occupation between each of the time points measured in the NLS data. This percentage varies over time, and in all cases is higher than 25%. These numbers go in line with the reports from the U.S. Bureau of Labor Statistics, according to which, individuals born between 1957 and 1964 (i.e., the same cohorts explored observed in this study) have had an average of 12.4 jobs during their active working life. Of these, 5.6 jobs were held between ages 18 to 24 and 4.5 jobs between ages 25 to 32 (and decreased progressively until 2.1 jobs between 45 and 54) (U.S. Bureau of Labor Statistics, 2021). According to the same report, this is explained by the short duration of some of these jobs (i.e., among those aged 18 to 24, 74.6% had a job that lasted less than 2 years)[2]. There are no statistically significant

[2] For a summary of the report, see Bureau of Labor Statistics, U.S. Department of Labor, *The Economics Daily*, Baby boomers born from 1957 to 1964 held an average of 12.4 jobs from ages 18 to 54 at https://www.bls.gov/opub/ted/2021/baby-boomers-born- from-1957-to-1964-held-an-average-of-12-4-jobs-from-ages-18-to-54.htm (visited *December 30, 2022*). The original report is available at https://www.bls.gov/news.release/archives/nlsoy_08312021.htm#.

differences between low- and high-SES mothers in the regularity of changing jobs during the time of the survey, although low-SES ones are, on average, slightly more likely to change their jobs.

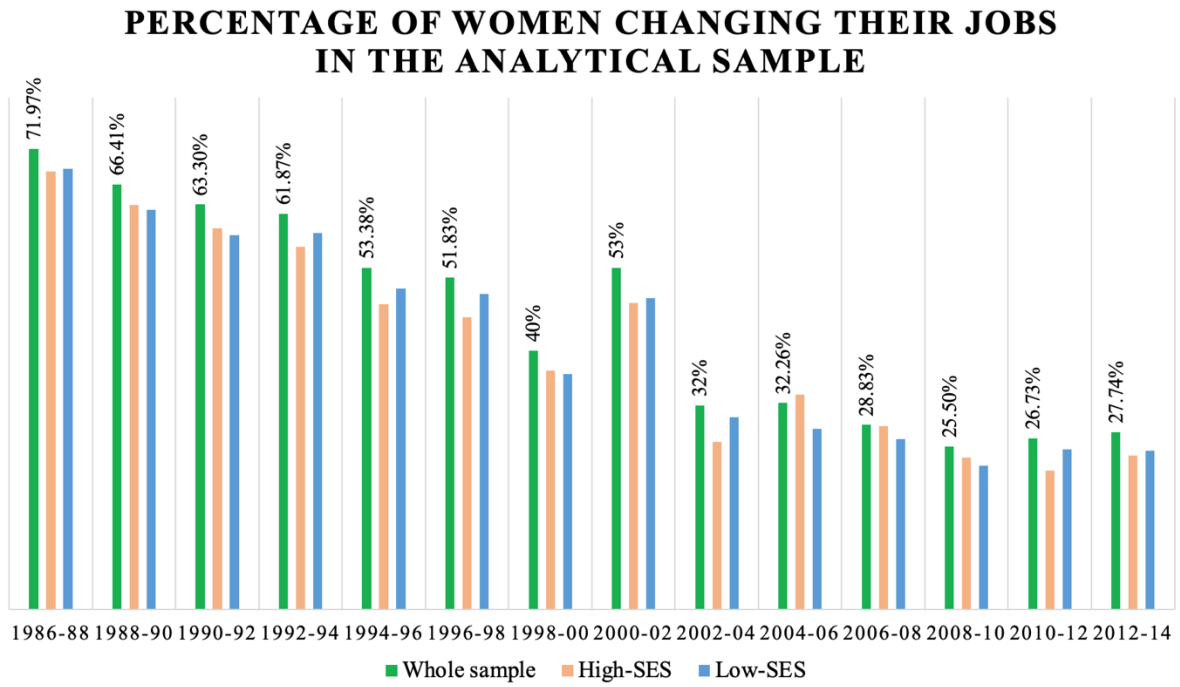

Figure 1. Percentage of women changing their occupation by SES. Own elaboration from the analytical sample.

It is relevant to note that the percentage of these changes varies considerably over time, with more women changing their jobs during the first decades of this study. This might be driven by two reasons: a life-course explanation, and a survey-design artifact. First, since the NLSY79 data is a cohort-type survey, the women observed are in the first steps of their professional careers during the first years of the survey, which explains the larger number of jobs held during that period. Second, in the first waves of the survey carried out in the 80s and 90s, and given the less-advanced technological resources, the NLS interviewers asked the participants for details about their jobs and afterward coded them manually. However, during the late 90s, a new system was implemented, and the interviewers started to carry electronic devices with pre-recorded information, so the new question asked from the 1994 interview onwards was "[these] were your main activities when your last reported your job, are they still the same?". This increases the precision of the coding and ensures certain continuity when the person in question is still doing the same job. This also means that the estimates obtained from the second half of

the sample (i.e., from 2000 onwards) can be interpreted as conservative coefficients, as compared to the more optimistic ones in the 80s/90s given the (potentially) over-represented changes in maternal jobs[3].

After aggregating all the waves' information, and as shown in **Figure 2**, 46,9% of the total number of person-year observations show a change between the current and the previous occupation. Among those whose occupation changes from *t-1* to t, 52,6% increase their skills (upgrading), and 47,4% show declines in their skills (downgrading). In the case of literacy skills, 54,1% of the changes in occupation reflect an upgrade in skills, and 45,8% a downgrade. Highly educated mothers are slightly less likely to show downgrading skills patterns, although the differences between the two socioeconomic groups are not significant.

The high percentage of skills downgrading, which seems counterintuitive with a standard career trajectory, can be explain by the two factors. First, since the sample is formed by young women in reproductive age, it is likely that a large part of these downgrading responds to mothers trying to accommodate their families' needs by finding less-demanding jobs, as previous literature has shown (Tomlinson et al., 2009). A second explanatory factor would be related to the type of measurement I am using. It might be the case that some mothers simply stop using certain skills because they transition to a more management-based position in which those skills are not central part of the role. In these cases, even if the use of skills will be downgraded, the new job will be superior in the job hierarchy. This should not affect my results, since as far as this paper is concerned, what matters for the intergenerational transmission of skills is how central skills are for a mother's life, which is what the measure employed here captures, and not that much about other aspects of the job transition. In any case, I control for income and other changes associated to the job to account for these possibilities.

[3] Note that the results presented in this study are robust to restricting the waves included to those from 1996 onwards (once the % of mothers changing occupations drops to 50%). These time restricted results available from the author upon request.

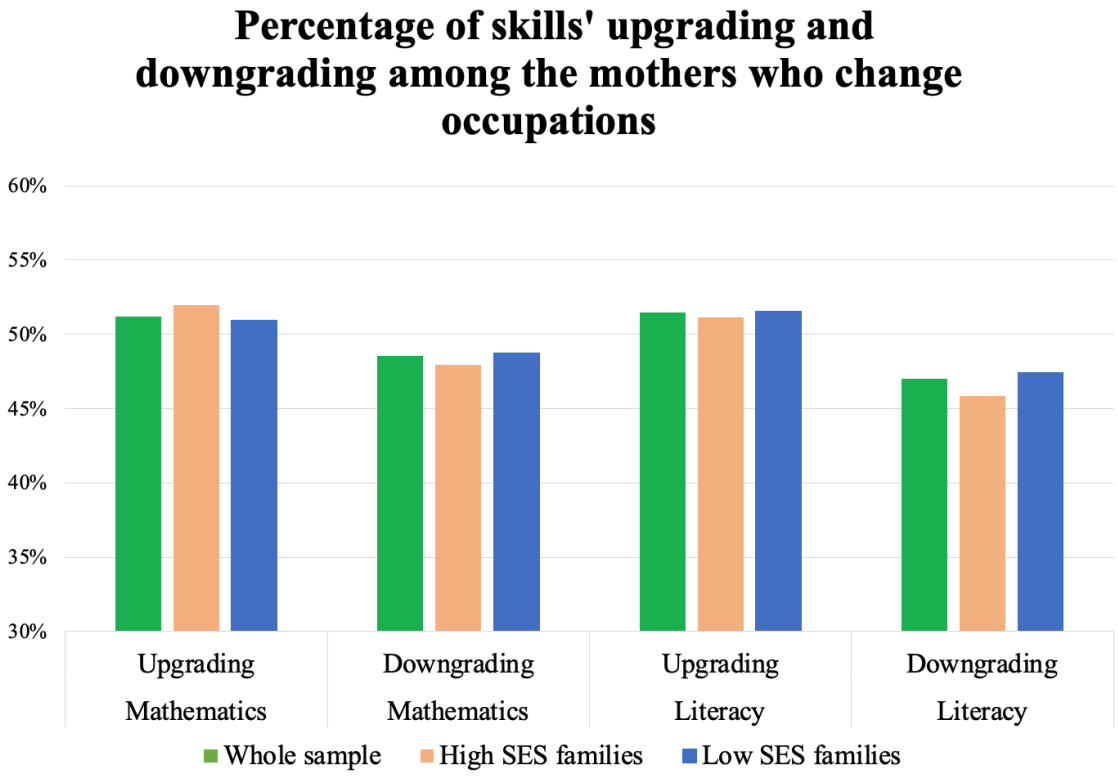

Figure 2. Percentage of skills upgrading and downgrading among the mothers who change occupations. Own elaboration from the analytical sample.

Finally, it is informative to show the correlations that exist between mothers' and children's skills. The correlation between mothers' occupation-specific mathematical skills and children's mathematical skills is 0.19, and the correlation between mothers' occupation-specific literacy skills and children's literacy skills is 0.21. These numbers are consistent with the correlations shown by between mothers' occupational-specific skills and children's abilities in the UK, which range between 0.10 and 0.24. They also go in line with the correlations found in the United States for crystallized intergenerational intelligence (between 0.15 and 0.24), and they are much larger than the ones detected for personality traits (between 0.07 and 0.10) (see Table 5 in Anger (2012) for a summary). All in all, this suggests that the occupation-specific skills of the mother could be relevant to understanding children's skills development.

All the descriptive statistics of the variables included in this paper can be found in **Table A2** in the Appendix.

4.2. Main models

Table 3 shows the results from the OLS baseline models. In a cross-sectional analysis, an increase of one point in mothers' mathematical skills at time *t-1* is associated with an increase of 0.122 points in the child's mathematical skills at time *t*. This estimate is slightly bigger (0.149 points) for the literacy skills model (2). The magnitude of these effects is around one-ninth of a standard deviation.

Moreover, the children of highly educated mothers show, on average, around 0.2 points higher mathematical and literacy skills than those children of non-tertiary educated mothers. As expected according to the existing literature, there are also gender and race differences in children's skills. Girls outperform boys in literacy skills (0.17 points higher on average). The racial gradient in skills suggests that white children show the highest levels of mathematical and literacy skills, followed by Hispanic children (the reference category) and black children. Moreover, older mothers have children with higher mathematical and literacy skills, and children in larger families show lower levels of skills.

Table 3. Baseline. OLS models.

	Dependent Variable: children's skills	
	Child Maths Skills	Child Literacy Skills
	(1)	(2)
Mothers' Mathematical Skills t-1	0.122***	
	(0.013)	
Mothers' Literacy Skills t-1		0.149***
		(0.012)
Mother's education	0.197***	0.209***
	(0.017)	(0.017)
Male child	-0.004	-0.172***
	(0.013)	(0.014)
Race: black (ref. category Hispanic)	-0.098***	-0.087***
	(0.019)	(0.020)
Race: white (ref. category Hispanic)	0.398***	0.238***
	(0.018)	(0.019)
Age of mother at birth	0.019***	0.017***
	(0.002)	(0.002)
Family size	-0.031***	-0.057***
	(0.005)	(0.005)
Residence with the mother	0.014	0.016
	(0.047)	(0.049)
Dummy controls for the job sector	Yes	Yes
Constant	-0.7901***	-0.735***
	(0.822)	(0.075)
Observations	16,959	16,877

Note: Standard Errors are in parentheses and clustered at the mother level. ***=*0.001,* **=*0.01,* *=*0.05.*

Figure 3 (and **Table A4** in the Appendix) shows the main results from the TWFE and the IPW-TWFE models. In the basic TWFE specification, an increase of one point in the mothers' mathematical skills at time *t-1* implies an increase of around 0.05 points in the children's mathematical skills at time *t*, and in the case of literacy skills of approximately 0.04 points. These estimates are around 5% of a standard deviation.

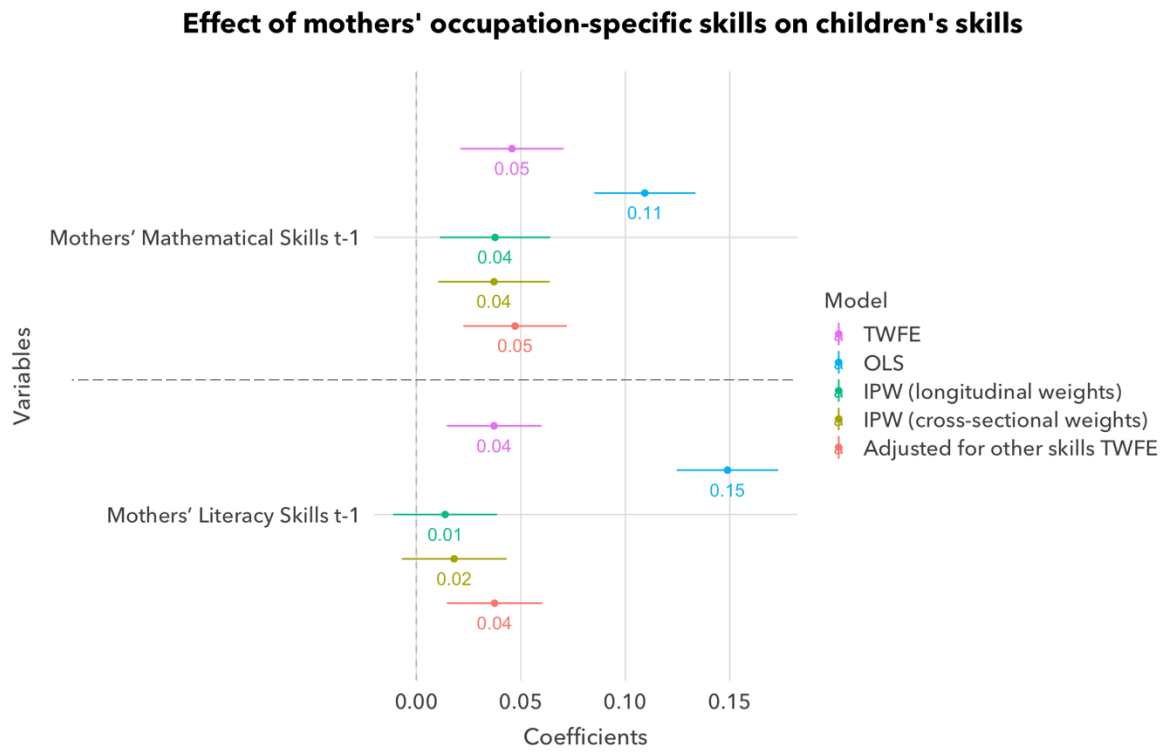

Figure 3. Estimates from main TWFE and OLS models. Corresponds to Table 3 (OLS models) and Table A4 (the rest of the models). Confidence intervals 95%.

The IPW-TWFE models aim to account for the potential selection into changing occupations for certain mothers. In the case of mathematical skills, despite using cross-sectional or longitudinal weights for the inverse weighting, I find that an increase in mothers' occupation-specific skills brings with it a rise in their children's skills. The magnitude of this effect is only slightly smaller than the TWFE results without the inverse probability weighting and is still significant. In the case of literacy skills, however, once I account for the probability of changing occupations (both with cross-sectional and longitudinal predictors), the estimates are no longer significant. This suggests that the literacy skills effects detected in the previous models might be driven by selection.

4.3. Introducing the time dimension

Figure 4 shows that, as compared to those who have just transitioned into a new job, the children of mothers who have been in the new job for many more years benefit especially from the occupation-specific skills of the mothers. In the case of literacy skills, children seem to obtain especially high returns when their mothers have been six years in the job. For mathematical skills, this difference becomes evident after 10 years on the job. This suggests

that the more time mothers spend on the job, the more skills they acquire, and therefore, the more their children benefit from their occupation-specific skills.

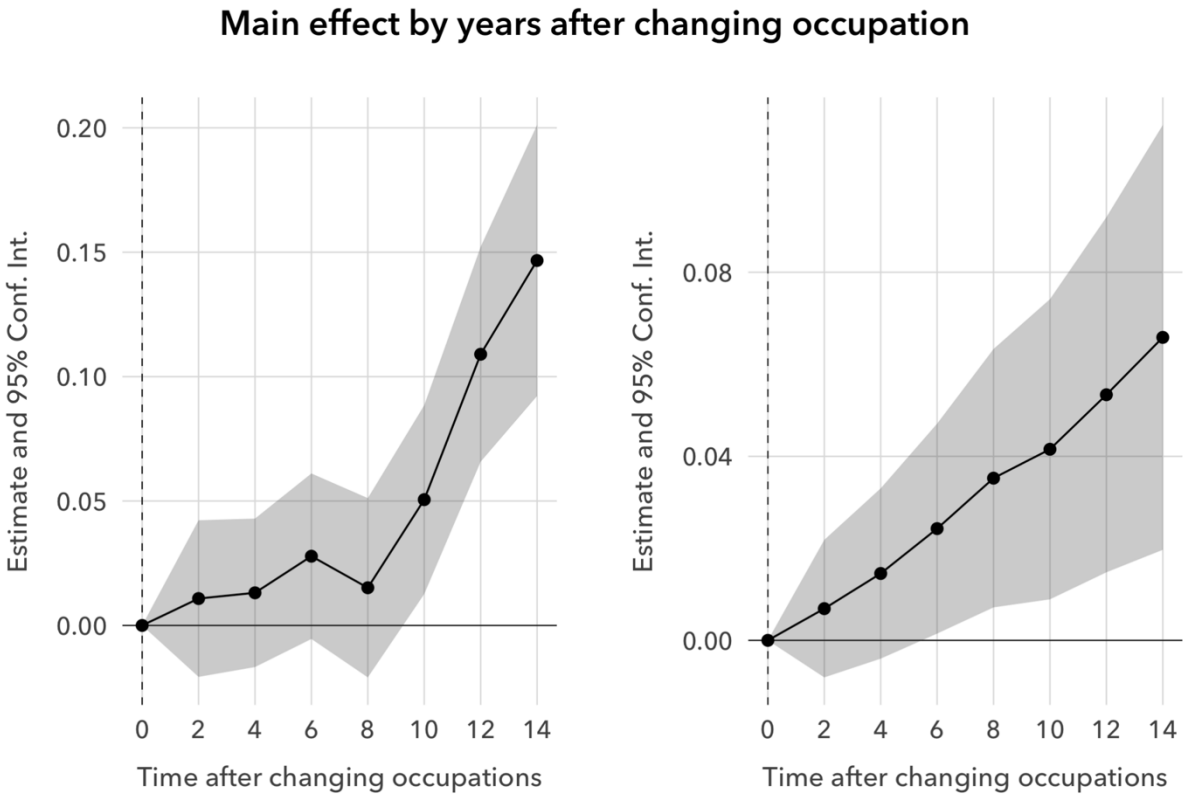

Figure 4. Estimates from main TWFE and OLS models. Corresponds to Table A5. Confidence intervals 95%.

4.4. Multidimensionality of skills

Models (3) and (4) in **Table A4** aim to examine the third hypothesis of this paper, which suggests that the intergenerational transmission of skills will be subject-specific. To address this, in the model with mathematical skills as the main outcome of interest, I also include variations in literacy skills (and the other way around for the literacy skills outcome). The rationale behind these two models is accounting for the possibility of children's skills being fostered by any type of parental skills variation, which would be substantively different from direct transmission of the content of the skills. What the results show in this sense is that increases in children's mathematical skills are fostered by mothers' mathematical skills changes and not by variations in the mothers' literacy skills. Similar results are found for the literacy skills dimensions when introducing changes in mathematical skills as one of the predictors.

4.5. Asymmetric models

The current TWFE models assume that the effect of changes in mothers' skills on children is symmetric. However, as explained in the analytical strategy section, it is a possibility that increases and decreases in the mothers' skills have different effects on children's skills, which is something that the TWFE specification could not detect.

Table 6 below shows the results of the ASYM-TWFE models that disaggregate the main effect of mothers' skills in upgrading and downgrading changes. In both dimensions, mathematical and literacy, when mothers show improvements in their occupation-specific skills, children increase their skills by 0.05 and 0.03 points respectively. These estimates are consistent with the results obtained in the baseline TWFE models. Unsurprisingly, a decline in mothers' occupation-specific skills does not foster any variation in children's skills.

Table 6. Asymmetric TWFE.

	Dependent Variable: children's skills			
	Mathematical Skills		Literacy Skills	
	Upgrading Skills	Downgrading Skills	Upgrading Skills	Downgrading Skills
	(1)	(2)	(3)	(4)
Mothers' Mathematical Skills t-1	0.05**	-0.01		
	(0.02)	(0.02)		
Mothers' Literacy Skills t-1			0.03*	-0.00
			(0.015)	0.02
Observations	8,920	8,039	9,130	7,747

Note: Standard Errors are in parentheses and clustered at the mother level. Note that the *N* of these models is significantly lower than in the previous ones because they exploit exclusively the variation produced by increases or decreases in each of the skills dimensions, whereas the previous models were accounting for both types of variations. All the models include controls for the job sector. ****=0.001, **=0.01, *=0.05.*

4.6. Alternative pathways

As explained in the theoretical section, there is a potential issue of omitted variable bias, that comes from the fact that when mothers change jobs, several other factors can change at the

same time that could be responsible for the increase in children's skills, and that would suggest that it is not necessarily a matter of acquiring new skills. To account for this possibility, I construct several models that include controls for time-varying (i) children characteristics, (ii) family-related characteristics, and (iii) job characteristics. All these factors might change together with the job or trigger a job change themselves.

Figure 5 shows the main estimates from the TWFE models once several characteristics of the children are accounted for. Both the mathematics and literacy skills results remain constant despite controlling for the age of the child and the health limitations experienced. When I include a control for childcare, two different patterns emerge. On the one hand, the literacy skills coefficient loses significance, which can be justified by the fact that childcare absorbs part of this positive effect, as shown by the positively significant coefficient of the child being in childcare for literacy skills (**Table A7**). On the other hand, the baseline of the mathematical skills variable stays constant and even increases the size when we account for childcare. This increase is likely driven by a negative correlation between the mothers' mathematical skills and the use of childcare. Moreover, in a further model specification, I exclude those children who have shown any type learning disability in the past, so that the possibility of parents changing jobs as a response to these disabilities is ruled out. The results remain constant despite imposing this restriction.

Another important characteristic of the children that are not included in this figure is children's gender. This is because it is a time-invariant characteristic in the sample, and therefore, the TWFE model cannot estimate its effect. To overcome this, I rerun separate models for boys and girls. The results in **Table A9** (Appendix) show that whereas both gender groups benefit from their mothers' acquiring new literacy occupation-specific skills, girls are especially likely to respond positively to increases in maternal mathematical skills. This suggests that given the usual lower baseline level of mathematical skills of the girls as compared to the boys, there is more room for benefiting from their mothers' extra skills.

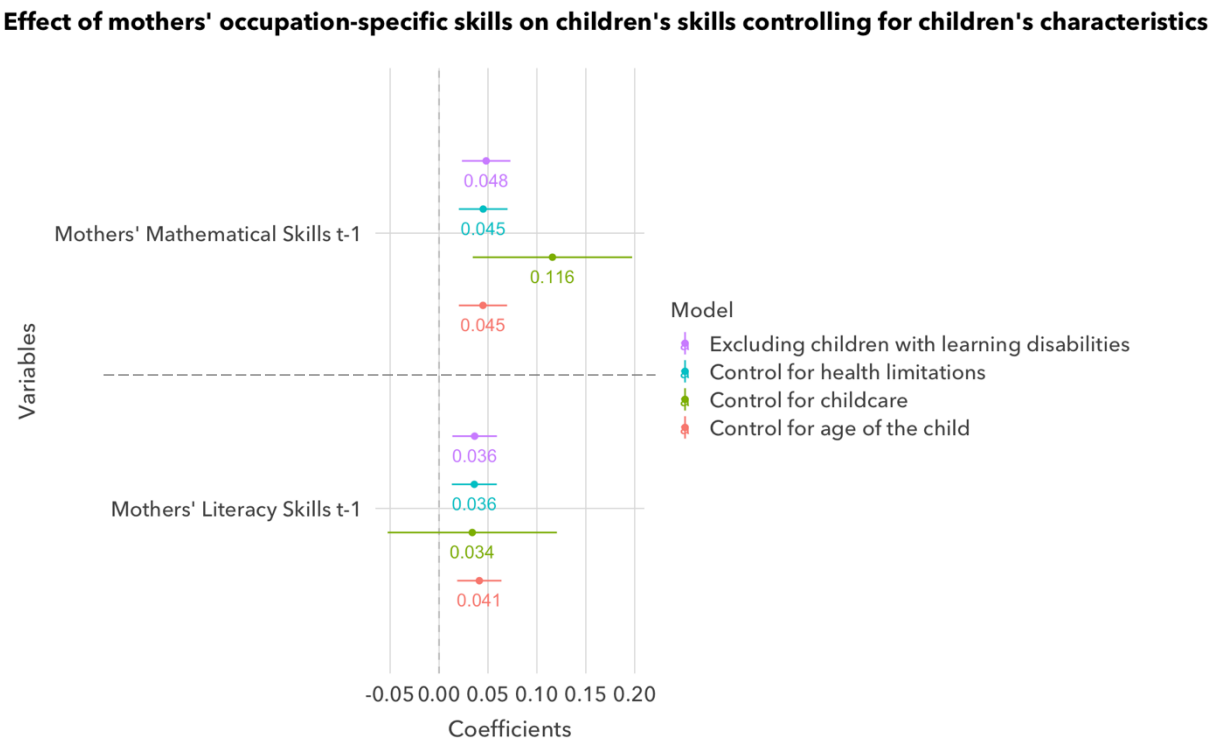

Figure 5. Estimates from stratified TWFE with child characteristics controls. Corresponds to Table A7 in the Appendix. Confidence intervals 95%.

Figure 6 displays the results once several family-related changes are taken into consideration. That is the case of changes in the location or region of the family, changes in family size and marital status, having a newborn at home, or mothers enrolling in continuing education. None of these factors seems to absorb the effect of mother occupation-specific skills on children's skills. This is especially important in the case of mothers' continuing education because it would be an alternative pathway through which mothers might acquire skills that positively impact their children.

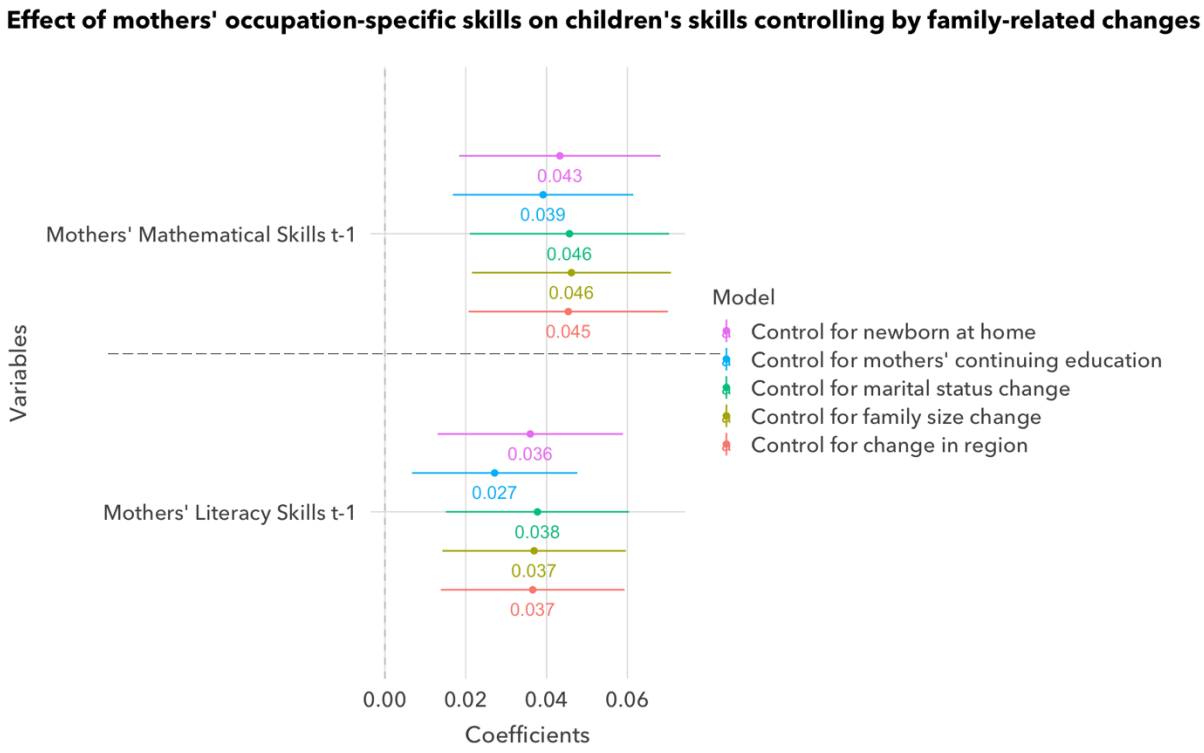

Figure 6. Estimates from stratified TWFE with family characteristics controls. Corresponds to Table A10 in the Appendix. Confidence intervals 95%.

Finally, **Figure 7** shows the results once job-changing characteristics are considered. For instance, if the new occupation of the mother, on top of requiring higher skills, also presents a better job quality, this factor can be partially responsible for the positive effect on children's development. In the case of mathematical skills, the main estimates remain positive and significant despite controlling for a variety of factors such as changes in firm size, job quality, supervisory responsibilities, working hours of the mother and the partner, household income, and restricting the sample to those who have been more than four years in the job (so that they have had enough time to develop the skills associated to the new job). Of particular interest is the fact that despite accounting for the changes in total household income and working hours of the partner/father, the main effect of mothers' occupation-specific skills remains constant. This evidence supports *hypothesis 4*.

However, in the case of literacy skills, the results are more unstable. When the controls for firm size, supervisory responsibility, and working hours are introduced the main estimates stop being statistically significant. This is consistent with the results from the IPW-TWFE that suggested that the results of the literacy skills dimension were driven by selection.

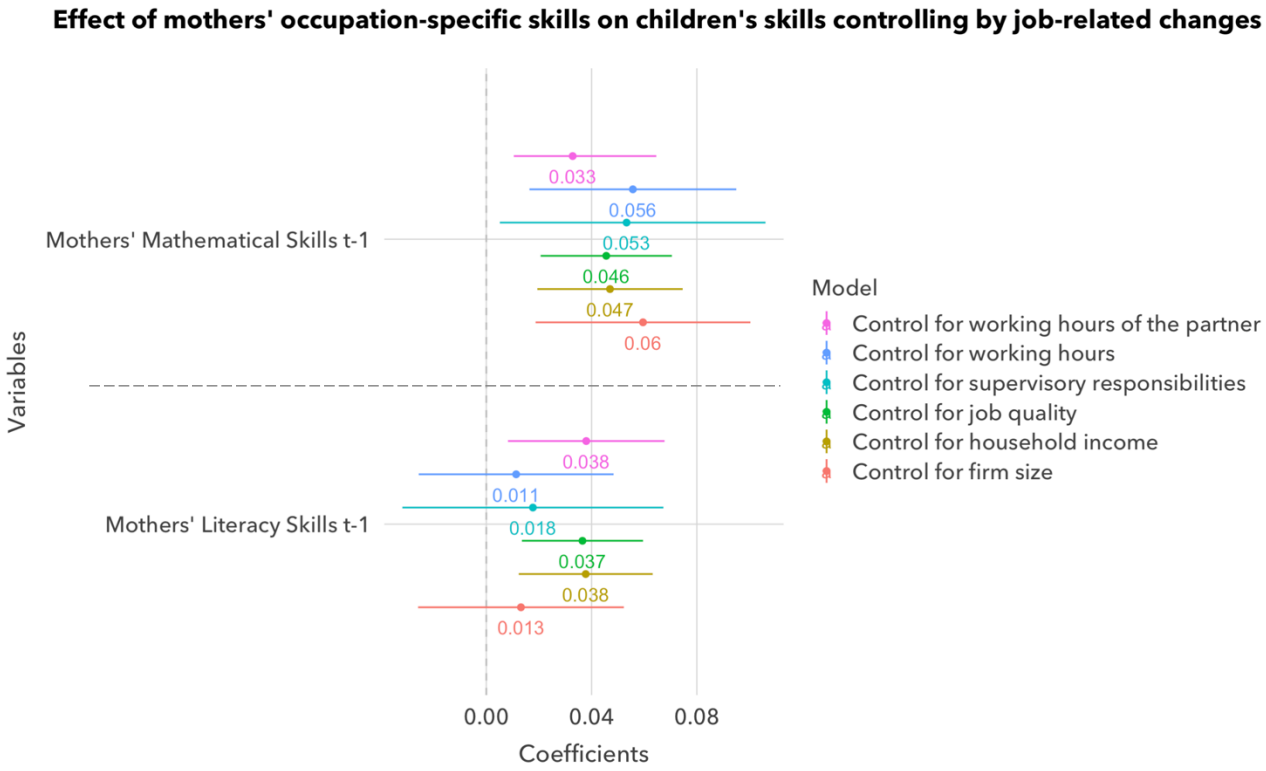

Figure 7. Estimates from stratified TWFE with job characteristics controls. Corresponds to Table A11 in the Appendix. Confidence intervals 95%.

4.7. Stratified models

An unresolved question so far is whether children from high- and low-SES families equally benefit from changes in their mothers' skills. **Table 12** shows the results from the TWFE models run in stratified samples for those with and without tertiary education separately. The results show that, for mathematical skills, children with tertiary-educated mothers benefit significantly from occupation-specific skills increases. However, this effect is not significant for low-educated mothers. This suggests that there is an educational gradient in the relevance of occupational-specific skills and that children in highly educated families get the highest returns from their mothers' skills changes. The results, in line with the previous model specifications, are not significant for the literacy skills model.

Table 12. Stratified TWFE models.

	Dependent Variable: children's skills			
	Non-Tertiary Educated Mothers		Tertiary Educated	
	Child Maths Skills (1)	Child Literacy Skills (2)	Child Maths Skills (3)	Child Literacy Skills (4)
Mothers' Mathematical Skills t-1	0.021 (0.014)		0.057* (0.0231)	
Mothers' Literacy Skills t-1		0.023 (0.013)		0.021 (0.024)
Observations	12,827	12,827	4,154	4,154

Note: TWFE models. Standard Errors are in parentheses and clustered at the mother level. ****=0.001, **=0.01, *=0.05.*

On top of education, given the nature of occupation-specific skills it is worth it to examine whether the effect of these changes in maternal skills on children's development varies in terms of the occupational sector. **Figure 8** shows that there are three main sectors for which maternal skills seem to matter more: public administration, professional services, and personal services. In the three cases, these are sectors usually associated with service-class occupations.

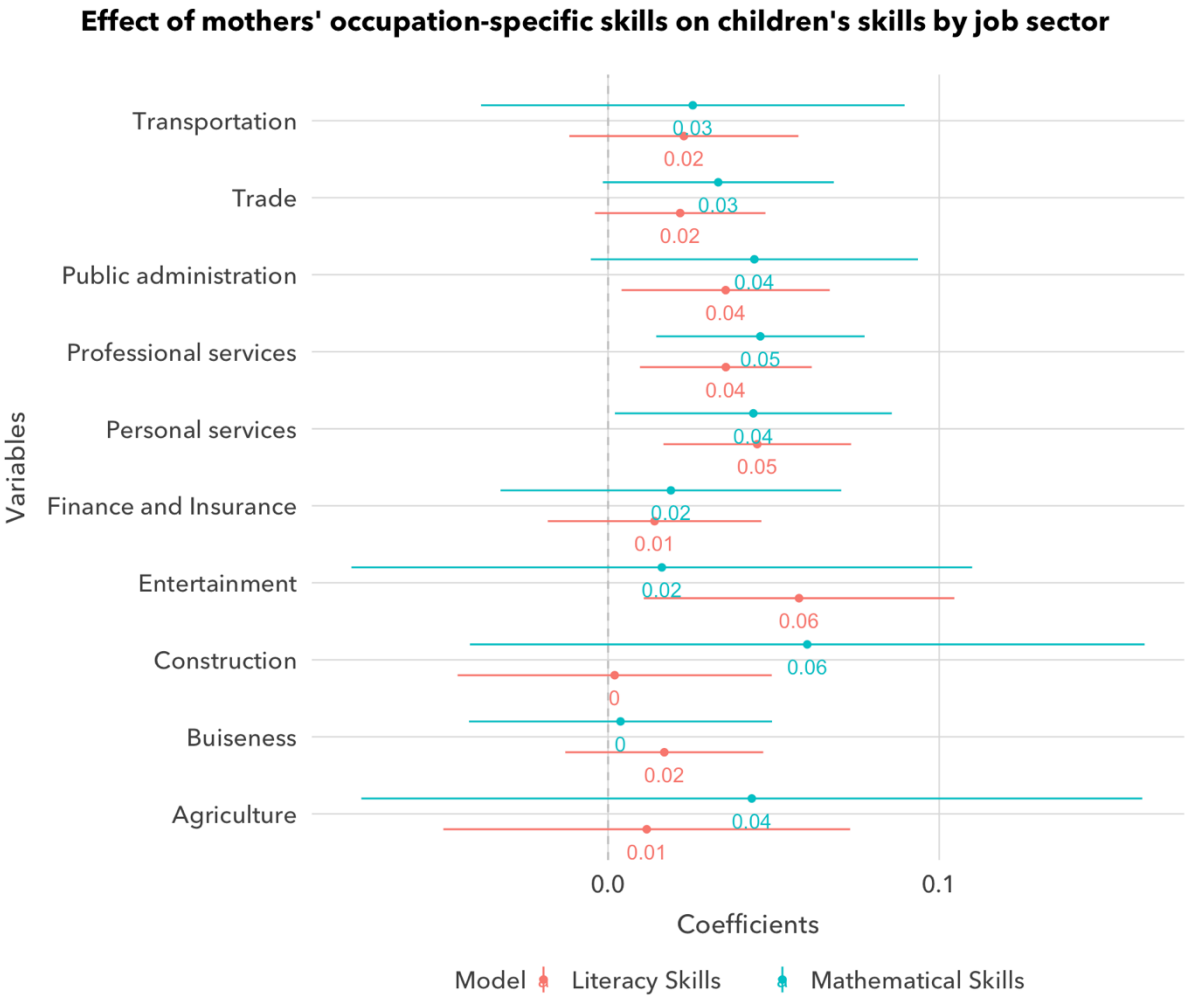

Figure 8. Estimates from stratified TWFE by job sector. Corresponds to Table A8 in the Appendix. Confidence intervals 95%.

4.8. Sensitivity checks

The causal identification of the effect of mothers' occupation-specific skills on children's skills will be challenged if mothers changed their jobs as a response to certain children's characteristics, which would originate an issue of reverse causality. There are four ways in which the current analytical strategy partially addresses this concern.

First, I exploit the time dimension of this effect by measuring the impact of changes in mothers' skills at time t-1 on children's skills at time t. This means that there is a period of two years between mothers' occupational changes and children's skills variations. Moreover, this study assumes that when mothers change their jobs is because there has been a previous process of

skills development happening latently that has materialized through an occupational change. This implies that the two years time frame is the most conservative option.

Second, the asymmetric model helps with the potential issue of reverse causality too. In the case of skills downgrading, it would be intuitive to consider that reverse causality plays a role because mothers can decide to downgrade their skills and transition to a less demanding job as an adaptation to children's lower developmental rhythms. However, the fact that the results are driven mostly by skills upgrading suggests that this is not what is driving the results.

Third, several of the factors included in the alternative pathways section account for the possibility of parents changing their work arrangements as a response to variations in children's development. For instance, I exclude those children with learning disabilities and control for health limitations of the children to account for the possibility of parents modifying their occupation as a response to children's problems.

Fourth, and connected to the rationale of the previous point, I include controls for changes in parental working arrangements. An example of the potential risks that this strategy aims to tackle is: what if mothers transition from a full to a part-time employment arrangement to be able to spend more time with their children because they are noticing some developmental problems (despite these not being captured in the children's health or learning disabilities controls)? Reassuringly, I find that despite taking into consideration potential changes that occurred in the working hours of the mother or the partner of the mother, there is still (in the case of mathematical ability) an effect of changes in mothers' occupation-specific skills on the children's skills.

In this section, I implement four further robustness tests to discard the possibility of (i) children's skills, (ii) health limitations, (iii) learning disabilities or (iv) behavioural problems at time *t-1* determining mothers' skills change at time *t* in my analytical sample.

These results are displayed in **Table A13**. First, I find that there is either a substantively or statistically significant impact of changes in children's mathematical and literacy skills at time t-1 on mothers' skills at time t. Similar results are found for the health limitation and learning disabilities variables, as well as the behavioural problems variable. This all suggests that

mothers do not modify their skills as a response to previous variations in children's characteristics, which would compromise the causal identification of this study.

5. DISCUSSION AND CONCLUSIONS

This paper examines whether mothers' occupation-specific skills impact children's skills development. Given the central role that occupations have on individuals' skills sets formation, it seems consistent to suggest that they may play an important part in the process of intergenerational transmission of skills that is responsible for social reproduction. I merge longitudinal household data from NLSY-CYA with O*NET data that measures the type of specific skills that are required for each job. The analytical strategy of this paper exploits changes in occupation-specific skills driven by job changes experienced by mothers. With this aim, I implement a series of two-way fixed effects models that I combine with inverse probability weighting, as well as asymmetric fixed effects models.

The main results of this paper are consistent with the first hypothesis suggested and show that when a mother transitions to an occupation in which higher levels of mathematical skills are required at time *t-1*, her child will develop more mathematical skills at time *t*. Although small, the size of these effects detected is not negligible. If a mother increases the occupation-specific skills in one unit (on a scale from 0 to 7), the child is expected to increase her mathematical skills by around 5% standard deviation, which is larger than the effect of most of the time-varying socio-demographic, family, and job predictors included in these models.

Whereas in the case of mathematical skills, these results are constant across several specifications and very robust, this is not the case for literacy skills once inverse probability weighting techniques are implemented. The inconsistency of the literacy skills result might be explained in different ways. First, there might be an underlying process of selection in the transition into occupations that require more literacy skills. This would be the case if, for instance, there are some changes associated to the mothers' lives that foster both their job change and their children's developmental changes. However, to some extent, this option is contemplated when alternative pathways, such as changes in residence or mother's enrollment in higher education, are accounted for in the models. Moreover, this would not explain why the

effect disappears in the case of literacy but not mathematical skills. Another option would be that there is selection both for mathematical and literacy skills, but since the effect size of the literacy models is smaller in general than the mathematical one, the inverse probability weighting techniques only make the literacy effect disappear but not the mathematics one.

Apart from these potential selection processes, the lack of a significant effect in some of the literacy skills models could also be explained by the distinct level of difficulty of mathematical and literacy skills. Whereas high levels of mathematical skills are usually harder to sustain over time unless they are often used (i.e., by-hand complex divisions), the upgrades in literacy skills might be less often fostered by occupational changes but more associated with the baseline educational level. And therefore, less likely to be affected by changes in jobs such as the ones considered in this paper.

Crucially, three pieces of results give indirect support to the suggested mechanism in this paper, which is that parents learn certain skills as part of their jobs, and they transmit these to their children. First, I find that the more time mothers spend on the job, the larger the benefit for their children's skills. This means that the more familiar a mother gets with her job and tasks, the easier will be for the children to acquire these skills (*hypothesis 2*).

Second, the results also suggest that the transmission of occupation-specific skills is particular to each of the dimensions of skills examined (*hypothesis 3)*. This is, changes in mothers' literacy skills do not impact children's mathematical skills, which is consistent with Autor & Dorn's (2013) statement about different skill dimensions not being perfect substitutes for each other.

Third, the asymmetric fixed-effects models implemented allow me to differentiate between skills upgrading and downgrading. The findings show that the effect of maternal skills changes on children's skills is driven by skills upgrading but not downgradings (*hypothesis 4)*. This is consistent with my theoretical expectations that assumed that even if mothers transition to a job in which a lower level of skills is required it would be unlikely that they lose previously acquired skills.

In the case of mathematical ability, these results are robust to the introduction of several factors that could work as alternative pathways through which mothers' jobs impact children's skills formation (*hypothesis 5)*. In the case of mathematical ability, none of the child-, family- or job-

specific controls challenge the role of occupation-specific skills as the main channel connecting mothers' jobs and children's skills. However, the effect of mothers' literacy occupation-specific skills disappears when the number of working hours, the size of the firm, or the assumption of supervisory responsibilities are considered, which reinforces the selection argument stated above.

Lastly, I account for the possibility of children from different socioeconomic backgrounds obtaining different returns from their mothers' changes in occupation-specific skills. In this sense, the results suggest that children with highly educated mothers benefit more from the marginal increases in mathematical occupation-specific skills. This goes against the idea of a ceiling effect existing for high-SES families *(hypothesis 6b)* and is in line with the previous theories suggesting that the information and ability asymmetries make more privileged parents more able to channel their skills towards their children *(hypothesis 6a).*

This paper makes four main contributions to the literature. First, this is, to the best of my knowledge, the first empirical test of whether changes in maternal occupational skills impact the process of skills formation of the offspring. This idea has been only studied from a theoretical perspective (Jonsson et al., 2009) or in an associational way (Barg & Klein, 2023). Second, this study goes a step further and disentangles the asymmetric causal effect of occupation-specific skills on children's skills, differentiating between skills upgrading and downgrading, and offers a closer look to the mechanism behind this effect by exploring the multidimensional and cumulative character of this skills transmission. Third, it also examines the stratified nature of the intergenerational transmission of occupation-specific skills, which has important implications for understanding the process of social reproduction. Finally, this paper explores the US case, which had been previously overlooked despite the rich available data which provide external assessments of the level of occupation-specific skills and children's development and therefore improves the previous literature using self-reported levels of skills.

The main limitation of this paper comes from the fact that only two dimensions of skills are included given data restrictions. This means that other types of occupation-specific skills of the mother which are important for children's development, such as social or motor skills, are omitted in this paper. A second limitation is that the potential mechanisms linking mothers' and children's skills are only indirectly examined, but not directly tested. Particularly, the changes in parental strategies or home environments that are fostered by occupational changes and

eventually impact children's development should be examined in future research. Also motivated by data limitations, this paper only considers mothers' skills but not fathers. I have tried to account for the fathers or the partner of the mother by including information about their working hours or the variations in total household income, but there are not enough available observations on fathers' job transitions in the dataset employed. Further research would benefit from having a more comprehensive approach to the family unit in this sense. Moreover, an important avenue for future research would be to explore which type of selection processes could be responsible for the different impact that mathematical and literacy skills seem to have, which is something that this paper has not been able to deepen in given space limitations.

A final nuance to make is that occupations are not necessarily a perfect proxy for occupation-specific skills for two reasons. First, even if O*NET accounts for the specific job tasks that are part of the job and derives the skills indexes from this and other job indicators, it does not allow me to differentiate conceptually between the job tasks and the job skills, which brings some conceptual undefinition to the paper. Second, a possibility is that the skills upgrading happens latently for some time, and the job change is just a consequence of this. In this case, I cannot know whether the change in skills is related to the new job or not. However, it is relevant to notice that given the fact that I am comparing those who transition into a new job because of their higher level of skills with a group that combines those who did not improve their skills plus those who improved them but not enough to get a new job, the estimates obtained are if something conservative and downwardly biased when compared to the ones I would obtain if I was sure that all those in the non-job-change control group had not upgraded their skills at all.

Overall, these results suggest that the intergenerational transmission of skills does not only operate at the educational level as previous literature has suggested (Attanasio et al., 2020; Bowles et al., 2009; Lundborg et al., 2014; Sacerdote, 2002) but also through the transmission of skills that are associated to the specific job of the mothers. These results open new doors for policy programs trying to tackle social reproduction during the childhood period to examine mothers' skills from a more holistic perspective that includes other dimensions of the mothers' and children's lives.

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APPENDIX

Table A1. Description of the O*NET skills.

Variable	Skill	Description by O*NET
Mathematics skills	Science	Using scientific rules and methods to solve problems.
	Mathematics	Using mathematics to solve problems.
	Programming	Writing computer programs for various purposes.
	Systems analysis	Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes.
	Systems evaluation	Identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system.
	Operations analysis	Analyzing needs and product requirements to create a design.
	Technology design	Generating or adapting equipment and technology to serve user needs.
Literacy skills	Literacy comprehension	Understanding written sentences and paragraphs in work-related documents.
	Speaking	Talking to others to convey information effectively.
	Writing	Communicating effectively in writing as appropriate for the needs of the audience.
	Active listening	Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.

Table A2. Descriptive statistics.

Variable	Mean	Std. Dev	Range
Mothers' occupation-specific mathematical skills	1.42	0.59	0 to 7
Mothers' occupation-specific literacy skills	3.29	0.63	0 to 7
Children's mathematical skills	0	1	-2.5 to 2.5
Children's literacy skills	0	1	-6 to 2
Job Sector	-	-	10 to 999
Age of the mother at birth	25.78	6.12	16 to 50
Residence	72% with the mother	-	0/1
Race	50% white, 30% Hispanic, 20% black	-	1/2/3
Gender of the child	51% boys	-	0/1
Age of the child (in months)	99	49	60 to 180
Health limitation	6% with a health problem	-	0/1
Learning delay	0.9%	-	0/1
Behavioural problems	52% have ever had some sort of behavioural problem	-	0/1
Mothers' education	29% tertiary educated	-	0/1
Annual household income	50,805	67,555	0 to 974,100
Mothers' continuing education	4.7% in continuing education	-	0/1
Marital status	13% never married, 60.3% married, 7.2% separated, 17.1% divorced, 1.4% widowed	-	0/1/2/3/6
Family size	3.671	1.61	1 to 16
Newborn at home	19.85%	-	0/1
Region	Northeast (14.83%), Central (25%), South (40.61%), West (19.45%)	-	1/2/3/4
Working hours	36.5	11.74	0 to 160
Working hours of the partner	44.12	11.85	0 to 160
Supervisory Responsibilities	36% increased responsibilities, 3% decreased, 61% stayed the same	-	1/2/3
Job quality	4.42% reported very bad quality	-	0/1
Firm size	1132 workers	8555	1 to 99,995

Table A4. TWFE models.

Dependent Variable: children's skills								
	TWFE		TWFE adjusted for the other skills dimension		IPW TWFE (cross-sectional weights)		IPW TWFE (longitudinal weights)	
	Child Maths Skills	Child Literacy Skills	Child Maths Skills	Child Literacy Skills	Child Maths Skills	Child Literacy Skills	Child Maths Skills	Child Literacy Skills
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mothers' Mathematical Skills t-1	0.046*** (0.013)		0.048*** (0.013)	0.003 (0.013)	0.037** (0.014)		0.038** (0.013)	
Mothers' Literacy Skills t-1		0.037** (0.012)	0.016 (0.015)	0.037** (0.012)		0.018 (0.013)		0.014 (0.013)
Observations	16,959	16,877	16,959	16,877	16,959	16,877	16,959	16,877

Note: Standard Errors are in parentheses and clustered at the mother level. All the models include controls for the job sector. ***=0.001, **=0.01, *=0.05.

Table A5. Effect of mothers' job changes by years after changing occupation.

	Dependent Variable: children's skills	
	Mathematical Skills (1)	Literacy Skills (2)
Mother's Skills * 2 years after new job (ref. category= 0 years)	0.012 (0.016)	0.007 (0.01)
Mother's Skills * 4 years after new job (ref. category= 0 years)	0.013 (0.015)	0.015 (0.01)
Mother's Skills * 6 years after new job (ref. category= 0 years)	0.028 (0.017)	0.024* (0.012)
Mother's Skills * 8 years after new job (ref. category= 0 years)	0.015 (0.018)	0.035* (0.014)
Mother's Skills * 10 years after new job (ref. category= 0 years)	0.051** (0.019)	0.042* (0.017)
Mother's Skills * 12 years after new job (ref. category= 0 years)	0.109*** (0.022)	0.053** (0.02)
Mother's Skills * 14 years after new job (ref. category= 0 years)	0.147*** (0.028)	0.066** (0.023)
Observations	16,959	16,877

Note: TWFE models. Standard Errors are in parentheses and clustered at the mother level. ****=0.001, **=0.01, *=0.05.*

Table A7. Two-way fixed effects with children' related controls.

	Dependent Variable: children's skills							
	Age of the child		Health Limitation		Excluding those who have some learning disability		Childcare control	
	Child Maths Skills	Child Literacy Skills	Child Maths Skills	Child Literacy Skills	Child Maths Skills	Child Literacy Skills	Child Maths Skills	Child Literacy Skills
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mothers' Mathematical Skills t-1	0.045*** (0.013)		0.045*** (0.013)		0.048*** (0.013)		0.116** (0.041)	
Mothers' Literacy Skills t-1		0.041*** (0.012)		0.036** (0.012)		0.036** (0.012)		0.034 (0.044)
Age of the child	0.000 (0.000)	-0.001*** (0.000)						
Health Limitation			0.004 (0.031)	-0.052 (0.030)				
Childcare							-0.103** (0.039)	0.154*** (0.038)
Observations	17,285	17,285	16,917	16,917	17,170	17,170	4,904	4,904

Note: TWFE models. Standard Errors are in parentheses and clustered at the mother level. All the models include controls for the job sector. ***=*0.001,* **=*0.01,* *=*0.05.*

Table A8. Stratified TWFE by Job Sector

	Dependent Variable: children's skills	
	Predictor	
	Mothers' Mathematical Skills t-1	Mothers' Literacy Skills t-1
Agriculture	0.043	0.0117
	(0.068)	(0.0353)
Construction	0.060	0.0020
	(0.049)	(0.0218)
Transportation	0.025	0.0229
	(0.026)	(0.0180)
Trade	0.033	0.0218
	(0.018)	(0.0136)
Finance and insurance	0.019	0.0140
	(0.026)	(0.0173)
Business	0.004	0.0170
	(0.025)	(0.0157)
Personal services	0.044*	0.0450**
	(0.022)	(0.0148)
Entertainment	0.016	0.0577*
	(0.054)	(0.0239)
Professional services	0.046**	0.0356**
	(0.016)	(0.0136)
Public administration	0.044*	0.0355*
	(0.022)	(0.0168)
Observations	16,959	16,877

Note: TWFE models. Standard Errors are in parentheses and clustered at the mother level. All the models include controls for the job sector. ****=0.001, **=0.01, *=0.05.*

Table A9. Two-way fixed-effects models stratified by gender.

	Dependent Variable: children's skills			
	Girls sample		Boys sample	
	Child Maths Skills	Child Literacy Skills	Child Maths Skills	Child Literacy Skills
	(3)	(4)	(5)	(6)
Mothers' Mathematical Skills t-1	0.067***		0.023	
	(0.018)		(0.018)	
Mothers' Literacy Skills t-1		0.031*		0.044**
		(0.016)		(0.017)
Observations	8,756	8,756	8,575	8,575

Note: TWFE models. Standard Errors are in parentheses and clustered at the mother level. All the models include controls for the job sector. ***=0.001, **=0.01, *=0.05.

Table A10. Two-way fixed-effects models with family-changes controls

	Dependent Variable: children's skills									
	Baseline models with mothers' extracurricular training control		Baseline models with marital status changes control		Baseline models with moving regions control		Baseline models with newborn at home control		Baseline models with changes in family size control	
	Child Maths Skills	Child Literacy Skills	Child Maths Skills	Child Literacy Skills	Child Maths Skills	Child Literacy Skills	Child Maths Skills	Child Literacy Skills	Child Maths Skills	Child Literacy Skills
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mothers' Mathematical Skills t-1	0.039***		0.046***		0.045***		0.043***		0.046***	
	(0.011)		(0.013)		(0.013)		(0.013)		(0.013)	
Mothers' Literacy Skills t-1		0.027**		0.038**		0.037**		0.036**		0.037**
		(0.010)		(0.012)		(0.012)		(0.012)		(0.012)
Mothers' Continuing Education	0.029	0.014								
	(0.026)	(0.025)								
Married			0.008	-0.215***						
(ref. never married)			(0.051)	(0.048)						
Separated			-0.014	-0.260***						
(ref. never married)			(0.057)	(0.053)						
Divorced			0.020	-0.252***						
(ref. never married)			(0.056)	(0.053)						
Widowed			0.028	-0.530***						
(ref. never married)			(0.131)	(0.125)						
Moving regions					0.018	0.025				
					(0.029)	(0.027)				

Newborn at home							-0.023	0.041*		
							(0.018)	(0.017)		
Family size									0.012	-0.007
									(0.007)	(0.007)
Observations	17,064	16,982	17,064	16,982	17,064	16,982	17,064	16,982	17,064	16,982

Note: Standard Errors are in parentheses and clustered at the mother level. Models constructed based on the baseline model *(Equation 1)* plus controls. All the models include controls for the job sector. ***=*0.001,* **=*0.01,* *=*0.05.*

Table A11. Two-way fixed-effects models with job-related controls

	Dependent Variable: children's skills											
	Baseline models with income control		Baseline models with working hours control		Baseline models with supervisory responsibilities control		Baseline models with job quality control		Baseline models with firm size control		Baseline models with working hours of the mothers' partner control	
	Child Maths Skills	Child Lit Skills	Child Maths Skills	Child Lit Skills	Child Maths Skills	Child Lit Skills	Child Maths Skills	Child Lit Skills	Child Maths Skills	Child Lit Skills	Child Maths Skills	Child Lit Skills
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mothers' Mathematical Skills t-1	0.044**		0.056**		0.053*		0.046***		0.06**		0.033*	
	(0.014)		(0.020)		(0.027)		(0.013)		(0.021)		(0.016)	
Mothers' Literacy Skills t-1		0.040**		0.011		0.018		0.037**		0.013		0.038*
		(0.013)		(0.019)		(0.025)		(0.012)		(0.020)		(0.015)
Household Income	0.00	-0.00000*										
	(0.00)	(0.00000)										

Working Hours			-0.001	0.0001								
			(0.001)	(0.001)								
Supervisory Responsibilities					0.042***	-0.017						
					(0.013)	(0.011)						
Job Quality							0.026	-0.033				
							(0.035)	(0.033)				
Firm Size									-0.0	-0.0		
									(0.00)	(0.00)		
Working hours of the partner											0.0002	-0.0001
											(0.001)	(0.001)
Observations	14,549	14,549	9,476	9,476	6,435	6,435	16,992	16,911	8,901	8,901	11,387	11,387

Note: Standard Errors are in parentheses and clustered at the mother level. All the models are constructed based on the baseline model *(Equation 1)* plus controls. All the models include controls for the job sector. ***=0.001, **=0.01, *=0.05.

Table A13. Reverse causality checks.

	Dependent Variable: Mother's occupation-specific skills							
	Mothers' Maths Skills	Mothers' Literacy Skills	Mothers' Maths Skills	Mothers' Literacy Skills	Mothers' Maths Skills	Mothers' Literacy Skills	Mothers' Maths Skills	Mothers' Literacy Skills
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Children Mathematical Skills t-1	-0.002							
	(0.005)							
Children Literacy Skills t-1		-0.007						
		(0.005)						
Behavioural Problems			0.001	-0.0003				
			(0.008)	(0.008)				
Health Limitations					-0.011	-0.005		
					(0.008)	(0.008)		
Learning Disabilities							-0.089	-0.081
							(0.046)	(0.045)
Observations	16,877	16,877	26,071	26,071	15,900	15,900	2,635	2,635

Note: TWFE models. Standard Errors are in parentheses and clustered at the mother level. All the models include controls for the job sector. ***=0.001, **=0.01, *=0.05.