Public Daycare Participation and Cognitive Development: Evidence from French Primary Schools*

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Abstract

This paper estimates the effects of participation in public daycare centers when children are 0-2 years old on their literacy and numeracy skills at 6. Using French administrative data on standardized tests at the beginning of primary school, we use the interaction between local daycare availability and being born when it is more likely to get a daycare spot as an instrumental variable for the endogenous daycare attendance. We find a positive and significant impact of daycare attendance on compliers, who tend to switch from parental care to daycare and to be biparental families in rural municipalities. Quantile regressions reveal that the impact of daycare is significantly stronger for the bottom end of the skills distribution than for the top one: in line with the 'compensatory' model, daycare has an equalizing effect. Quality of childcare matters: nearly all of the positive effect is attributable to publicly managed daycare centers and longer opening hours have a significantly positive impact on cognitive skills.

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1 Introduction

The efficacy of universal early childhood care programs in fostering human capital development is debated in both US and European policy spheres (The Council of the European Union, 2019).

In the context of the more general research question on the effect of early education (0-2 years old) on children's cognitive development (measured at 6), our paper focuses in particular on what kind and management of daycare works. Our instrument allows us to identify the impact of early childhood attendance, and select compliers who are more likely to switch to daycare from pa rental care.

In this paper, we combine administrative data on standardized tests on the universe of French children, fine-grained local administrative data on daycare supply, and two different large, nationally representative surveys. We rely on an individual-level instrument that interacts local daycare availability and plausibly exogenous variation in the period when the child is born, which affects the probability of being granted access to daycare. The identification comes from the interaction (Bruneel-Zupanc and Beyhum, 2024) of an excluded but endogenous quasi-IV - the local daycare availability - with one exogenous but included quasi-IV - a child's month of birth , which is plausibly random in the French context We use two-sample two-stage least squares (TS2SLS) to overcome the data limitation of not having the cognitive measures and information on daycare attendance in the same dataset, in particular using the *Enquête Famille Logement* (FL) survey to measure the first-stage, and administrative data on test scores from DEPP (a branch of the French Ministry of Education) for the reduced form.

We find a significant and positive reduced-form effect of daycare availability on numeracy and literacy skills for the compliers with the instrument. The instrument has a strong effect on the probability of attending daycare, as the first-stage coefficient is over 50% of the baseline daycare attendance. Quantile regressions uncover significant heterogeneity of the impact of daycare along the skills distribution. This provides evidence that childcare attendance may reduce inequality in cognitive abilities at school entry, which are strong predictors of later academic performance (Duncan et al., 2007). Finally, we identify the characteristics of compliers (Marbach and Hangartner, 2020). The main instrument we use - interaction between birth in spring and local daycare availability - isolates compliers whose main counterfactual type of care is home care. This may explain why the results are relatively strong: the potential cognitive benefit of daycare vs. home care may be stronger than the one of daycare vs. other formal childcare. Almost all of the positive impact of daycare is driven by publicly managed daycare centers. Longer opening hours and types of daycare considered of higher quality (collective daycare) have a significant impact on cognitive development 3 years after the child attended them. This suggests that even in countries where the coverage of formal childcare is high, such as in France, there is still scope to increase early accumulation of human capital by improving the quality of formal childcare.

This paper fits into the strain of literature on the cognitive medium- and long-term benefits of childcare attendance using regional variation in availability, such as being born in a municipality where access to daycare centers is guaranteed (Gupta and Simonsen, 2016), or difference-in-differences using the staggered expansion of childcare reforms (Cascio, 2009; Havnes and Mogstad, 2011; Noboa-Hidalgo and Urzua, 2012; Felfe et al., 2015; Felfe and Lalive, 2018; Jessen et al., 2020; Pora, 2020; Cornelissen et al., 2018; Andresen, 2019). Among those, the ones that do not use individual-level data on daycare attendance, but rely on reduced-form estimates (Baker et al., 2008; Haeck et al., 2018; Baker et al., 2015; Havnes and Mogstad, 2011, 2015) are particularly relevant, as we also do not have full-coverage administrative data on childcare attendance. The main limitation is that it is not possible to determine whether the effects of the child care reform are influenced by differences in the take up of child care services and to investigate the role of the quality of the child care center and the counterfactual form of care. We focus on formal childcare for children aged 0-2, while most of the evidence on childcare is studied in the context of preschool, where older children (3-5) are treated.

This paper brings two main contributions to the literature. First, it fills a gap in the literature on the causal identification of long-term impact of different standards and management type of daycare, as highlighted by European Commission (2022): most papers on the topic are either correlational (Slot et al., 2015; Melhuish et al., 2008; Sammons et al., 2008) or are meta-analyses (van Huizen and Plantenga, 2018; Ulferts and Anders, 2016) that draw conclusions on the quality by comparing results from different contexts, thus the results are likely to be biased by other unobserved differences. In the previous literature, this has been done for children aged 3 to 5 (Chetty et al., 2011), while we focus on children who are between 3 months and 3 years old. Differently from the US context, in France class size is mandated by a national law, so we focus on different types of daycare centers, on different types of management (public, private for profit, non profit) and on opening hours.

Second, we explicitly identify the characteristics of the compliers, and the type of care they are switching from. We are the first to link the literature studying differential impacts of daycare attendance along the skills distribution with the small literature that estimates differential impacts based on the counterfactual type of care (Kline and Walters, 2016; Feller et al., 2016; Zhai et al., 2014). We find results in line with the latter: if the counterfactual is parental care, the impact of daycare attendance is larger. The different counterfactual also explains why daycare seems to have a much more positive effect on disadvantaged children: it substitutes for lower levels of parental investment and educational stimulation.

Our quantile heterogeneity analysis builds on Havnes and Mogstad (2015), Kottelenberg and Lehrer (2017) and Bitler et al. (2014). The main differences are that our outcomes are medium-term cognitive skills and not earnings nor short-term cognitive tests and that we do not include a before-after axis, but eligibility is defined - fuzzily - by being born in spring. Differently from Kottelenberg and Lehrer (2017) and Bitler et al. (2014), we can estimate our quantile regressions on the whole population, without relying on a survey. Stronger effects at the bottom of the distribution, found in this paper and in Havnes and Mogstad (2015); Kottelenberg and Lehrer (2017) and Bitler et al. (2014) allow us to reconcile small or insignificant average effects of universal childcare provision with the strong positive impacts found in target programs (for example, Blau and Currie 2006, Karoly et al. 1998, Heckman et al. 2010, Heckman et al. 2013). This takeaway message is coherent with the results of Fort et al. (2020), who find a negative effect of daycare attendance in an advantaged population, and Drange and Havnes (2019), who exploit the random assignment of children to daycare spots.

The rest of the paper is structured as follows: Section 2 describes the context, Section 3 describes the different datasets we use and their limitations, Section 4 details the empirical strategy, Section 5 describes the results and robustness checks and Section 6 concludes.

2 Context

This paper only focuses on policies for childcare, i.e. for children aged from 0 to 2, as opposed to pre-school or kindergarten (*école maternelle*), for children aged 3 to 5. In particular, toddlers can enrol in formal childcare from their 3rd month. Maternity leave in France varies between 3 months and a half to 5 months and a half, but most mothers stay at home for 4 months (Pailhé and Solaz, 2012). Since preschool begins the year the child turns 3, children can be enrolled in childcare arrangements when they are up to 45 months old[1].

Virtually all children enrol in a center-based pre-school in the year they turn 3 (INSEE, 2019): in the 2012-2016 period, there is little variation in this figure, that is always above 97%[2]. Thus, similarly to the Danish context studied by Gupta and Simonsen (2016), the results of this paper are better interpreted as the consequences of additional early center-based care.

2.1 Childcare alternatives

Although access to publicly-funded childcare is widely available in France, the specific type of childcare, whether it be in a center or a smaller group setting at a provider's home, is not assured[3].

Apart from parental care, there are four main childcare arrangements (Cour des Comptes, 2013): nannies that operate in the child's house (*garde à domicile*), licensed childminders (*assistant.e.s maternel.le.s*), daycare (*crèche*) and, for children aged 2, the possibility to attend kindergarten one year in advance.

Different types of daycare exist (see Figure 7.10):

- Collective daycare (*crèches collectives*)
    - A particular type of those is the micro-crèche, which can host up to 10 kids and are subject to less stringent rules - for example, they do not need to have a director.

[1] For example, a child born in January begins preschool in the year when he turns 3, that is in September, 9 months after its third birthday in January (36 + 9 = 45).

[2] Children born in 2016 are in the sample and are affected by the reform of mandatory pre-school at 3, in place since September 2019. Since the enrolment rates in pre-school were already extremely high, this has likely little impact in increasing the enrolment rates. It may have changed the likelihood to find a spot in pre-school at 2 years old, but this was evident for children born in 2017 (who were 2 in 2019), that are not included in this sample. Including year fixed effect in both the main specifications does not change the results (column 3 and 4 in table 7.30.

[3] Differently from Nordic countries (Rostgaard, 2014), in France, the right to choose among different childcare options is emphasized, so that for example the benefit that families receive from the Family branch of the French Social Security is called "benefit for the free choice of childcare" (*complément de libre choix du mode de garde*, CMG).

- Occasional daycare (*halte garderies*), which take in children on an occasional basis and often for fewer hours during the day.
- *Multi-accueil*, which can combine occasional and regular care.
- *Jardins d'enfants* or *jardins d'eveil*, which take in older children (from 18 months) and are more focused on facilitating the passage to pre-school.
- Finally, a *crèche familiale* is a solution that lies between a licensed childminder and a daycare center: in this option, childminders are employees of the daycare center but usually operate in their own houses and get together to make children socialize once or twice a week. The director of the *crèche familiale* makes regular home visits to childminders.

Different daycare options can be managed by different actors. The greatest majority are managed by local governments (53.2% of daycare centers) or by a municipality-run social action center (6.9%). A great number (31%) is also managed by non-profit associations, often founded by parents themselves as associations - in this case, parents usually can spend some time in the daycare (e.g. half a day per month) along with the daycare workers. When daycare is managed by private actors (7.3%), those are often the companies for which the parents work. Private (for-profit or non-profit) daycare centers need to be authorized by the department's public authority, after consulting the mayor of the municipality in which the facility is located. Overall, childcare policy decisions happen mainly at the municipality level.

2.1.1 Quality

In the childcare literature, it is common to evaluate the quality using both the structural and the process quality (Duncan and Magnuson, 2013; van Huizen and Plantenga, 2018). The former focuses on constitutional aspects of the childcare arrangement, namely the class size and the teacher education, while the latter focuses on the quality of the teacher-child interactions, which are much more difficult to measure.

In France, structural quality indicators are set by law, and enforced by local Social Security branches (*Caisse d'Allocations Familiales*, CAF). Table 2.1 summarizes them. The level of education is higher among daycare employees, and each daycare center (except microcrèches) needs to have a director with the qualification of a nursery nurse, doctor or early childhood educator, gained with at least a bachelor's degree. Since daycare workers have a specific education in pedagogics, the quality of interactions may be higher, mimicking better a high educated home environment[4], while childminders have characteristics more similar to informal carers (mothers and grandmothers). The relatively low salaries of childminders and nannies (around 1000€ per month, less than 4€ per hour, CNAF-DSER 2016), combined with the fact that demand fluctuates in different years and periods of the year, causes a high turnover. Some nannies and childminders, for example, are themselves mothers or grandmothers (Auzet et al., 2014). In the department of Côtes-d'Armor in Brittany, where childminders are much more common

[4]There is in fact a strong association between the socio-economic status of parents and the quantity and style of spoken words (Hart and Risley, 2003), the use of child-directed speech (Rowe, 2008), and the utilization of gestures (Rowe and Goldin-Meadow, 2009). These factors, in turn, have been found to be predictive of vocabulary expansion and language development of the child.

Table 2.1: Structural quality indicators of different subsidized childcare arrangements. Source: Cour des Comptes (2013).

	Education of staff	Staff salaries	Kids/teachers ratio
Daycare	Subject-specific secondary school or university level	$\approx$ 18,000€/year	≤ 5 if kids do not walk, ≤ 8 if they do, or ≤ 6 for all kids.
Licensed childminders	No formal qualifications, but 120-hours training over the first 3 years of activity	$\approx$ 11.000€/year.	≤ 4 kids
Nannies	No formal qualifications	9,13€ net per hour	1 to 1, unless employed by multiple families

than in the rest of France, still less than a third of childminders practices the profession for more than 10 years (Auzet et al., 2014). The lower kids/teachers ratio if families choose the option of a childminder or a nanny, however, may lead to more quality interactions between the adult and the child. However, in daycare centers there is a greater number of staff members, so that children have a higher number of adults to engage with and there is a potential for staff members to learn from one another, help and monitor each other.

Regular quality inspections are conducted for both crèches and assistantes maternelles, encompassing observations, interviews, and self-assessments (OECD, 2016). These inspections are formulated to oversee both the structural and procedural aspects of quality. Different types of daycare centers are subject to the same rules, making at least the structural quality uniform across France. However, standards are usually more related to building safety than daycare workers' effectiveness in fostering psycho-motor development and socialization of children (De Bodman et al., 2017). Moreover, daycare centers set their opening hours: when the opening hours are shorter, there is a higher cost for parents, especially those working full-time and odd hours, who need to find a complementary type of childcare.

2.1.2 Allocation of daycare slots

Different levels of public institutions are involved in funding childcare (a detailed description is reported in Appendix 7.1). At the same time, while some rules are set for the entire France (for example, teacher/students ratio), a great deal of responsibility resides at the local level. In particular, municipalities - and sometimes single daycare centers - have a great deal of freedom in deciding how to allocate the slots.

Since the level of decision is extremely local and most often no information is publicly available, we describe qualitatively how the process unfolds in most municipalities. National guidelines advise families to contact either the person in charge of the early childhood services at the municipality or department level, or directly the director of the daycare center. This way, families get to understand admission criteria and what documents they need to provide. Only in some cases there is a clear scoring based on characteristics that must be proven. For example, in the Pays de la Loire region, they depend on the income, the family structure, the handicap of the child and the presence of other siblings in the same structure. The city of Lyon also attributes points based on the residence of the family and how many times the application has been presented. In general, families try to show that they need a daycare place, but there is a high degree of arbitrariness, that can also be related to local politics since the person in charge of the early childhood services is appointed by the elected mayor. There is also high heterogeneity in the number of preferences that the family can express in favour of one daycare center or another.

Le Bouteillec et al. (2014) find that, across France, children with older siblings and twins have the highest probability of being offered a place. Among mother characteristics, unemployed mothers and public sector employees are more likely to have their children in daycare - although this may be caused by both higher demand for these categories and higher supply of spots reserved for them.

2.1.3 Preferences and actual childcare arrangements

A priori, considering only structural quality indices and prices for families, licensed childminders and daycare seem two similarly high-quality and low-price childcare arrangements.

However, among formal childcare arrangements, parents prefer daycare to childminders. This is evident from both the Elfe and the Mode de garde (MDG) survey. In the case of the Elfe panel, a similar question is repeated in the 2-month wave and the 2-year one. In both cases, the question is framed in terms of ideal childcare arrangement rather than in terms of preferences[5]. The Mode de garde survey, instead, frames the question in terms of “first choice” of childcare arrangements. From both surveys the first choice of formal childcare is daycare: results from Elfe are summarized in Figure 7.19, while according to the MDG survey, only 1.6% of families whose children go to daycare say that it was not their first choice, while it is 5.5% for families that entrust their children to a childminder.

This is also in line with the results of the EMBLEME survey, conducted by CAF, which focused on the work-family balance of 6000 families that had a child in 2013. According to this survey, daycare centers are by far the most preferred formal childcare option (Laporte, 2019).

Figure 7.21 summarizes the reasons that lead parents to prefer daycare or a childminder. Daycare is mainly chosen because of the potential benefits, while childminders are preferred for contingent reasons. Among the benefits, the general sense that it is enriching for the child and the fact that the child gets to socialize with other children are the most important factors in the choice of daycare. Childminders are particularly chosen for their longer working hours (Figure 7.17), for lack of alternatives and for proximity to the family’s home.

A qualitative study included in the yearly publication of the National early childhood observatory (ONAPE, 2011) comes to similar results through in-depth interviews: parents particularly

[5]The question at 2 months reads: “What do you think is the “ideal” childcare arrangement for your child (your twins)?”. The one at 2 years old reads: “Ideally, what type of childcare would you prefer?”

Table 2.2: Main childcare arrangements according to Elfe, Mode de garde survey and Enquête Famille Logement.

Source	Parents	Grandparents and family	Childminder	Daycare	Nanny	Kindergarten	Other
FL, age 0	60%	4%	25%	9%	-	-	2%
FL, age 1	44%	5%	31%	17%	-	-	2%
FL, age 2	45%	5%	29%	18%	-	-	2%

Notes: The "Other" category groups together childcare by unregistered childminders, friends, neighbors or other outsiders, *jardins d'eveil*. Figures may not add up to 100% due to rounding.

value the fact that daycare operators are trained to propose a program of early-learning activities and that daycare allows children to be prepared for pre-school, as opposed to childminders.

It is thus mainly because of supply constraints that in the distribution of actual childcare arrangements the number of children in daycare is lower than in parents' preferences. Two further elements in this direction is that once parents get a spot in a daycare center, it is very unlikely that they change to another childcare arrangement, as shown by comparing flows in and out of each arrangement (Figure 7.22), and that the time to find a spot in daycare is usually longer than for other options (Figure 7.20).

While unfortunately there is no exhaustive administrative data on the childcare arrangements, the three surveys, despite the differences in sampling methods and the number of observations, are coherent on the distribution of childcare arrangements[6].

One-fourth of children attends multiple childcare arrangements, according to the Elfe survey. The fact of having a complementary childcare arrangement is relatively evenly distributed among the various principal childcare arrangements (Figure 7.23). The most common secondary arrangement is grandparents, that especially take care of the children during the hours when childminders and daycare are closed. It is also evident from Figure 7.23 that children that are mainly taken care of by their parents get at least some exposure to formal childcare methods, namely childminders, daycare and kindergarten.

Unfortunately, we are unable to measure and study all the potential differences in childcare, in particular with regards to the quality of daycare, how long the children used each method and the complementary type of care: for this analysis, we only rely on a binary variable for daycare attendance or not.

[6]The main difference is between the Mode de garde survey and the other two. In fact, the perk of the Mode de garde survey is that it does not simply ask what the "principal" childcare arrangement is, but it also asks parents to fill in a time-use survey on the usual weekly schedule of the child. Then, the principal childcare arrangement is defined as the one that is more used during working hours, Monday to Friday, from 8 a.m. to 7 p.m.

3 Data

3.1 Data on educational outcomes

Educational results are derived from the standardized assessments of the "ÉvalAide - Évaluer pour mieux aider" program, which targets first- and second-grade students in primary school. This program is managed by the DEPP (*Direction de l'évaluation, de la prospective et de la performance*), the statistical and research arm of the French Education Ministry. It evaluates the cognitive abilities of all French students at the start and midpoint of first grade, and at the start of second grade, leading to three assessments per student. The administrative dataset encompasses all elementary school children in France from 2018 to 2023. For the primary analysis, we utilize the assessment administered in September of the first grade, thus producing a cross-sectional dataset. Concentrating on the September evaluation of the first grade, each student completes 8 items in the French domain and 8 items in the Mathematics domain. In the principal specification, given the varying evaluation scales of each item, we standardize the scores individually and calculate the unweighted average for both Mathematics and French items. Consequently, this results in a dataset where the unit of analysis is the student, each characterized by a Mathematics and a French score, alongside several covariates such as gender, date of birth, and the school attended. The results are robust to using the rank[7] of each student instead of the score (Table 7.14)[8]. We remove 2.81% of students who did not take any tests from the DEPP dataset. For missing single items, we use the average of the available ones[9]. In the definition of the sample, we only include children who attend primary school in metropolitan France (mainland France and Corse) and who attend first grade when they are 6 years old. The share of children aged 7 or 5 years in the first grade is negligible (Figure 7.26), and they are part of two very selected populations[10]. The main analysis does not hold in these two small subsamples, but it is robust to the inclusion of these children (Table 7.13). The final dataset has 3,525,219 individual observations for Maths, 3,536,394 for French. Descriptive statistics for the DEPP data are reported in Table 7.9.

Standardized test scores effectively represent underlying skills: they are administered uniformly with objective marking. Teachers grade them according to a strict Ministry guideline (Ministère de l'Éducation nationale et de la Jeunesse, 2023), and the multiple-choice format minimizes any margin for teacher's interpretation.

[7] Ranks go from 0 to 100 and a higher number means a better rank.

[8] To compute the rank, we first compute the rank of each item, and then take the unweighted average rank for all items for each student in Math and French. In the main specification, we use the score rather than the rank, as this increases the comparability with other results in the literature on universal childcare that measure cognitive skills using standard deviations (Gupta and Simonsen 2016; Andresen 2019; Drange and Havnes 2019; Filatriau et al. 2013; Heim 2018 among others).

[9] When the values for the birthday and the gender are missing, we recover them from the tests in January of the first grade or September of the second grade. In case of multiple values for the birthday, we keep the most recent one when the difference is minimal (only one out of the day, month and year of birth is different), or drop the observation otherwise (0.05%). When the same student is evaluated twice in the same item, either in the same class or in different classes, we average the different scores (this occurs in less than 0.01% of the cases).

[10] Children aged 7 either had to repeat first grade, a rare situation, or preschool teachers opted to keep them in preschool for an extra year. Instead, parents of 5-year-old children decided to send their children earlier to school, after getting the approval of the preschool teacher and director, which is granted on an exceptional basis.

3.2 Data on childcare availability

Daycare availability is assessed using the French Social Security system (CAF)[11] administrative data on daycare places. We aggregate yearly data from 2007 to 2016 at the municipality level (about 35,000 units). We only observe daycare centers funded by CAF through the PSU benefit[12].

We gather birth data from INSEE (Bulletin état civil) registries spanning 2005-2016. The statistics cover live births, recorded by the mother's residence rather than the birth location[13].

Following Pora (2020), since places in daycare centers may be filled up by children aged from 0 to 2 years old, we define availability for each municipality m and year t as:

$$\text{Availability}_{m,t} = \frac{\text{Places in daycare centers}_{m,t}}{\text{Births}_{m,t-2} + \text{Births}_{m,t-1} + \text{Births}_{m,t}} \tag{1}$$

3.3 Data on childcare attendance

Administrative, universal data on childcare attendance does not exist in the French context. To overcome this, we use FL (*Enquête sur la famille et les logements*), a survey administered along with the census in 2011, to estimate the relevance of the instrument on the childcare attendance. We complement it with two other surveys for descriptive statistics and robustness checks, Elfe (*Étude Longitudinale Française depuis l'Enfance*), administered in 2011 and MDG (*Enquête Modes de garde et d'accueil des jeunes enfants*), administered in 2012. The main features of the three surveys are reported in table 7.22.

FL is a cross-sectional survey, the unit of observation are children aged 0-3 (born in 2007-2011), weighted[14] to be representative for the French population.

3.3.1 Data limitations

One limitation of this analysis is that we do not observe the municipality of birth nor the municipality where children live in the DEPP dataset. We thus measure daycare availability in the municipality where the elementary school is. However, kids must attend elementary school in the catchment area where they live. Reassuringly, 92% of children attend elementary school in the municipality where they reside (Fabre, 2021), and when we control for the share of children coming from outside the municipality in the school, results are unchanged (Table

[11] Data for most years is available in the open data CAF website.

[12] Microcrèches are funded by CAF through the CMG, and some centers are funded by employers. While microcrèches and employer-funded daycares are more concentrated in large cities, our dataset includes the vast majority of daycare spots (97.9% according to ONAPE 2011).

[13] The statistics are drawn up on the basis of civil status bulletins issued by mayors, at the time and in the commune where the births took place, and transcripts of birth declarations issued by the courts. The unit of observation is the municipality × year: for Paris, Marseille and Lyon we observe the births at the municipality and not at the *arrondissement* level

[14] In particular, the weights of the FL survey are computed by INSEE such that the weighted sample is representative of the population of children aged less than 4 that live mainly in private houses with at least one of their parents. The non-response weighting process takes into account the non-response at the municipality level and at the individual level, by multiplying the sampling weights by the inverse of the individual probability of response.

7.12).

A key limitation is the FL survey, used to show the relevance of the instrument, targets children born in 2008-2011, while test scores are evaluated for those born in 2012-2016. Childcare availability increased by only 0.5% from 2011 to 2012 and remained unchanged in most municipalities (see Figures 7.28 and 7.29). Additionally, daycare demand consistently exceeds supply, with fewer families securing daycare spots than those who prefer it in the Elfe and MDG surveys (Figure 7.19), which survey families of children born in 2011-2013.

Another important limitation of studying daycare in the French context is that the criteria for daycare places allocation differ by municipality. However, municipalities needs to pay around 3000€ per daycare spot: this leads municipalities to consider the residency of the child as a key criterion for the allocation, so that public funds spent by the municipality benefit residents (and voters) of the municipality. Indeed, according to a qualitative survey by DREES (Micheau et al., 2010), residency is ranked first among the allocation criteria municipalities choose. Accordingly, we use the municipality as the primary level to define availability. Alternatively, we could measure availability at the EPCI level—administrative groups where municipalities jointly manage public services. Results remain consistent with availability defined at the EPCI level (first stage in table 7.18, column 2; reduced form in table 7.11, columns 3 and 4). Results are also robust when availability is defined at the municipality level in urban areas and at the EPCI level in rural areas (first stage in table 7.18, column 3; reduced form in table 7.11, columns 5 and 6). Results are also robust to the exclusion of Île-de-France (column 4 of table 7.19 for the first stage, column 1 and 2 of table 7.11 for the reduced form). The rationale to show this robustness check is that mobility in the Parisian region differs due to its more developed public transport system.

Finally, some daycare places may be shared part-time by multiple children, and the choice between part-time and full-time daycare may relate to other factors affecting the child's cognitive ability (e.g., whether the mother works). Unfortunately, we cannot observe whether children attend daycare full-time or part-time in the FL survey. While this can be observed in the MDG sample, the low number of observations makes the survey unsuitable for this analysis.

4 Empirical strategy

4.1 Reduced form

We instrument daycare attendance with the interaction of being born in Spring and local daycare availability. The reduced-form and first-stage regressions are:

$$\begin{aligned}\text{Test score}_{im} =& \gamma_1 Spring_i \times Availability_m + \\ & \gamma_2 Availability_m + \gamma_3 Spring_i + \mathbf{X}_{im} + \alpha_d + \epsilon_{im}\end{aligned} \tag{2}$$

$$\begin{aligned}Daycare_{im} =& \beta_1 Spring_i \times Availability_m + \\ & \beta_2 Availability_m + \beta_3 Spring_i + \mathbf{X}_{im} + \xi_d + \eta_{im}\end{aligned} \tag{3}$$

Where m indexes the municipality, i indexes individual children, and d the department. The coefficient of interest is γ_1, which captures the reduced-form coefficient of the instrument - the interaction between local daycare availability and Spring births - on the outcome variable.

The rationale to incorporate Spring births is that crèche availability varies throughout the year. The minimum age to entry daycare is 3 month old (Cour des Comptes, 2013) and most openings occur in September when older children start kindergarten (see Graph 7.15). Even if a child leaves mid-year, the age of the new child must match, making mid-year placements harder (Fagnani, 2014). Crèche allocation meetings are usually held in May or June, for autumn spots, and kids usually need to be already born for the parents to apply (Le Bouteillec et al., 2014). Spring has fewer births (INSEE, 2020), leading to more available places and less competition.

The rationale for factoring in the local availability is that being born in Spring is not relevant by itself if there is no daycare center where parents can apply.

We show the instrument's relevance by regressing it on daycare attendance probability from the FL survey. FL covers children born 2008-2011, while DEPP data includes those born 2012-2016; nonetheless, the instrument significantly increases daycare attendance probability (Table 5.1). Spring births in municipalities with an additional daycare spot, keeping the birth rate constant, raise attendance probability by 7.5 percentage points, notable given the 12% average attendance rate.

For the exclusion restriction to hold, the effect of being born in Spring in a municipality with specific daycare availability on cognitive skills must only be mediated by daycare attendance. A violation would occur if municipalities that spend more on daycare also invest more in other skills-enhancing public policies, such as public libraries. However, birth months in this context are plausibly random, so children born in different months should not benefit more from other municipal policies.

Formally, the identification arises from the interaction of an excluded but endogenous quasi-IV - local daycare availability - with one exogenous included quasi-IV - random assignment to the month of birth (Bruneel-Zupanc and Beyhum, 2024). Local daycare availability is endogenous, but it is excluded, meaning its effect on cognitive skills is mediated solely through daycare attendance. On the other hand, being born in Spring is arguably exogenous, but included, i.e. the month of birth has a direct effect on the cognitive test scores.

Spring is exogenous and included. Birth in Spring is arguably exogenous: while possibly linked to unobservable traits, Spring births do not vary by maternal education, employment, or IPS—a socio-economic status measure[15] - (Figure 7.3), and most observable characteristics are balanced between kids born in Spring or not, as shown in the balance table 7.8. Empirical evidence shows birth timing is uncommon in France (Moreau, 2023); in 2005, only 14% of births were planned for specific times (Régnier-Loilier and Wiles-Portier, 2010). Previously, birth seasonality correlated with maternal occupation (Grenet, 2009), though this trend is decreasing

[15]The IPS is an indicator that assigns to every profession a numerical indicator that sums the average socio-economic and cultural conditions. For a given profession, the value of the index corresponds to the average of the first factor score from a multiple correspondence analysis of family characteristics, collected through a panel of qualitative questions to students (Rocher, 2016).

except among elementary school teachers (Régnier-Loilier and Wiles-Portier, 2010). Excluding such teachers, the study's first stage remains robust, indicating results aren't influenced by this timing (column 1 in Table 7.16).

Being born in Spring is included: the month of birth has a direct impact on the cognitive scores as there is a consensus in the literature that older children generally perform better than younger ones[16] and DEPP data shows a strong linear correlation between test score ranks and birth month (Figure 7.4)[17]. Controlling for the month of birth - either linearly or with month fixed effect - clearly changes the coefficient of $Spring_i$, but leave the coefficient of the interaction $Spring_i \times Availability_t$ virtually unchanged (Table 7.17). Additional robustness checks involve running placebo tests with interactions for births in Summer, Fall, and Winter; none show significant positive effects in reduced form (Table 7.15) or the first stage (Table 7.10). The Spring definition (births in March, April, or May) remains robust when including children born in June or February (Table 7.17).

Daycare availability is endogenous and excluded. Local availability[18], in itself, is likely to be endogenous for two main reasons: (i) municipalities with more childcare might also offer better environments for child development for other reasons; (ii) parents may choose to sort into different municipalities.

To mitigate (i), we include municipality observable characteristics, including municipality-level policies that are likely to have an impact on kids' cognitive development, in particular the number of child-parent drop-in center (*lieux d'accueil enfants parents*) and libraries, that often organize activities for toddlers[19] (Tables 7.26 and 7.27).

To address (ii), we show that that local daycare availability is uncorrelated with the quality of high schools (Figure 7.24), which affects household location decisions (Bayer et al., 2007; Fack and Grenet, 2010). Clearly, parents or parents-to-be may decide their residence place for characteristics of the municipalities that are correlated with the daycare availability. However, thanks to the interaction, we don't need the local daycare availability to be endogenous for the identification to hold (Bruneel-Zupanc and Beyhum, 2024).

The local daycare availability is excluded: the effect of it on cognitive scores is likely to be only mediated by the actual daycare attendance. One could argue that the effect is mediated through maternal labor market participation: with the provision of daycare services, mothers are enabled

[16]For international evidence of it, see Bedard and Dhuey (2006), for a review of the ample literature on it, see Urruticoechea et al. (2021).

[17]After controlling linearly for the month of birth, being born in Spring has a positive correlation with cognitive scores (Figure 7.5).

[18]In the literature, local availability is often used with staggered childcare reforms (Baker et al., 2008; Haeck et al., 2018; Baker et al., 2015; Kottelenberg and Lehrer, 2017; Cascio, 2009; Havnes and Mogstad, 2011; Noboa-Hidalgo and Urzua, 2012; Havnes and Mogstad, 2015; Felfe et al., 2015; Felfe and Lalive, 2018; Jessen et al., 2020; Pora, 2020), but there is no substantial increase in childcare supply in the French context. In our cross-sectional analysis, it compares Danish municipalities that offer daycare spots with those that do not (Gupta and Simonsen, 2010, 2016).

[19]The other municipality covariates are: degrees of urbanization, labor force participation for men and women aged 25-54 (i.e. those more likely to be parents) in the 2013 census, percentage of occupational categories (self-employed, manual workers, managers, middle managers) in the 2013 census, percentage of employed in different industries every year, the percentage of homeowners and vacant houses in the 2013 census, median income in the municipality in 2013

to work, thereby exerting a direct, positive influence on the child's cognitive development. Although this mechanism cannot be completely ruled out, Pora (2020) reports no significant effect of daycare openings in France on maternal labor supply and the $Spring_i \times Availability_m$ instrument shows no impact on maternal employment likelihood (Table 7.21).

The monotonicity assumption is likely to hold: it is unlikely that parents who would send their child not born in Spring to daycare without local daycare options would choose not to when both conditions are present. The coefficient of the interaction in the first stage is never negative in all subsamples and under all robustness checks, which is a necessary but not sufficient test of monotonicity.

To account for unobservable time-varying differences at the municipality level, we include municipality × year fixed effects, which also absorb the variation in the local daycare availability, since it is defined at the municipality and year level. Instead of a $Spring_i$ dummy, we include month birth fixed effects.

$$\text{Test score}_{im} = \gamma_1 Spring_i \times Availability_m + \alpha_{mt} + \alpha_{\text{Birth month}} + \epsilon_{im} \tag{4}$$

$$Daycare_{im} = \beta_1 Spring_i \times Availability_m + \delta_{mt} + \delta_{\text{Birth month}} + \eta_{im} \tag{5}$$

4.2 Two-sample two-stage least squares (TS2SLS)

To compute a LATE estimator for the impact of attending daycare for compliers to the interaction instrument the coefficient of the instrument on the dependent variable (intention to treat, ITT) needs to be rescaled by the coefficient of the instrument on the daycare attendance (percentage of compliers) (Imbens and Angrist, 1994). To bridge the results from the first-stage and reduced-form regressions, we use the two-sample two-stage least square estimator, or TS2SLS (Inoue and Solon, 2010). Compared to a back of the envelope calculation, results are similar (section 7.3), but the two-sample two stage least square (TS2SLS) estimator allows to rescale more accurately the two coefficients, taking into account the covariates and adjusting the standard errors for the reduced degrees of freedom.

The FL survey is our "first stage sample" and the DEPP administrative dataset is the "second stage sample". The main assumptions for the TS2SLS to be consistent are:

1. The two samples are i.i.d. random vectors from the same underlying population. Both datasets are cross-sectional, so serial correlation is not an issue. The DEPP data includes all children attending primary schools in France. While some children are missing test scores due to absences, the number is low (see Data section 3) and does not indicate selection bias (Figure 7.25). For the FL survey, non-response issues are addressed with weights. Therefore, the underlying population consists of children living with at least one parent in France at the age of 6 attending primary school. Given the minimal number of children not living with a parent[20], we can safely assume that the two datasets capture the same underlying population.

[20] According to DREES, around 80,000 children under 18 live in foster houses. The number of children aged 6 out of this population is likely to be negligible.

2. The coefficient of the instrument on the probability of attending daycare needs to be the same in the two samples.
3. The exclusion restriction of the instrument holds in both samples. We supported the exclusion restriction earlier, and if DEPP and FL sample represent the same population, it should hold true for both.
4. The covariance between the instrument and the daycare attendance needs to be the same in the two samples. It is impossible to test this, as we do not observe the daycare attendance in the DEPP data, but results robust to using different data sources for the first stage (Table 7.23) are reassuring.

In practice, the estimation of TS2SLS estimator boils down to (Khawand and Lin, 2015) generating an estimate of the first stage coefficient of the instrument and covariates on daycare attendance using the FL sample. Then, we use these coefficients to compute fitted values $\widehat{Daycare}$ in the DEPP dataset. Finally, we regress test scores on $\widehat{Daycare}$ and covariates to estimate the coefficient of attending daycare on cognitive scores.

4.3 Compliers analysis

The LATE parameter we estimated is a local treatment measure, so we want to know what are the characteristics of compliers to the instrument $Spring_i \times Availability_m$. This is especially relevant when the share of non-compliers is high (Marbach and Hangartner, 2020), as in our natural experiment, where less than 10% of the population comply with the instrument.

We defined availability as a continuous measure (Formula 1), but to define compliers more easily we use a binary specification, defining the binary availability as taking value 1 if there is at least one daycare center in the municipality (which happen in 25.6% of the municipalities, where 71.5% of children live).

$$\begin{aligned}\text{Test scores}_{im} = {} & \delta_1 Spring_i \times \mathbf{1}\{Availability_m > 0\} + \delta_2 \mathbf{1}\{Availability_m > 0\} \\ & + \delta_3 Spring_i + \mathbf{X}_{im} + \alpha_{d(m)} + \epsilon_{im}\end{aligned} \tag{6}$$

The results of this specification of the main regression are in the fourth column of Table 7.19. With this binary specification, $Daycare(Z)$ can take value $Daycare(1)$ if $Spring_i \times Availability_m$, is equal to 1 or $Daycare(0)$.

In order to identify the characteristics of compliers, we need to assume the independence of the instrument from the unit compliance, monotonicity and relevance (Marbach and Hangartner, 2020).

To get to the formula of the observables for compliers, first we divide the mean of the whole sample into 4 groups:

$$\begin{aligned}\mathbb{E}[X] = \mathbb{E}[X|D(1) = 1, D(0) = 0]\mathbb{P}[D(1) = 1, D(0) = 0] \textit{ (Compliers)} \\ + \mathbb{E}[X|D(1) = 0, D(0) = 1]\mathbb{P}[D(1) = 0, D(0) = 1] \textit{ (Defiers)} \\ + \mathbb{E}[X|D(1) = D(0) = 1]\mathbb{P}[D(1) = D(0) = 1] \textit{ (Always-takers)} \\ + \mathbb{E}[X|D(1) = D(0) = 0]\mathbb{P}[D(1) = D(0) = 0] \textit{ (Never-takers)}\end{aligned} \tag{7}$$

Thanks to monotonicity, we can rule out defiers. Rearranging the terms, we get the formula for the observable characteristics of compliers:

$$\begin{aligned}\mathbb{E}[X|D(1) = 1, D(0) = 0] = \frac{1}{\mathbb{P}[D(1) = 1, D(0) = 0]}\Big(\mathbb{E}[X] - \\ \mathbb{E}[X|D = 1, Z = 0]\mathbb{P}[D = 1, Z = 0] \textit{ (Always-takers)} - \\ \mathbb{E}[X|D = 0, Z = 1]\mathbb{P}[D = 0, Z = 1] \textit{ (Never-takers)}\Big)\end{aligned} \tag{8}$$

Thanks to the independence assumption, we can use the observed mean for always-takers and never-takers.

$$\begin{aligned}\bar{X}_{compliers} = \frac{1}{\text{Share of compliers}}\Big(\bar{X}_{sample} - \bar{X}_{always-takers} \times P(always - takers) - \\ \bar{X}_{never-takers} \times P(never - takers)\Big)\end{aligned} \tag{9}$$

In practice, we subtract the covariate mean of observable always-takers and never-takers, weighted by their share, from the covariate mean of the entire sample and bootstrap errors, using $K = 500$.

We then study what is the main counterfactual type of care for the compliers with the instrument by substituting the indicator variable for daycare attendance with an indicator variable for other types of childcare (childminder, grandparents, parents).

4.4 Quantile regression

The rationale to study the effect of daycare attendance on the distribution of cognitive skills is that, following Bitler et al. (2014), we want to assess the 'compensatory' hypothesis - which anticipates the most significant improvements among individuals at the lower end of the skill distribution (Cunha et al., 2010) -, in comparison to the 'skills-beget-skills' hypothesis - which anticipates the most substantial improvements among individuals at the higher end of the skill distribution (Cunha and Heckman, 2007)[21]. This is closely related to what is the counterfactual type of care for children at different points of the skills distribution.

[21] Most of the literature on universal childcare for children aged 0-2 (for example, all papers summarized in Table 7.1) find evidence in favor of the compensatory hypothesis. However, there is also some evidence finding greater gains for more advantaged children (Heckman et al., 2013; Deming, 2009; Gormley Jr et al., 2005), in particular when the disadvantage is defined using the birth weight (see evidence from the US Infant Health and Development Program, for example Duncan and Sojourner 2013), or no differential impact for more or less advantaged children (Carta and Rizzica, 2018).

To do it, as for the compliers analysis, we discretize the availability measure into a binary measure. Results are robust to using the continuous definition of availability (Figures 7.6 and Table 7.35).

This coefficient should be interpreted as an ITT, as in the main analysis, to be rescaled by the percentage of compliers with the instrument to find a LATE on the compliers that find a place in daycare thanks to being born in Spring in a municipality with a daycare center.

The model we estimate is:

$$\begin{aligned}\delta_1(\tau) =& F^{-1}(Score_\tau|Spring_i = 1, Av = 1) - F^{-1}(Score_\tau|Spring_i = 0, Av = 1)- \\ & [F^{-1}(Score_\tau|Spring_i = 1, Av = 0) - F^{-1}(Score_\tau|Spring_i = 0, Av = 0)]\end{aligned} \tag{10}$$

We use bootstrapped standard errors with K = 1000.

The support of the test scores is likely to be continuous, given that the standardized test scores are a continuous variable and that the number of observations is high, so the cumulative distribution function can be inverted and the quantile of the variable is defined. We do not include covariates in the quantile regression, as the baseline results are virtually unchanged when we include them (column 3 of Table 7.3). For the quantile coefficient to be interpreted as individual effect, the rank invariance assumption needs to hold (Heckman et al., 1997). This is unlikely to hold in this sample: the same child, with the same characteristics, is likely to be at a very different part of the distribution were they born in Spring, given the maturity effect at the moment where the test is administered. Nevertheless, as Bitler et al. (2014), Havnes and Mogstad (2011) and Havnes and Mogstad (2015), we use quantile regression to assess childcare's impact on skills distribution rather than individual effects. Larger quantile coefficients at the top than the bottom suggest childcare increases inequality; if smaller, it reduces inequality.

4.5 Effect of quality of childcare

Given that the teachers/students ratio is defined at the national level, we measure quality using the type of management (public, private, non-profit) and the type of daycare (see description in Section 2).

In particular, we compare the reduced form effect of being born in Spring in a municipality with a certain daycare quality to being born in a municipality without daycare centers. For example, in the case of management:

$$\begin{aligned}\text{Test score}_{im} =& \gamma_1 Spring_i \times \text{Availability in public}_m + \gamma_2 Spring_i \times \text{Availability in private}_m + \\ & \gamma_3 Spring_i \times \text{Availability in non-profit}_m + \gamma_4 \text{Availability in public}_m + \\ & \gamma_5 \text{Availability in private}_m + \gamma_6 \text{Availability in non-profit}_m + \\ & \gamma_7 Spring_i + \alpha_d + \epsilon_{im}\end{aligned} \tag{11}$$

Where the reference category is composed of municipalities without a daycare center. We use Holm-Bonferroni standard errors to account for multiple comparison. When rescaling the reduced form coefficient by the first stage of every management and type, we use two-sample two-stage least squares: in particular, we only include the type we want to test (e.g. public availability) in the first stage, and control for the other types (e.g. private availability and non-profit availability) in the second stage.

5 Results

5.1 Reduced form

Table 5.1: Overview of the results.

Model:	(1) First stage	(2) Reduced form	(3) Reduced form	(4) TS2SLS	(5) TS2SLS
Dependent Variable:	Daycare	Maths (SD)	French (SD)	Maths (SD)	French (SD)
Variables					
Spring × Availability	0.1137***	0.0128**	0.0150***		
	(0.0332)	(0.0048)	(0.0047)		
$\widehat{Daycare}$				0.239***	0.136***
				(0.024)	(0.017)
Fixed-effects					
Month of birth	Yes	Yes	Yes	Yes	Yes
Municipality × Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations:	45,480	3,524,383	3,535,553	3,524,383	3,535,553
Mean DV:	0.1201	0.00724	0.00429	0.00724	0.00429
F-test:	30.569				

Source. Authors' calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.
Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). Standard errors, clustered at the municipality level, are reported in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

The reduced form coefficient of the instrument on cognitive skills is significant and positive, with a magnitude of 1.5% of a SD (Table 7.3). The interpretation of the magnitude is detailed in section 7.2 in the Appendix: keeping the number of births constant, one more daycare place in a municipality increases the test scores of children born in Spring by 1.5% of a SD.

The results remain consistent with the inclusion of department fixed effects (columns 3 and 4, table 7.3) and municipality-level covariates (columns 5 and 6, table 7.3). Replacing the Spring birth indicator with month of birth fixed effects leaves results unchanged (columns 7 and 8, table 7.3). Results also hold with month and Municipality × Year fixed effects (columns 9 and 10, table 7.3), which absorb local daycare availability variations and any other time-varying differences at the municipality level. Adding School × Year fixed effects to account for advantaged students' self-selection into schools (columns 1 and 2, table 7.30) also yields robust results.

Results are also robust to using heteroskedasticity-robust standard errors instead of errors clustered at the municipality level (Table 7.38) or adding school-level characteristics to the reduced form regression (Table 7.28 for Maths and 7.29 for French). A potential issue is the inclusion of tests from September 2020, as these children missed the last 3 months of kindergarten due to school closures from March 14 to June 14, 2020. However, excluding these tests or adding year fixed effects does not affect the results (Table 7.30).

Results hold in all specific skills in Maths and French[22] (Table 7.32 for French, 7.31 for Maths) or ranks over test scores: keeping the number of children in the municipality fixed, a marginal daycare spot increase the rank position of a child born in Spring by 0.23 positions in Maths and 0.35 positions in French, on a scale of ranks from 0 to 100 (Table 7.14).

Table 7.4 provides the first stage results, estimated on the FL survey. While the relationship is estimated on children born before the ones in the main DEPP sample (born in 2008-2011 rather than in 2012-2016), it is useful to both show the relevance of the instrument and to rescale the reduced-form coefficient.

Local daycare availability significantly increases the likelihood of attending daycare for children born in Spring by 7.5 p.p. Given that 12% of children generally attend childcare, this effect is economically meaningful. Notably, the impact is consistent across FL and Elfe surveys (Table 7.23). In the Elfe survey, adding one daycare spot per municipality, with birth rates constant, raises the probability for Spring-born children by 10 p.p.

5.2 Two-sample two-stage least squares (TS2SLS)

The generated daycare attendance distribution is mainly between 0 and 1, matching the average actual daycare attendance rate in France (see Graph 7.2). Since we use LPM to predict the probability of attending daycare, some results are outside of the 0-1 interval. We also present results with probabilities capped at 0 and 1. Adjusting probabilities below 0 to 0 and above 1 to 1 does not alter the distribution's average and results are very similar (Table 7.5).

The TS2SLS coefficient on the daycare attendance ranges between 0.12 and 0.24 SD. These coefficients align with evidence from universal daycare in comparable countries. Meta-analysis (van Huizen and Plantenga, 2018; Magnuson et al., 2016; Shager et al., 2013; Camilli et al., 2010) shows results between 0.14 to 0.28 SD. Studies using local availability and eligibility as instruments report similar findings: 0.144 SD for US preschool attendance (Cascio, 2009), 0.15 for Spanish reading scores (Felfe et al., 2015), 0.149 for German school entry exams (Felfe and Lalive, 2018). The 0.19 SD effect on vocabulary in French children (Berger et al., 2021) supports the positive impact over time of daycare on cognitive skills. In contrast, US-focused literature often sees no medium-term significant effects (Currie and Thomas, 1995; Ludwig and Phillips, 2007), e.g., by the end of first grade (US Department of Health, 2012) or at age 8 (Schweinhart, 2005; Chetty et al., 2011).

5.3 Compliers analysis

Since in our context we cannot use any natural experiment, we must ensure our instrument does not target an unusual subset of compliers in order to draw informative policy conclusions.

[22]For Maths, these are number recognition, collocation of numbers on a line, problem-solving and geometry; for French, these are letter recognition, phonology, and oral comprehension.

We estimate that around 10% of the sample are compliers, with 10% always-takers, and 80% never-takers. The low share of compliers aligns with the conservative instrument definition, where being born in Spring in a municipality with a daycare is enough to be considered "treated," though daycare spots are almost always insufficient for all children.

Results for the compliers analysis are reported in the Appendix (Figures 7.8 and 7.9). At the child level, children who comply with the instrument are not different from the rest of the sample in terms of migrant background, gender, age or birth order. The mothers of compliers, however, are more likely to be born in France and French citizens, to be younger than the mothers of always-takers and never-takers, and to be employed. They do not differ in terms of socio-economic status (measured with the IPS) or level of education. Families are more likely to be biparental, but less likely to be married, while there is no significant difference in terms of number of siblings. Compliers are much more likely to live in rural municipalities. This explain the other differences in the characteristics of municipalities where compliers live: they houses are less likely to be overcrowded and the share of homeowners is higher, wages tend to be lower, with a higher share of self-employed and manual workers and a lower share of managers, but the median municipality income is not different. Overall, the subset of compliers does not exhibit particularly unusual characteristics.

Table 5.2 presents a the main cross-sectional first-stage specification and alternative specifications in which the dependent variable is take-up of alternatives to daycare: care by childminders, parents, or grandparents. The coefficient of the instrument is negative, large and significant for the parental care, suggesting that compliers' main counterfactual type of care is home care. This is in line with evidence from Maurin et al. (2008), who found that kindergarten at 2 attendance increases the labor force participation of mothers. The instrument thus seems to tackle a specific type of compliers: those who decreased parental care significantly. This may help to explain why the cross-sectional reduced-form results are positive: coherently with Kline and Walters (2016), Feller et al. (2016) and Zhai et al. (2014), the effect of daycare attendance may be larger when the counterfactual is parental care.

Table 5.2: Margins of adjustment of changes in daycare availability and changes in the instrument

Dependent Variables:	Daycare	Childminder	Parents	Grandparents
Model:	(1)	(2)	(3)	(4)
Variables				
Spring × Availability	0.0781*	-0.0296	-0.0729*	0.0409*
	(0.0401)	(0.0263)	(0.0383)	(0.0213)
Fixed-effects				
Municipality × Year	Yes	Yes	Yes	Yes
Month of birth	Yes	Yes	Yes	Yes
Fit statistics				
Dependent variable mean	0.12016	0.28026	0.51515	0.05657
F-test	11.577	16.276	12.828	6.6920

Clustered (Municipality) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

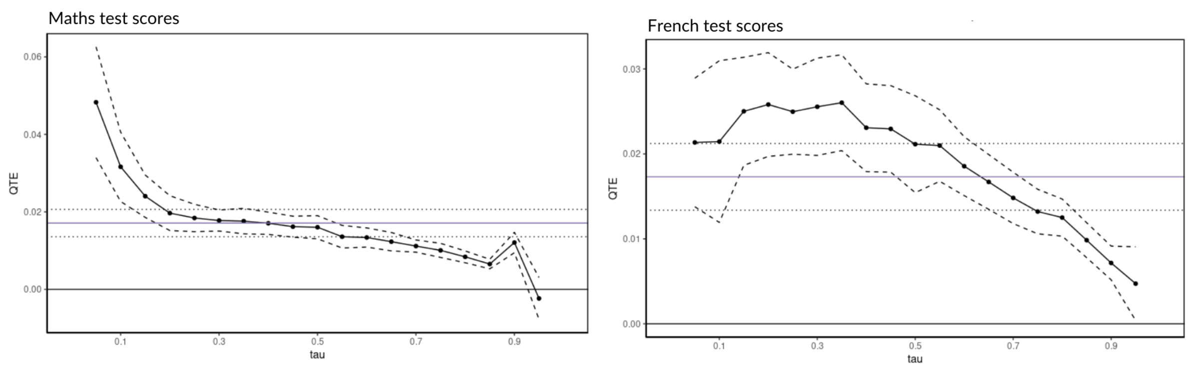
Source. Authors' calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.
Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). The first column is the baseline specification. The other columns estimate the same specification on different outcomes: respectively, the likelihood of being cared by a childminder (column 2), by parents (column 3) and grandparents (column 4). Heteroskedasticity robust and clustered at the municipality level standard errors are reported in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

5.4 What is the effect driven by?

The positive impact of childcare attendance on cognitive scores is mainly driven by children of families with a low socio-economic status, explaining its greater effect on those at the lower end of skill distribution. From a policy point of view, most of the positive effect is driven by publicly managed daycare centers.

5.4.1 Quantile regression

Figure 5.1: Results of the quantile regression defining the daycare availability as a binary variable (Equation 6) for French and Maths test scores. The solid purple line is the OLS coefficient for the whole sample, dotted lines are the confidence interval bounds.

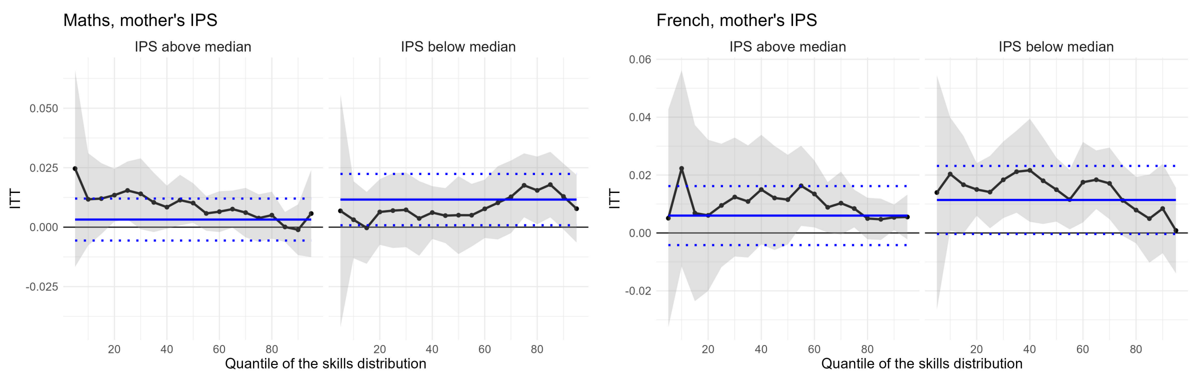


The results of the quantile regression (equation 6) are reported in Figure 5.1. The effects are significantly positive across the distribution, except at the 95th percentile (Figure 7.6). Lower percentiles show larger coefficients: specifically, up to the 15th percentile in Maths, they differ statistically from the average coefficient. For higher percentiles, particularly from the 85th onward in the French test distribution, the coefficients are statistically lower, though still significantly positive[23].

These results align with non-linear difference-in-differences from Norway (Havnes and Mogstad, 2015), Canada (Kottelenberg and Lehrer, 2017), and the US (Bitler et al., 2006). The reduced-form coefficient is positive across the entire distribution in France but significantly negative above the 80th percentile in Norway (Havnes and Mogstad, 2015), indicating that while daycare benefits all children in France, distributional effects are more limited than in Norway. Results also match the findings for single-parent families in Kottelenberg and Lehrer (2017), although with more volatility for individual quantiles. According to Bitler et al. (2014), similar reduced-form results show stronger effects at the lower end of the distribution and smaller positive effects at the top for pre-elementary school tests (PPVT), with no significant results for first-grade tests.

We link the larger effect at the bottom with the different counterfactual type of care. For children born in 2012, we can directly observe their parents' profession, and we can use the IPS index to split the sample between high- and low-SES families. Once we do that, we cannot reject the hypothesis that the coefficients are equal along the skills distribution, but higher for children of disadvantaged families (Figure 5.2). This connects the concept that daycare is more beneficial for low-income families (Fort et al., 2020; Drange and Havnes, 2019) with the distributional effects of daycare (Havnes and Mogstad, 2015; Kottelenberg and Lehrer, 2017; Bitler et al., 2014): children born in low-SES families tend to be at the bottom of the skills distribution, thus the decreasing slope in Figure 5.1.

Figure 5.2: Results of the quantile regression defining the daycare availability as a binary variable (Equation 6) for French and Maths test scores, disaggregating by high and low mother socioeconomic status. The solid blue line is the OLS coefficient for the whole sample, dotted lines are the confidence interval bounds.



[23]Results are robust to the exclusion of the Ile-de-France region (Figure 7.7).

5.4.2 Which daycare?

The positive effect of daycare is entirely driven by childcare centers run by local authorities, rather than those by private firms or non-profits (Table 5.3). This positive effect holds true across the skills distribution (Figure 5.3). The collective type of daycare, which is more common in publicly managed centers, drives the positive coefficient (Table 5.4). Overall, results suggest that even in countries with high formal childcare coverage like France, enhancing quality can further boost early human capital accumulation.

Figure 5.3: Results of the quantile regression defining the daycare availability as a binary variable (Equation 6) for French and Maths test scores, disaggregating by childcare management.

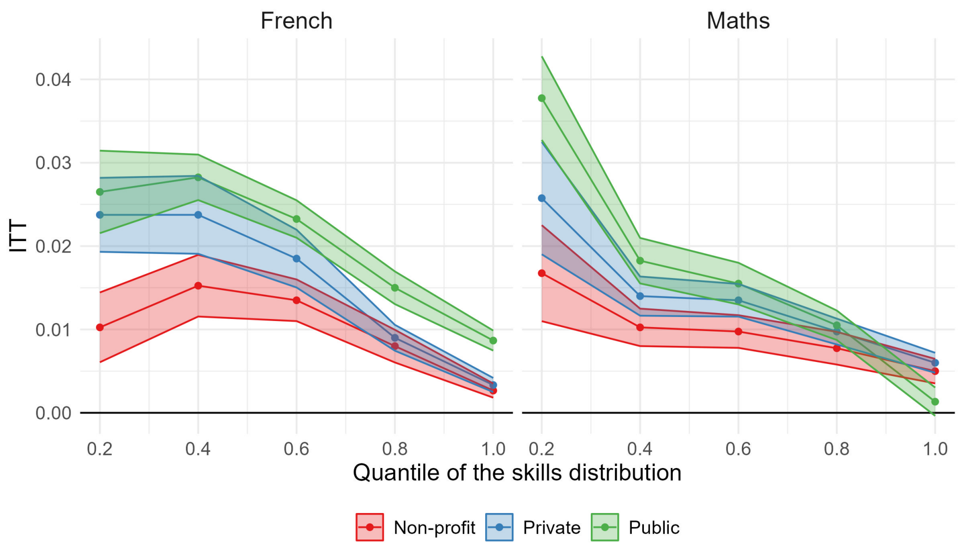


Table 5.3: Public vs. private daycare availability.

Model:	(1) First stage	(2) Reduced form	(3) Reduced form	(4) TS2SLS	(5) TS2SLS
Dependent Variable:	Daycare	Maths	French	Maths	French
Variables					
Spring × Public av.	0.0821**	0.0172**	0.0176**	0.030	0.109***
	(0.0394)	(0.0073)	(0.0073)	(0.039)	(0.033)
Spring × Private av.	0.1115	0.0072	0.0051	0.007	-0.121
	(0.1162)	(0.0182)	(0.0187)	(0.221)	(0.154)
Spring × Non-profit av.	0.0209	0.0031	0.0003	-0.001	0.051
	(0.0354)	(0.0090)	(0.0094)	(0.033)	(0.049)
Fixed-effects					
Month of birth	Yes	Yes	Yes	Yes	Yes
Municipality × Year	Yes	Yes	Yes		
Department				Yes	Yes
Municipality controls				Yes	Yes
Fit statistics					
Observations:	45,480	2,188,220	2,192,461	2,188,220	2,192,461
Mean DV:	0.1201	0.00724	0.00429	0.00724	0.00429
F-test:	30.569				

Source. Authors' calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.
Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). Standard errors, clustered at the municipality level, are reported in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 5.4: Collective vs. non-collective daycare availability.

Model:	(1) First stage	(2) Reduced form	(3) Reduced form	(4) TS2SLS	(5) TS2SLS
Dependent Variable:	Daycare	Maths	French	Maths	French
Variables					
Spring × Collective av.	0.2727*	0.0403*	0.0488**	0.1053***	0.0958***
	(0.1396)	(0.0223)	(0.0213)	(0.0119)	(0.0142)
Spring × Non-collective av.	-0.0051	-0.0096	0.0005		
	(0.0635)	(0.0151)	(0.0153)	()	()
Fixed-effects					
Month of birth	Yes	Yes	Yes	Yes	Yes
Municipality × Year	Yes	Yes	Yes		
Department				Yes	Yes
Municipality controls				Yes	Yes
Fit statistics					
Observations:	45,480	445,429	446,217	445,429	446,217
Mean DV:	0.1201	0.00724	0.00429	0.00724	0.00429
F-test:	30.569				

Source. Authors' calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.
Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). Standard errors, clustered at the municipality level, are reported in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

6 Conclusion

In this paper we show a positive impact of daycare attendance for children aged 0 to 2 on their numeracy and literacy skills measured when they are 6. The reduced form results, from the

DEPP administrative data, show that for all children in France, on average, the reduced form coefficient of the impact of the instrument on the cognitive abilities is small but significant. However, if reduced-form results are rescaled by the first stage estimated on the FL survey, the LATE coefficients are in the order of magnitude of 0.12-0.24 SD for compliers. There is significant heterogeneity in the impact of the reduced form coefficient across different types of daycare and management, even in a context where formal childcare is widespread such as France. Shedding some light on the counterfactual type of childcare, we find that the compliers tend to live in rural areas and that their main alternative type of care is parental care, which explains the positive impact of daycare on cognitive development.

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7 Appendix

7.1 Funding

Apart from kindergarten at 2, that is funded by the Ministry of Education, childcare arrangements are mainly funded through two benefits: the *prestation de service unique* (PSU) and the *complément de libre choix du mode de garde* (CMG). Childminders, nannies and some microcrèches are financed through CMG, which families receive from CAF, while daycare is mainly financed through PSU, a benefit that daycare structures receive from CAF, except for daycare centers funded by employers. Thus, salaries for daycare workers are centrally funded, while childminders and nannies need to set their own salaries.

The PSU benefit covers 66% of the hourly cost of childcare within the limit of the ceiling price set annually by the Cnaf, after the deduction of family contributions. This amount depends on whether the daycare center provides diapers and meals. The hours that are counted to receive the PSU are a ratio of "hours billed/hours of actual presence" from 2014 on, while before only the hours billed to parents were taken into account. While this reform happens during the period we are considering, it is not likely to impact the decision of the childcare arrangement, as there is little difference for the parents and the cost of the daycare is not one of the main reasons why parents prefer daycare (see Figure 7.21). However, it may marginally affect the quality of teacher/students interactions[24]. We run a robustness test with year fixed effect to account for the potential differences.

The total hourly cost for each child in daycare is estimated to vary between 8.91€ and 9.40€ in the period 2012-2016 (ONAPE, 2011), accounting for around 15.000€ per year for each child attending daycare full-time (ONAPE, 2011; De Bodman et al., 2017). This cost is higher than the expenditures for comparable programs in Norway in the 1970s (Havnes and Mogstad, 2015), Denmark (Gupta and Simonsen, 2016) and Canada (Baker et al., 2008), and the main reason is the lower teacher/children ratio, respectively of 1:8, 1:12 and 1:7.

Families pay a part of this amount that varies according to their resources and the number of children, except for kindergarten at 2, that is free. For example, in 2016, a family earning twice the minimum wage paid 5% of the total cost (134€ per month), and a family earning six times the minimum wage paid 30% of the total cost, 378€ per month (Figure 7.13). On average, families pay around 20% of the total cost (ONAPE, 2011), which is less than 2€ per hour (Figure 7.1). This represents on average 4% of the total income of the family, as estimated with the survey on childcare arrangements conducted by Drees (Villaume, 2015).

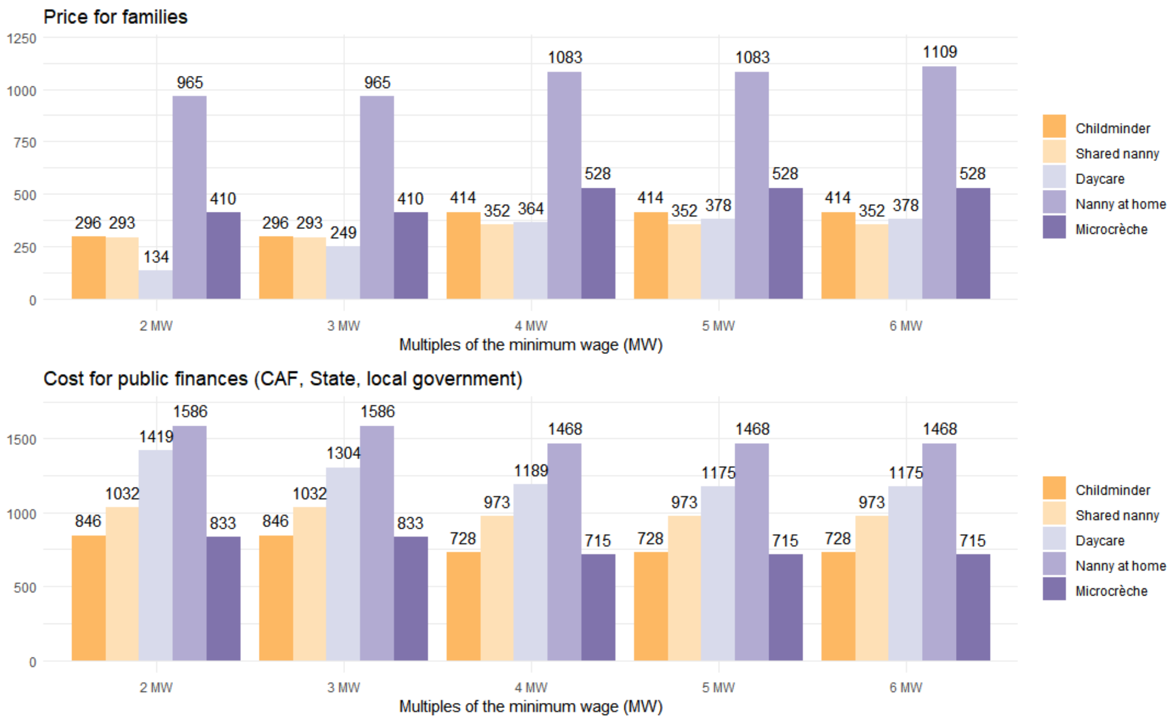
Social security (CAF) pays around 66% of the cost through the PSU, an amount decreasing in the income of the family. CAF is also in charge of granting funds for investment and renovations of daycare centers.

Local government - usually municipalities, sometimes with the help of the department - pay the remaining 10-20% of the cost. This amounts to around 3000€ per child/year: since it is politically costly to shut down a crèche, municipalities may be wary before opening a new daycare center, knowing that they will have to bear this cost (De Bodman et al., 2017). This cost is a worse burden for poorer and rural municipalities. In addition to the PSU, CAF can provide additional funding when a "childhood and youth" contract is signed between the CAF and the establishment, up to 55% of the quota normally paid by the municipality. Such a contract is signed with approximately half of the municipalities.

A further way the State finances childcare is through a monthly tax credit and the deduction of contributions, which amounts to 2€ per hour of childcare arrangement. This does not vary with the family income and amounts to 96€ per month in the case of daycare or licensed childminders (ONAPE, 2011).

[24] For example, in a website managed by daycare workers, they complain about this rule causing them to talk less to parents and other problems in invoicing informal gatherings such as end-of-year parties.

Figure 7.1: Median hourly price for families. Source: CAF.



The second way childcare arrangements are financed is through the *complément de libre choix du mode de garde* (CMG). In this case, childminders, nannies or microcrèches set their prices, families pay and receive a benefit from CAF, that depends on the number of dependent children, household resources and cost of childcare. Prices set still need to be lower than some thresholds[25]. Moreover, at least one member of the family needs to work at least one hour or receive unemployment benefits, and the childcare arrangement needs to be used for at least 16 hours per week.

While the family needs to pay at least 15% of the total price in case it receives the CMG, the benefit is relatively generous. A comparison of the monthly cost of each option for the family, the CAF and public finances (State, CAF, local government) is reported in Figure 7.13. An overview of how many families receive CMG and for which childcare arrangement is reported in Figure 7.18 and shows that is is mainly used to fund childminders, coherently with Borderies (2013). If a parent takes care of the child, they receive a flat-rate benefit (up to 500€ per month if the parent stops working, less if the parent works part-time) until the child reaches the age of three. In 2015, 61 per cent of low qualified mothers compared to 22 per cent of highly qualified mothers claimed this benefit (ONAPE, 2011). Clearly, this causes the characteristics of families choosing different options to be different (Table 7.7, based on FL survey data).

7.2 Interpretation of the coefficient of interest

We substitute the definition of $Availability_m$ (equation 1) in the reduced form regression (equation 2) to interpret the coefficient of interest:

[25] Childminders cannot earn more than an amount per day and child cared for (55.35€ in 2023, CAF), microcrèche cannot cost more than 10€ per hour/child.

$$
\begin{aligned}
\text{Test score}_{im} =& \beta_1 Spring_i \times \frac{\text{Places in daycare centers}_{m,t}}{\text{Births}_{m,t-2} + \text{Births}_{m,t-1} + \text{Births}_{m,t}} + \\
& \beta_2 \frac{\text{Places in daycare centers}_{m,t}}{\text{Births}_{m,t-2} + \text{Births}_{m,t-1} + \text{Births}_{m,t}} + \beta_3 Spring_i + \\
& \beta_4 \text{Month of birth}_i + \mathbf{X}_{im} + \alpha_d + \eta_{im}
\end{aligned} \tag{12}
$$

The derivative with respect to the number of places in daycare centers is:

$$
\frac{\partial \text{Test score}_{im}}{\partial \text{Places}_m} = \beta_1 Spring_i \times \frac{1}{\text{Births}_m} + \beta_2 \frac{1}{\text{Births}_m} \tag{13}
$$

Thus, the coefficient of interest β_1 capture by how much one marginal place in daycare increases the test scores for children born in Spring, keeping the births in the municipality fixed. This coefficient would be biased upward if increasing the number of places in a municipality increases the births[26]. However, it is unlikely that a marginal daycare spot increases the births in the two years before. Even the births in the same year are unlikely to be affected, first because birth timing is not common in France and second because among the many reasons that drive people to decide to have children, the marginal daycare availability is not likely to play a major role.

7.3 Two-sample 2SLS

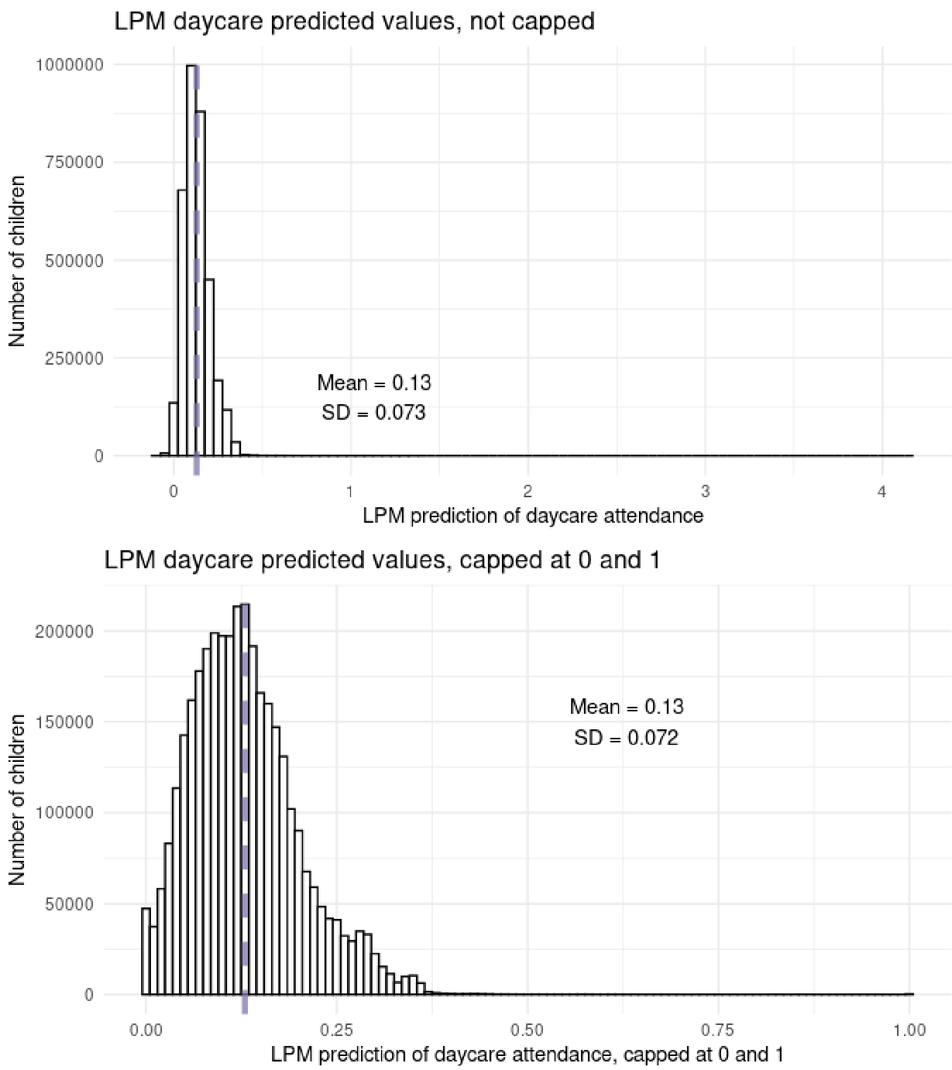
A back-of-the-envelope calculations of the rescaled effect of daycare attendance for compliers with the instrument, using the coefficients from the first stage and reduced form:

$$
\begin{aligned}
LATE_{Maths} =& \frac{E(\text{Test scores}|Interaction_{im} > 0) - E(\text{Test scores}|Interaction_{im} = 0)}{E(Daycare_i|Interaction_{im} > 0) - E(Daycare_i|Interaction_{im} = 0)} = \\
& \frac{0.0136}{0.0763} = 0.1782 \\
LATE_{French} =& \frac{0.0143}{0.0763} = 0.1874
\end{aligned} \tag{14}
$$

Where $Interaction_{im} = Spring_i \times Availability_m$.

[26] Let's say that the births depend on the places in daycare: $\text{Test score}_{im} = (\beta_1 Spring_i \times \beta_2) \frac{\text{Places}_m}{\text{Births}_m(\text{Places}_m)} + \beta_3 Spring_i + \beta_4 \text{Month of birth}_i + \mathbf{X}_{im} + \alpha_d + \eta_{im}$. Then, the true marginal effect of an additional place in daycare is: $\frac{\partial \text{Test score}_{im}}{\partial \text{Places}_m} = (\beta_1 Spring_i + \beta_2) \frac{\text{Births}_m - Places_m \frac{\partial \text{Births}_m}{\partial \text{Places}_m}}{\text{Births}_m^2}$. The bias is E(marginal effect assuming births do not depend on places – marginal effect assuming they do) $= (\beta_1 Spring_i + \beta_2) \frac{Places_m \frac{\partial \text{Births}_m}{\partial \text{Places}_m}}{\text{Births}_m^2}$. If the derivative of births with respect to places is positive, the sign of the bias is positive.

Figure 7.2: Distribution of the generated $\widehat{Daycare}$.



7.4 Graphs

7.4.1 Empirical strategy

Figure 7.3: Mother characteristics by month of birth of the child. Source: FL survey.

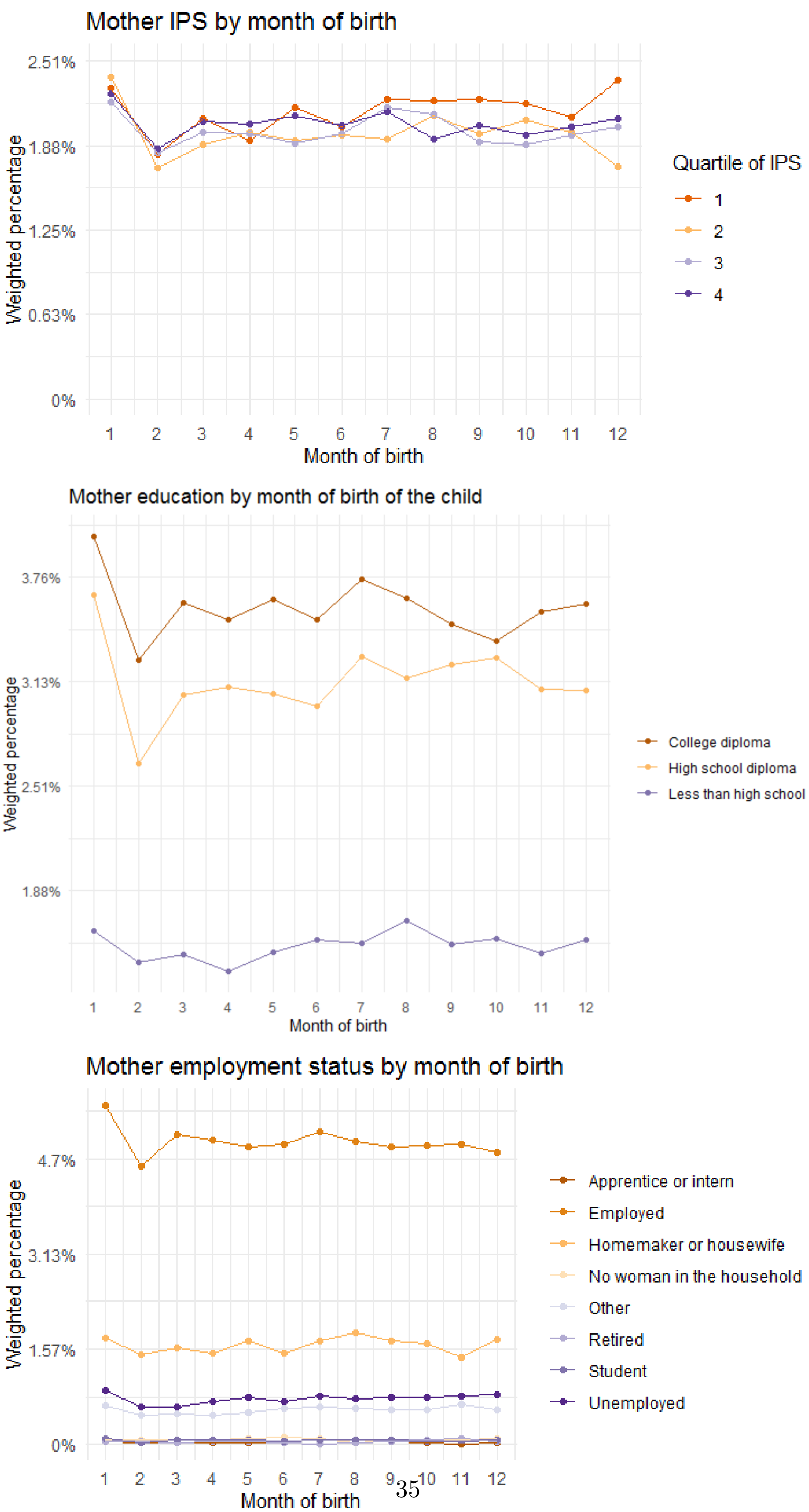


Figure 7.4: Unconditional Maths test scores by month of birth. Source: DEPP.

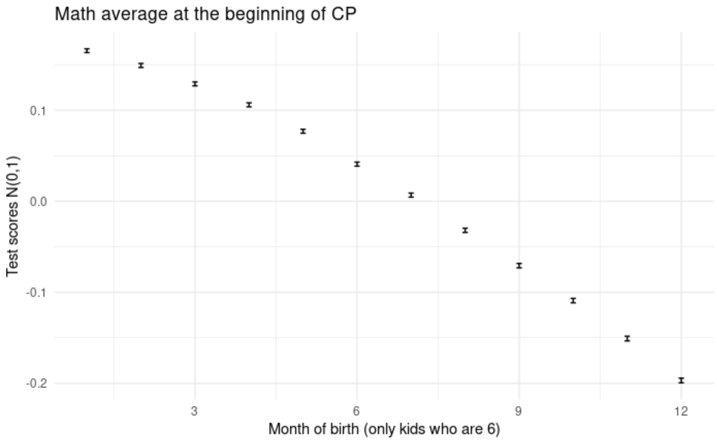


Figure 7.5: Maths test scores by month of birth, residuals after fitting an OLS regression with a linear month variable. Source: DEPP.

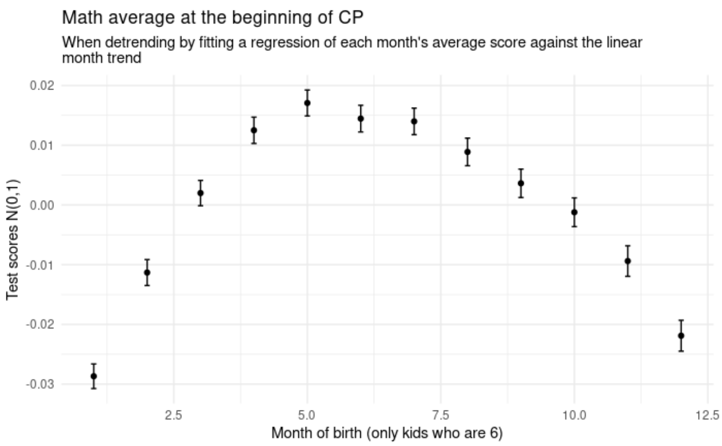


Figure 7.6: Results of the quantile regression using the main specification (Equation 2) for French and Maths test scores. The red line is the OLS coefficient for the whole sample.

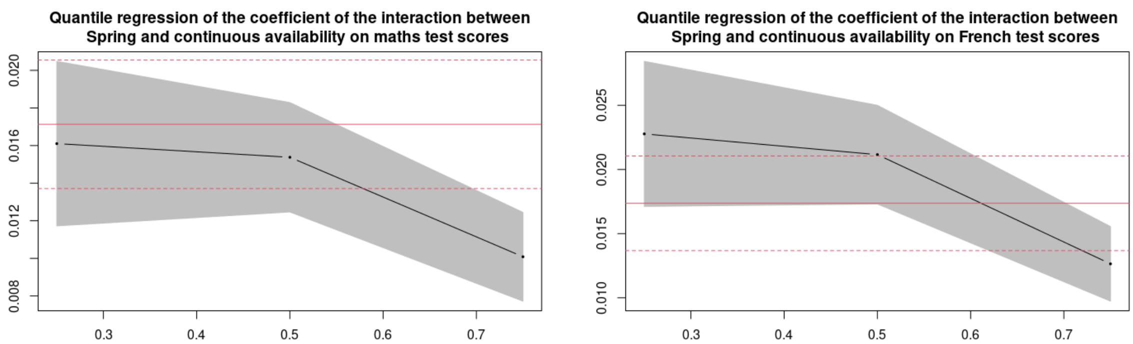


Figure 7.7: Results from the quantile regression with the binary definition of daycare availability, excluding Ile-de-France. Source: DEPP.

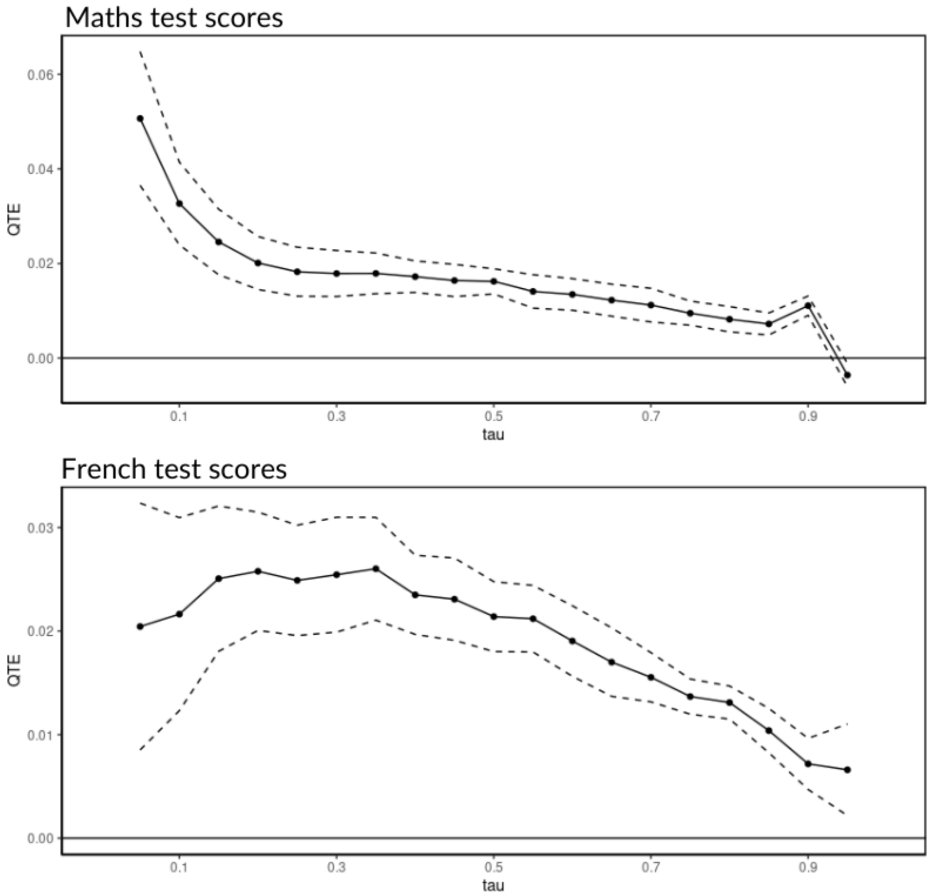


Figure 7.8: Compliers' analysis: child characteristics, mother characteristics, family characteristics. Source: FL.

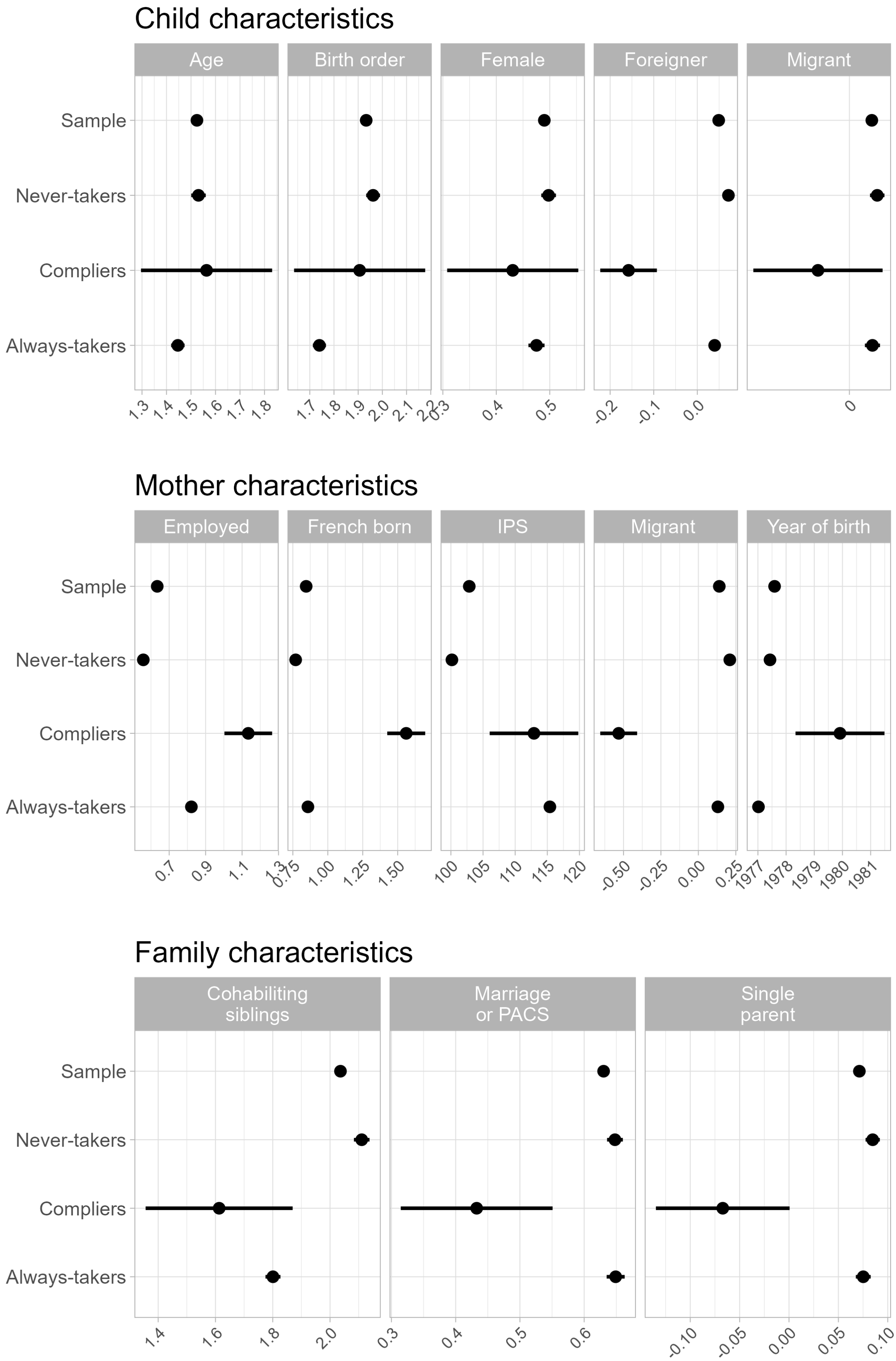
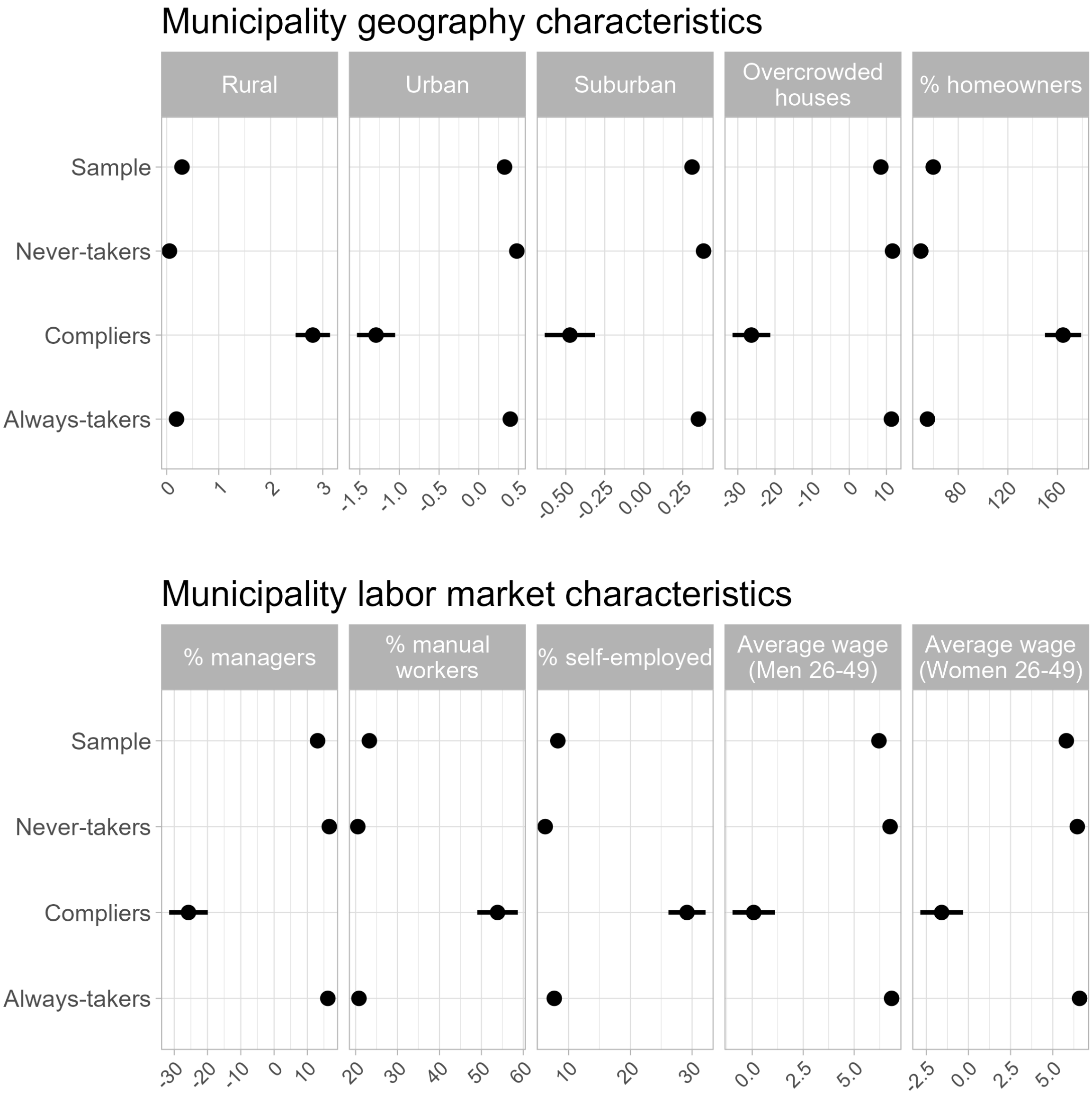


Figure 7.9: Compliers' analysis: municipality characteristics. Source: FL.



7.4.2 Daycare availability (Main source: CAF)

Figure 7.10: Childcare facilities financed by PSU, disaggregated by type and management. Source: CAF

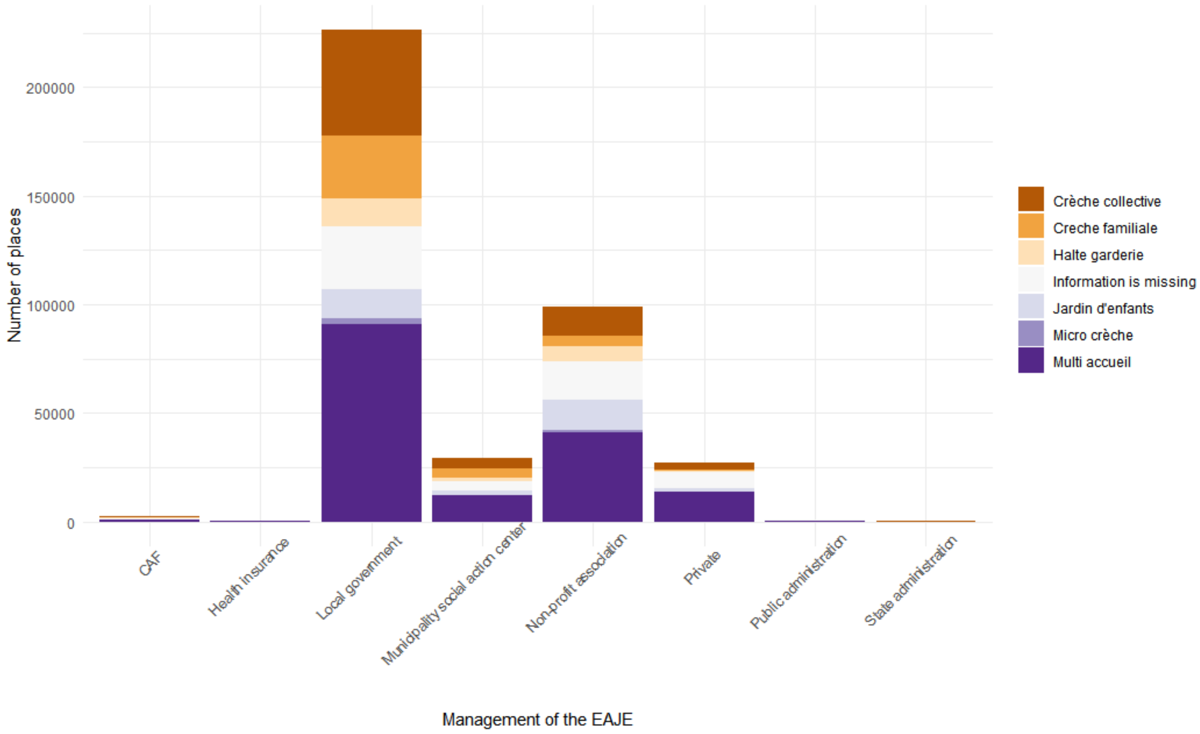


Figure 7.11: Distribution of daycare operating hours. Source: CAF

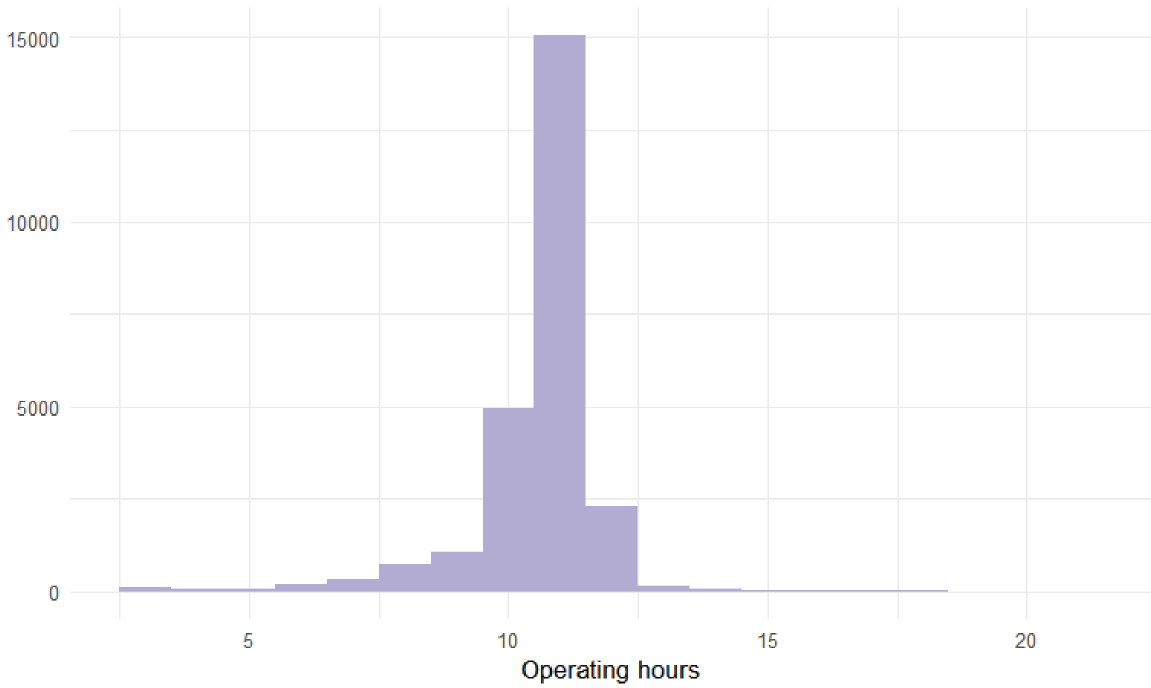


Figure 7.12: Evolution of the distribution of the number of days daycare centers are open in France. Source ONAPE (2011).

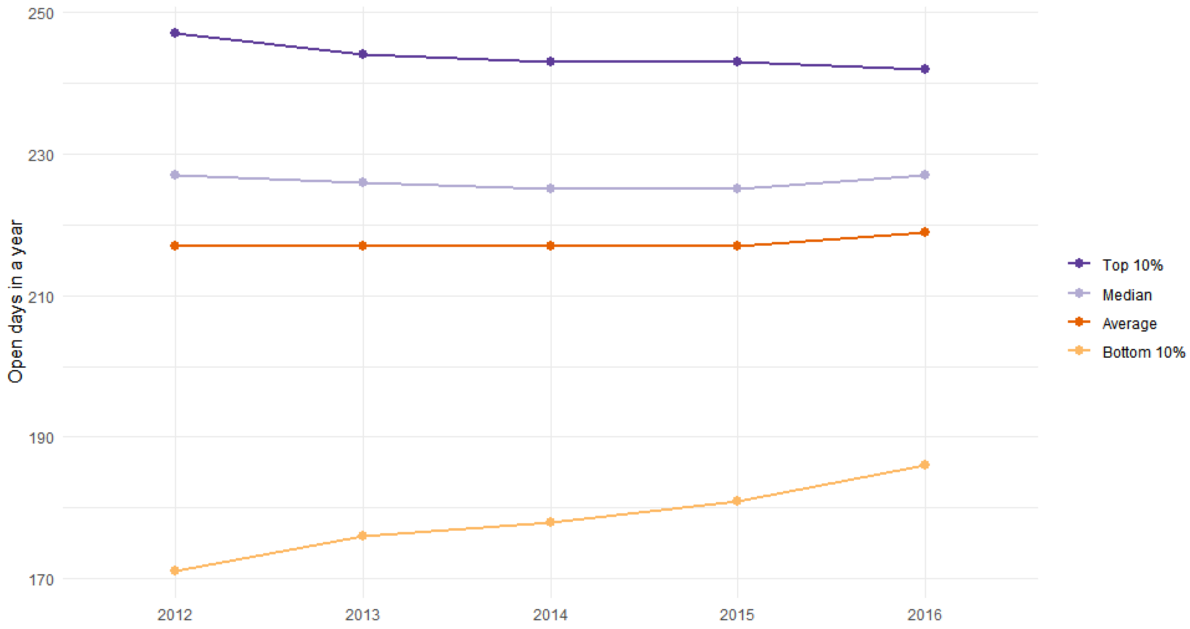


Figure 7.13: Price for families and costs for the public finances. Source: ONAPE (2011).

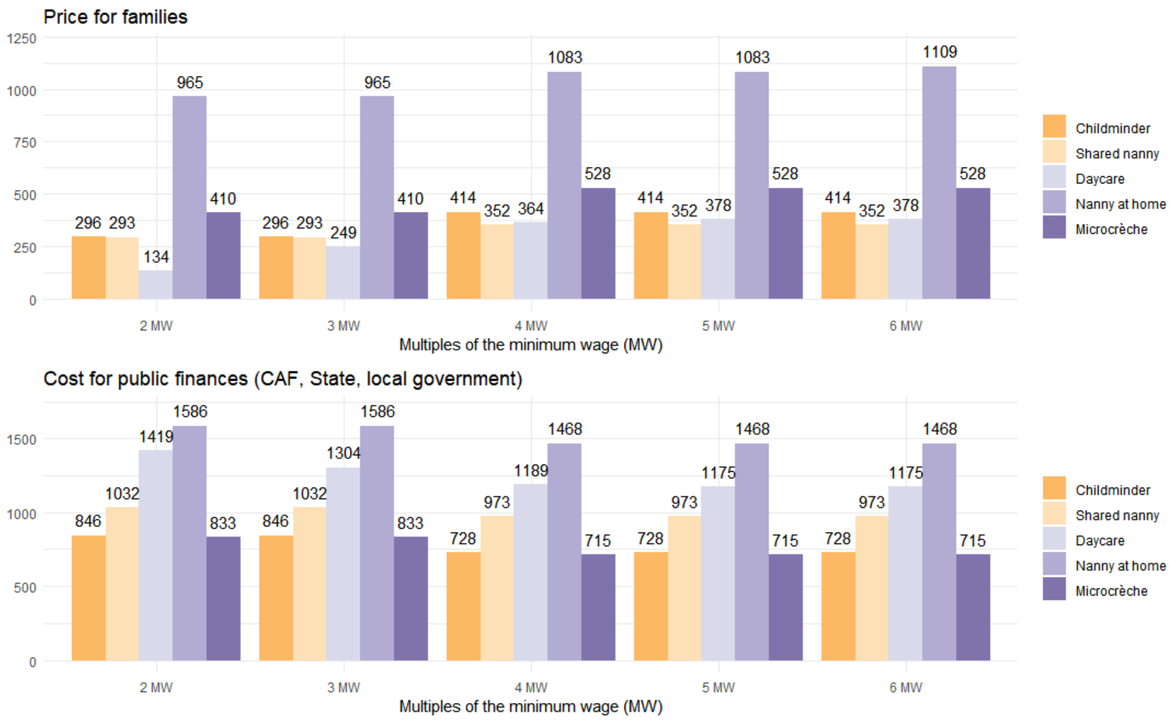
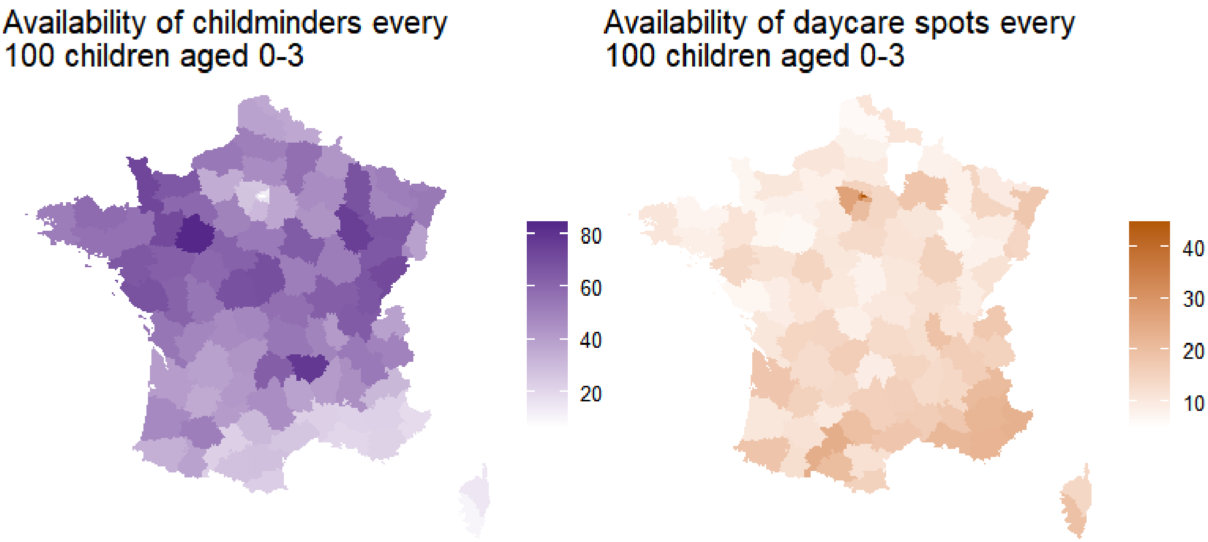


Figure 7.14: Regional variation in daycare and childminders availability in 2012. Source: ONAPE (2011).



7.4.3 Daycare fruition (Main sources: Elfe and Mode de Garde surveys)

Figure 7.15: Months when the child begins daycare, based on month of birth. Source: Elfe.

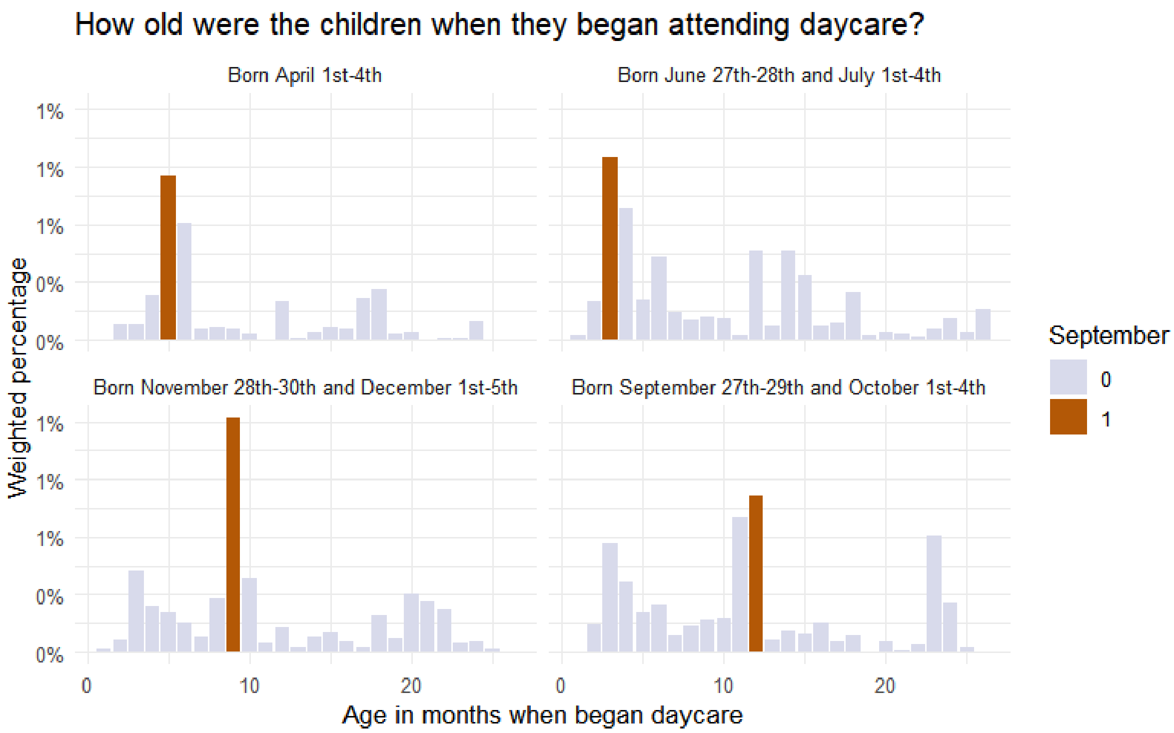


Figure 7.16: Distribution of days and hours spent in childcare by type of childcare arrangement. Source Elfe.

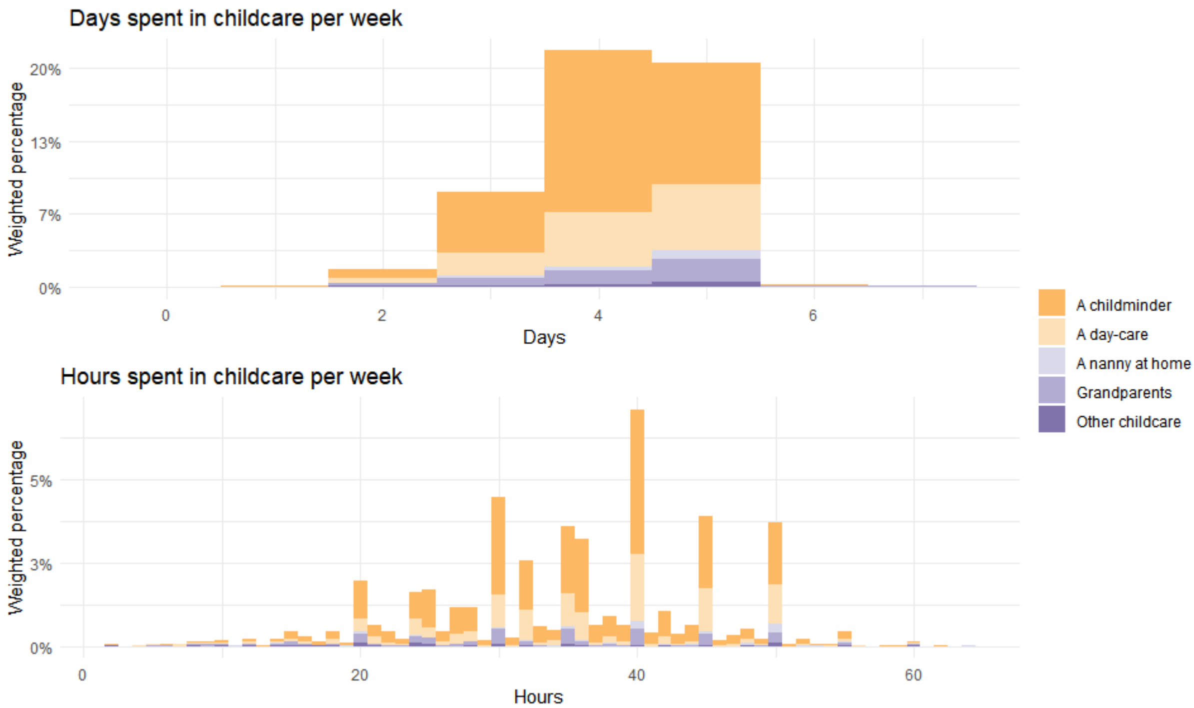


Figure 7.17: Satisfaction with the opening hours by type of childcare arrangement. Source: MDG.

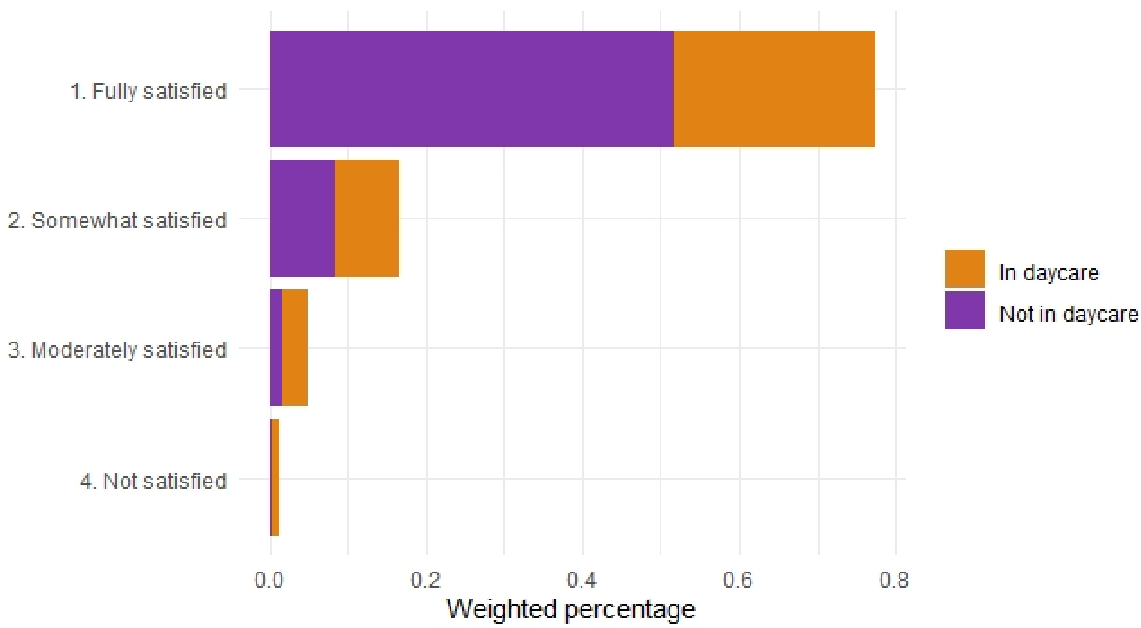
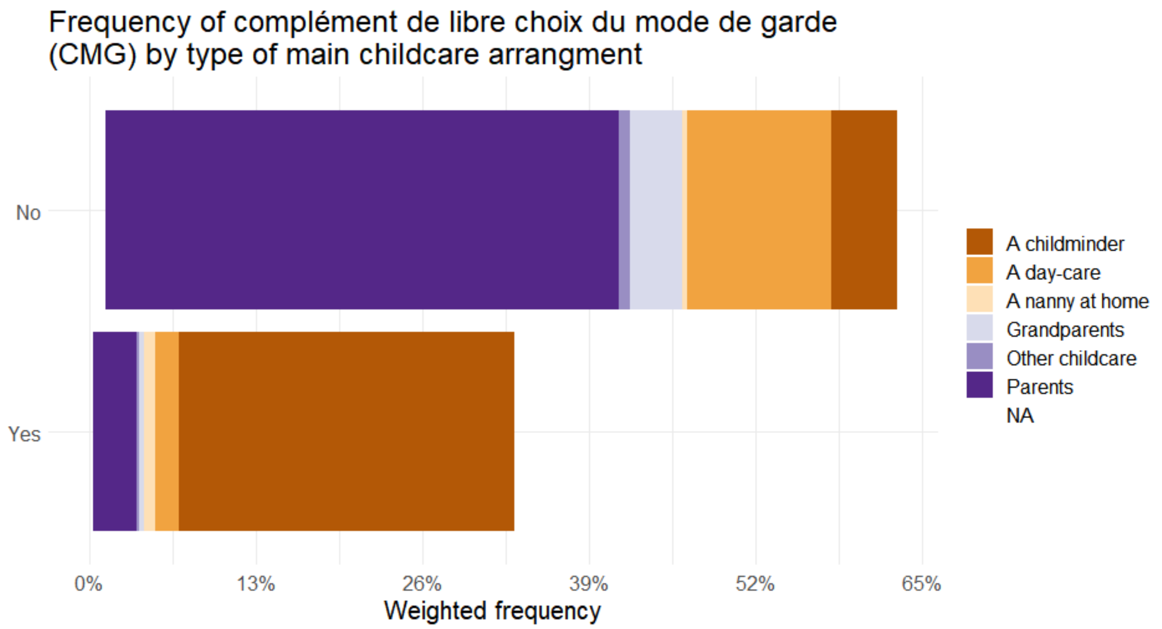


Figure 7.18: CMG when the child is 1 year old. Source: Elfe.



Notes: Families whose children attend a crèche and they receive CMG are those whose children attend a microcrèche financed through the CMG and not the PSU. Parents who look after their children themselves and receive CMG receive it for the complimentary childcare arrangement.

Figure 7.19: Ideal childcare arrangement according to mothers. Source: Elfe.

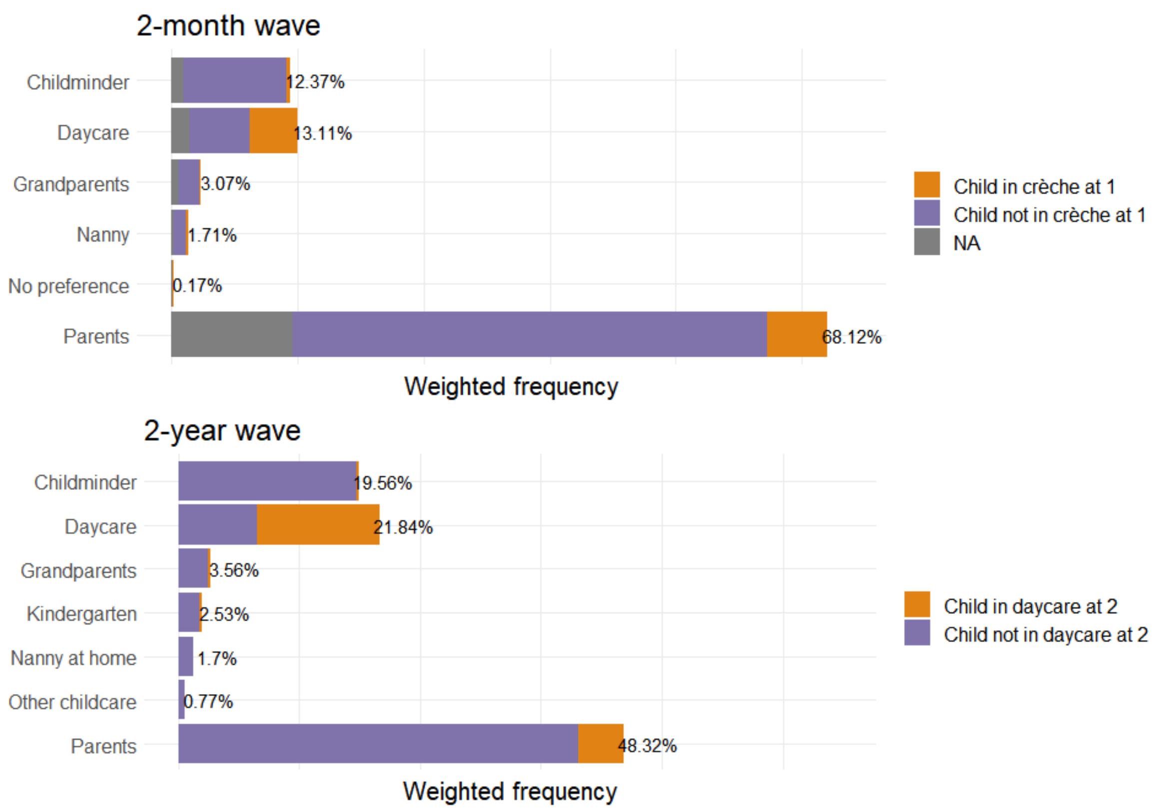


Figure 7.20: Months of research before finding the first paid childcare arrangment. Source: MDG.

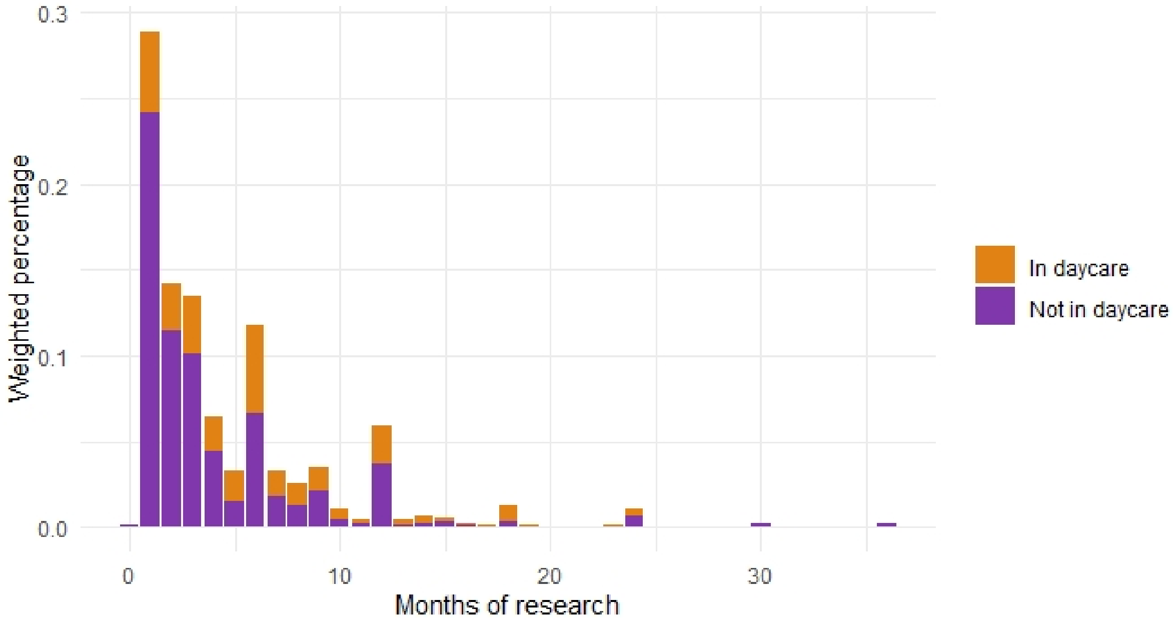


Figure 7.21: Reasons for the choice of daycare or a licensed childminder as preferred childcare arrangement. Source: own elaboration based on Enquête Mode de garde 2013.

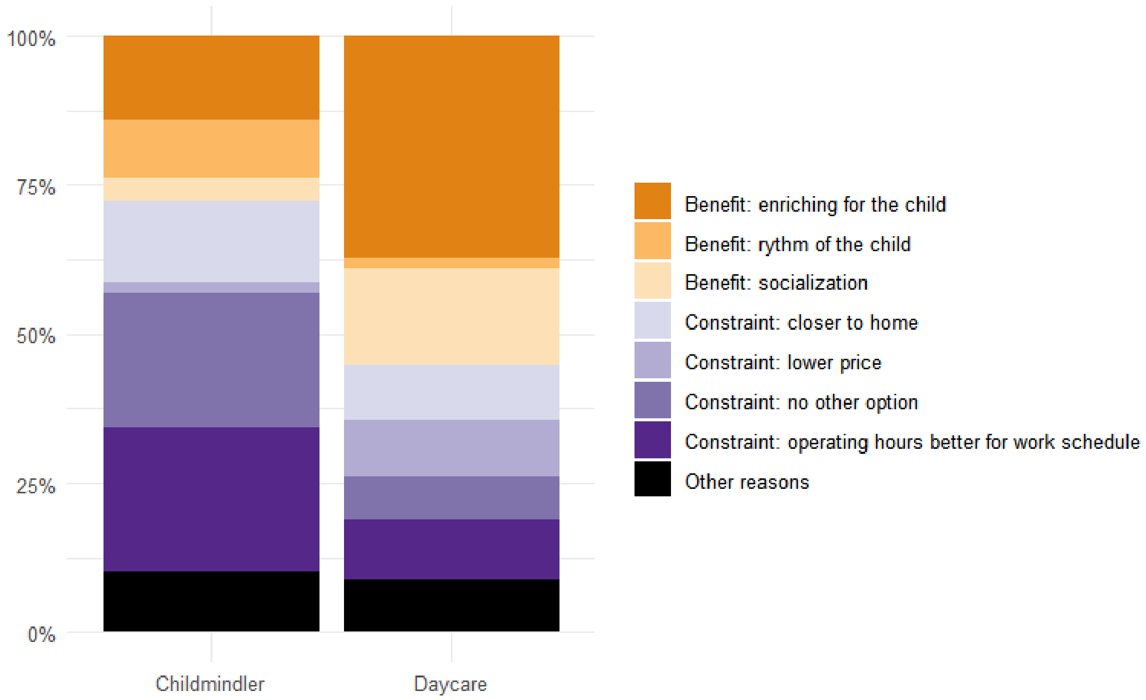


Figure 7.22: Alluvial diagram of the changes in childcare arrangement of children between 1 and 2 years of age. Source: Elfe survey

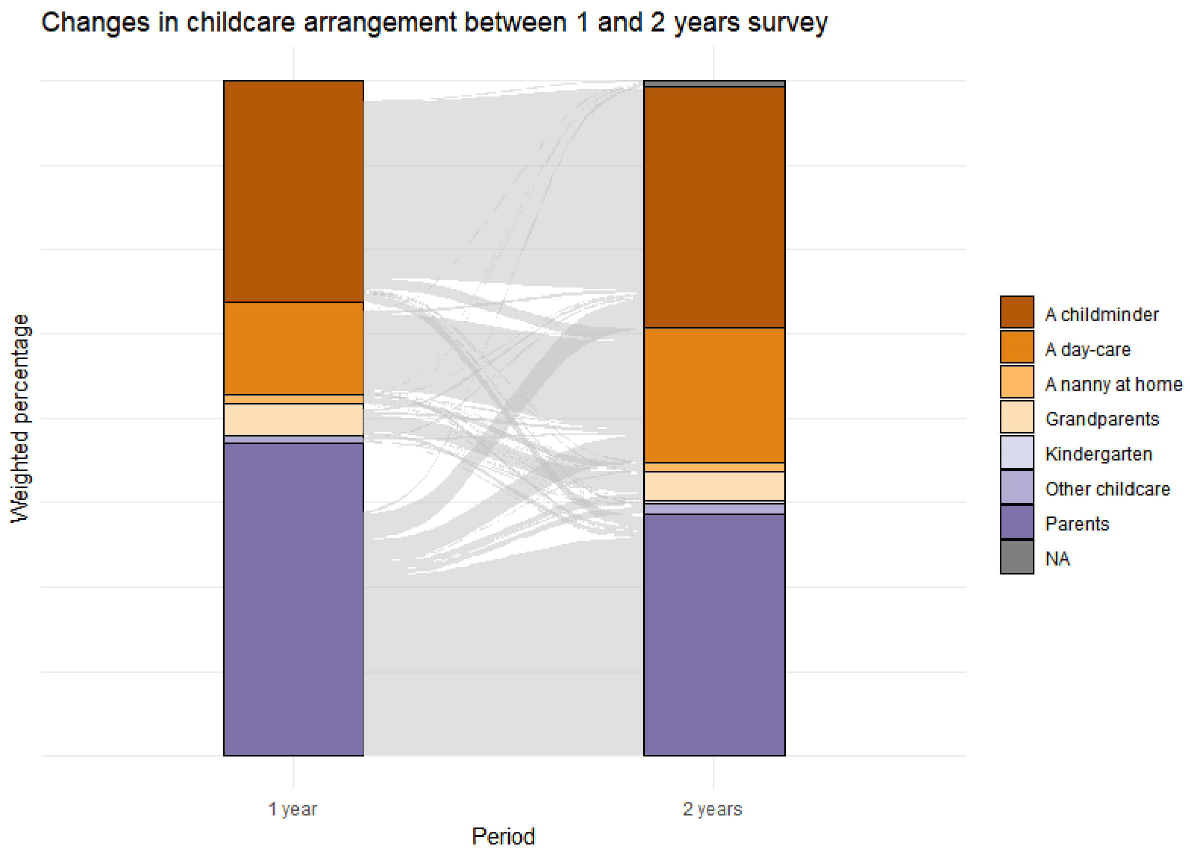
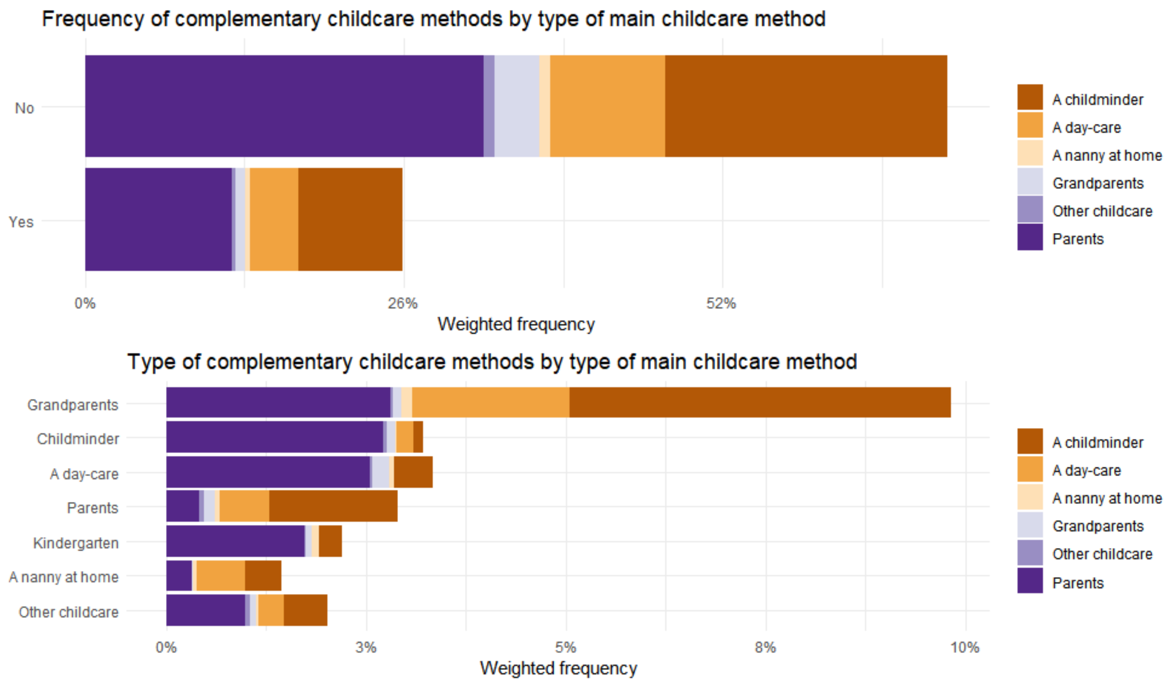


Figure 7.23: Frequency and type of complementary childcare method by type of main childcare method. Source: Elfe survey



7.4.4 Descriptive graphs from DEPP

Figure 7.24: Correlation between daycare availability and average value added at the municipality level in 2012. Source: DEPP High school value-added indicators, CAF, birth registries (INSEE).

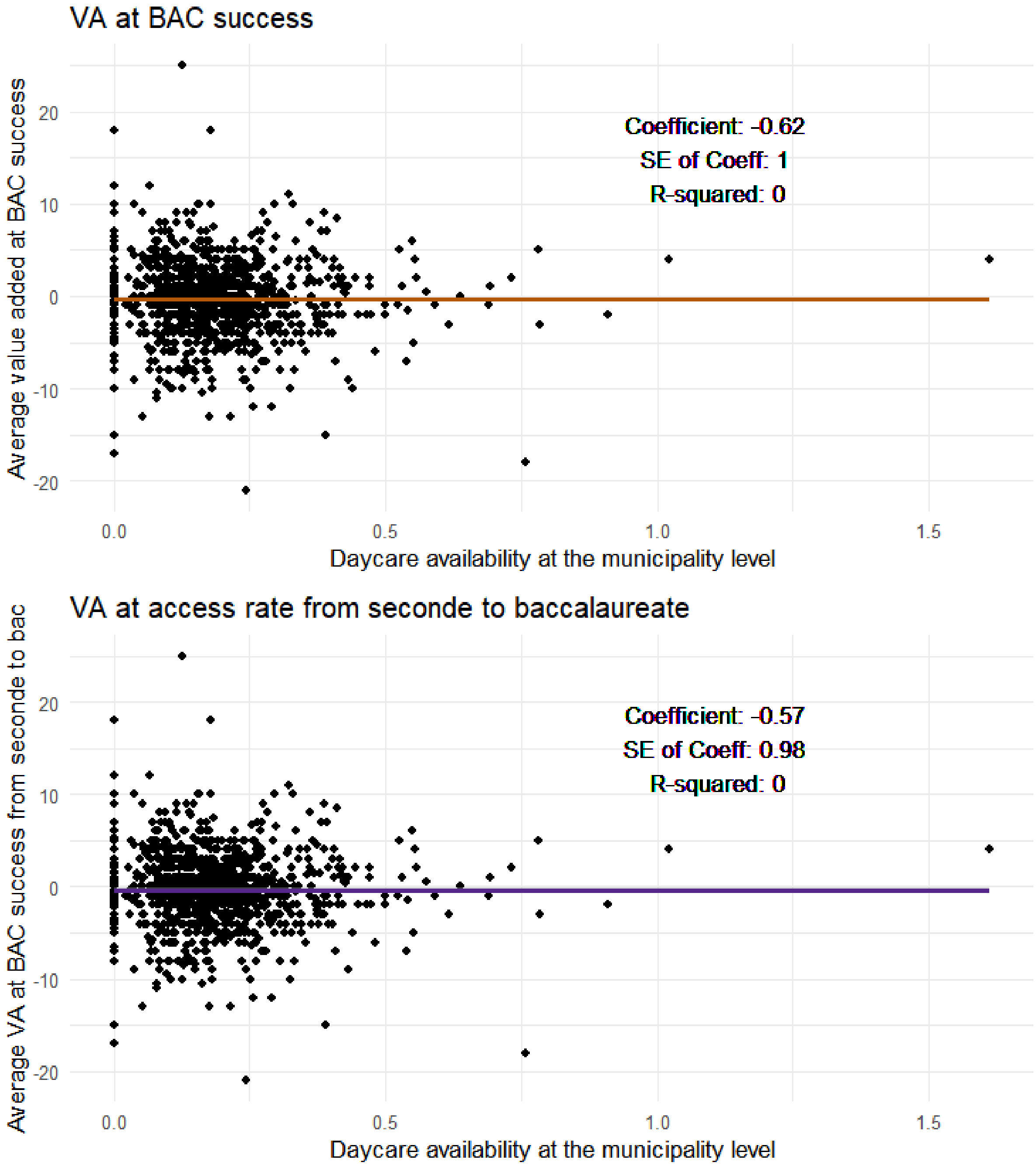


Figure 7.25: Patterns of missingness in DEPP data.

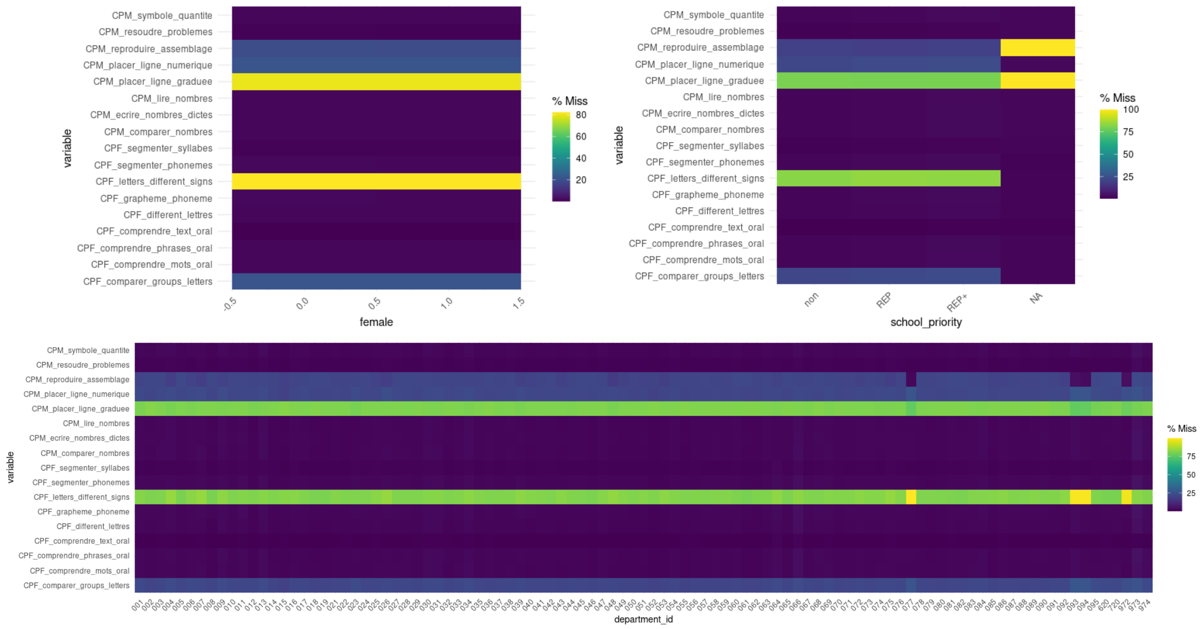


Figure 7.26: Distribution of children that are belated by one year or one year in advance. Source: DEPP.

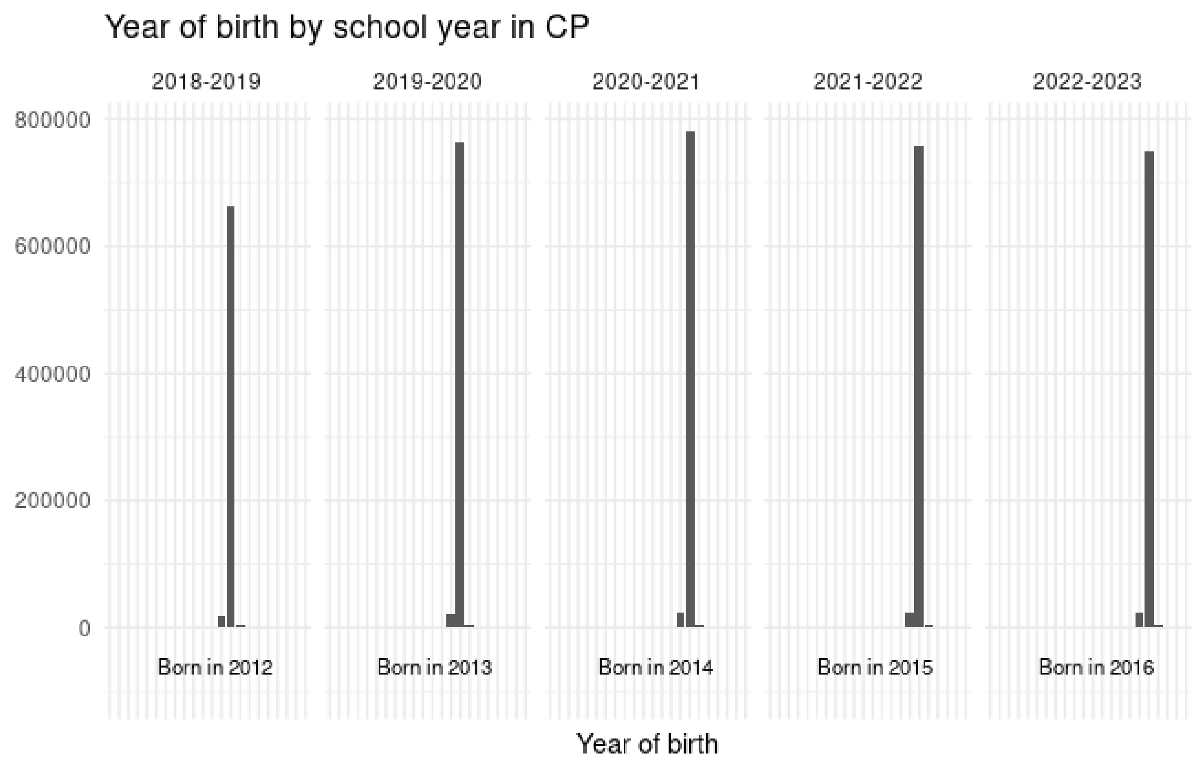
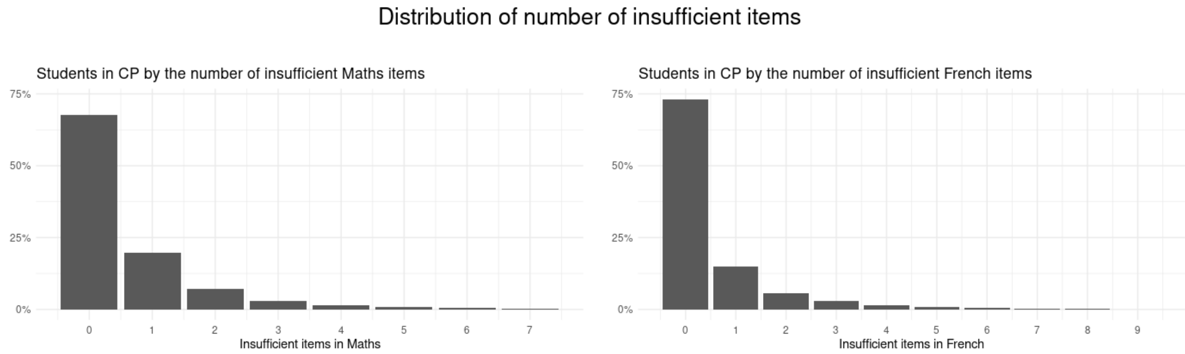


Figure 7.27: Distribution of number of children by number of insufficient items in Maths (left) and French (right). Source: DEPP.



7.4.5 Maps

Figure 7.28: Change in daycare availability from 2011 to 2016 per French region. Source: CAF and birth registries (INSEE).

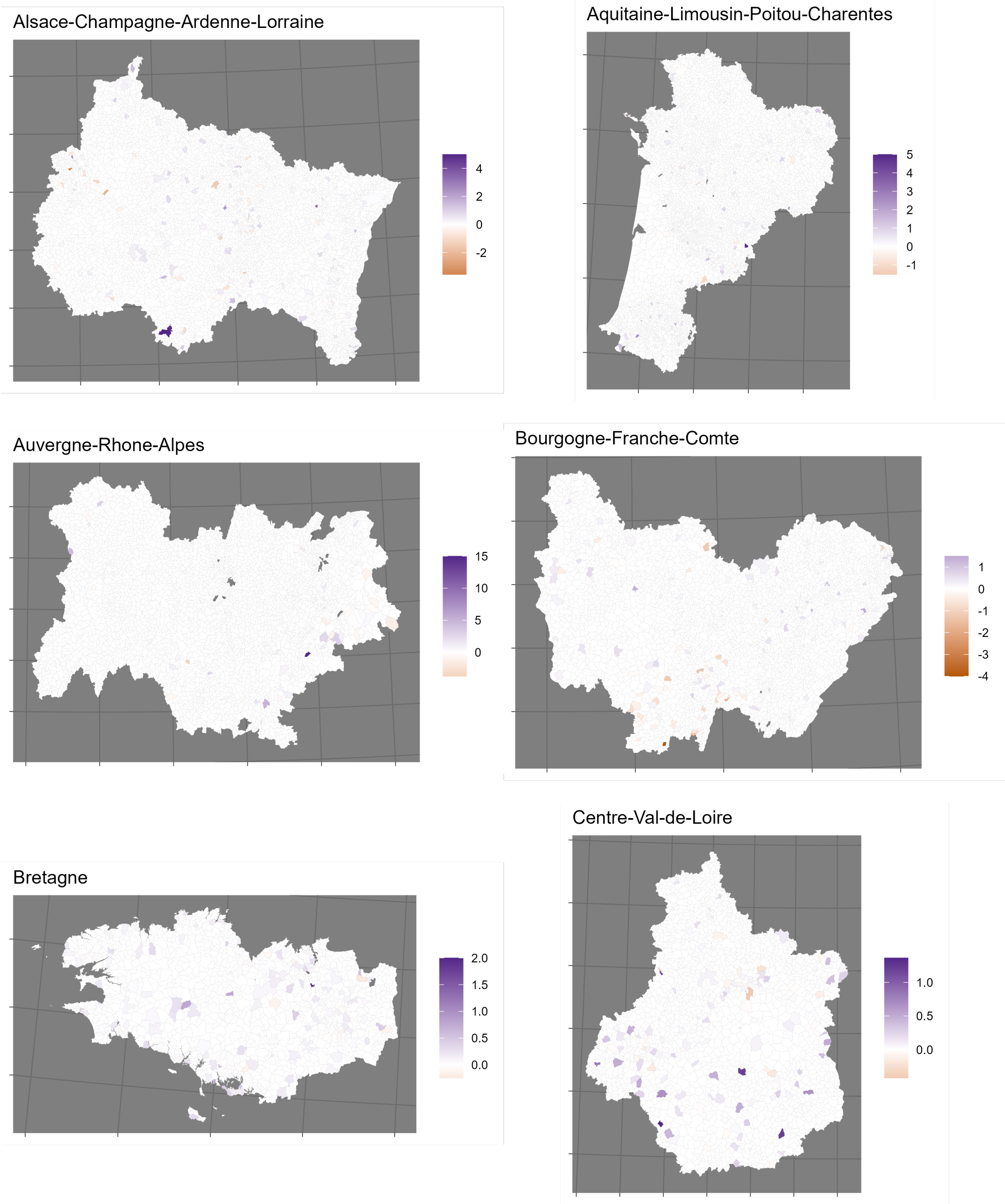
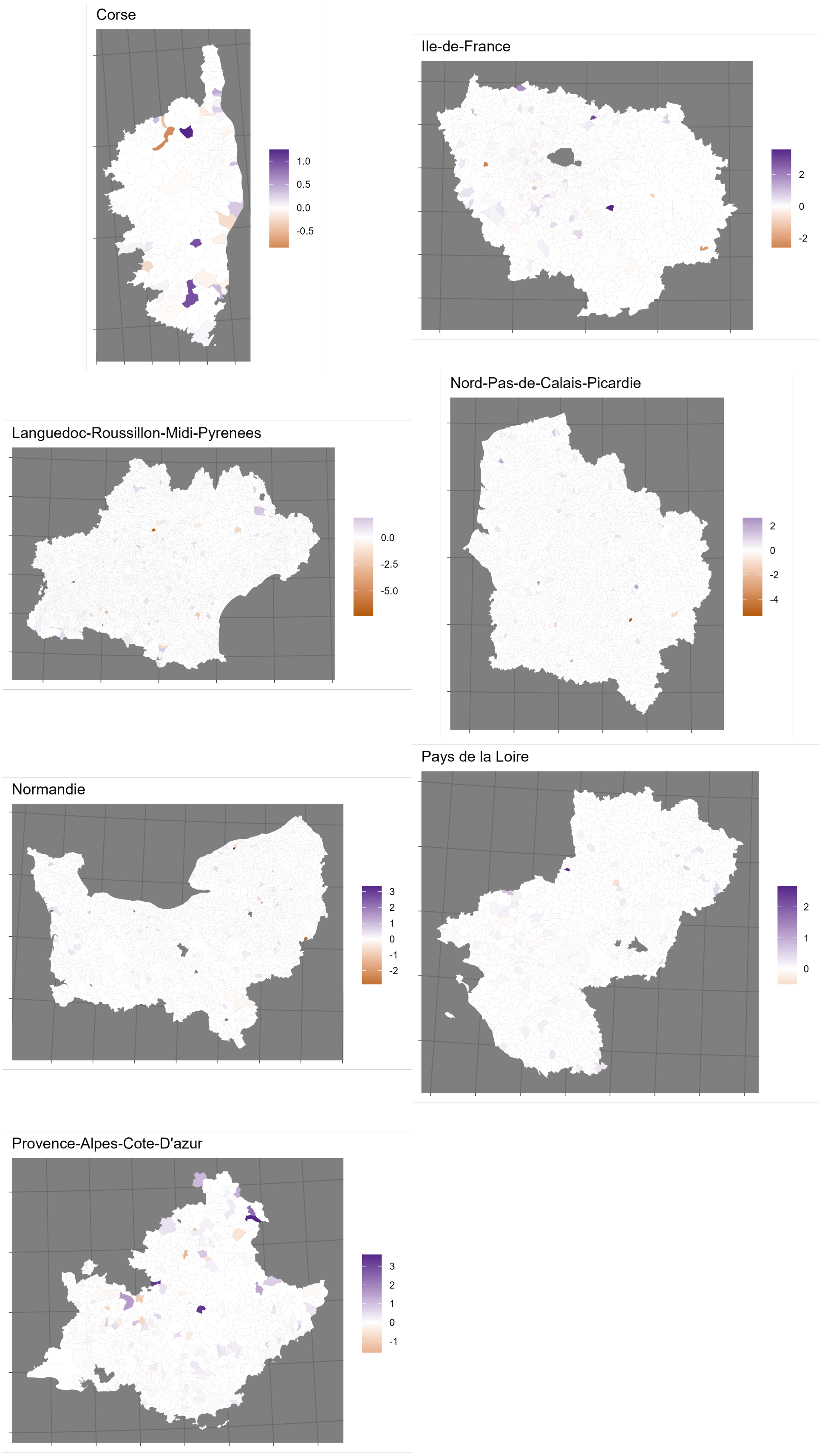


Figure 7.29: Change in daycare availability from 2011 to 2016 per French region. Source: CAF and birth registries (INSEE).



7.5 Tables

Table 7.1: Literature review on papers focusing on daycare at age 0-2 and the impact on medium- or long-run cognitive skills.

Paper	Dependent variable	Main regressor	Exogenous variation	Data	Context	Results
Gupta and Simonsen (2016)	GPA at 14	Being enrolled at 2	Municipalities providing guaranteed access	Administrative full coverage	Denmark, 1994	Positive for language, not significant for maths
Cornelissen et al. (2018)	School readiness exams	Any daycare attendance	Staggered introduction	Administrative full coverage	Lower Saxony, 1994-2006	Positive for those less likely to attend it
Felfe and Lalive (2018)	Language, motor, socio-emotional	Any daycare attendance	Staggered introduction	Administrative full coverage	Lower Saxony, 2009-2014	Positive on motor and socio-emotional skills
Andresen (2019)	Reading, maths and English at 10	Any daycare attendance	Staggered introduction, using MTE	Administrative full coverage	Norway, 2002-2007	Small and negative, with positive selection on unobservable gains
Drange and Havnes (2019)	Language and maths at 6-7	Any daycare attendance	Random assignment	Administrative full coverage	Oslo, 2004-2006	Positive, in particular for low income and low education families
Fort et al. (2020)	IQ and personality traits at 8-14	Any daycare attendance	RDD on income threshold	Administrative full coverage	Bologna (Italy), 1999-2005	Negative for IQ, agreeableness and openness
			In France			
Heim (2018)	French and math scores at 11 and 14	Beginning kindergarten at 2	(1) RDD on age threshold (2) local availability	Panel 2007 DEPP (N = 35.000)	France, 2007	(1) Positive (2) Negative/ non significant
Filatriau et al. (2013)	French and math scores at 6, 11, 14	Beginning kindergarten at 2	Local availability	Panel 97 DEPP (N = 6.000)	France, 1997	Positive on maths
Goux and Maurin (2010)	High school dropout	Beginning kindergarten at 2	RDD on age threshold	Insee census	France, 1999	Not significant

Table 7.2: Literature review on papers focusing on quality for daycare and pre-school (3 to 5 year olds).

Paper	Dependent variable	Main regressor	Exogenous variation	Data	Context	Results
Drange and Rønning (2020)	Language and maths at 6-9	1. Teacher-student ratio, 2. Share of teachers vs. other workers, 3. Tenure in a center, 4. % male, 5. % immigrant staff, 6. Sick leave of teachers	Random assignment	Administrative full coverage	Oslo, 2004-2007	Positive effect of male share, negative effect of sick leave
Bauchmuller et al. (2014)	Problem-solving at 15	1. Teacher-student ratio, 2. % male, 3. % trained staff, 4. % ethnic minority staff, 5. Staff turnover	Correlation	Administrative full coverage	Denmark, 2008	Positive effect of teacher-student ratio, % of trained teachers, % men
Goertz et al. (2018)	Language and maths at 7-9	% male	Time variation within-preschool	Administrative full coverage	Denmark, 2006-2007	Positive effect of % men
Araujo et al. (2016)	Language, maths, self-regulation at 6	1. Teacher-student interactions (video) 2. Teachers tenure	Random assignment	Post-intervention survey and admin	Ecuador, 2012	Positive effect of interaction quality
Currie and Neidell (2007)	Vocabulary, reading comprehension, behavioural problems, kids older than 4	1. Spending per capita 2. % budget spent on children 3. Teacher-student ratio 4. Teacher salary 5. Teacher education	Correlation	Administrative and NSLY survey	US, 1988-2000	Positive effect of spending per capita, in particular share spent on children

Table 7.3: Baseline reduced form results from DEPP.

Dependent Variables:	Maths	French	Maths	French	Maths	French	Maths	French	Maths	French
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables										
Spring × Availability	0.0152***	0.0157***	0.0155***	0.0159***	0.0138***	0.0137***	0.0155***	0.0159***	0.0128***	0.0150***
	(0.0050)	(0.0054)	(0.0050)	(0.0054)	(0.0046)	(0.0048)	(0.0050)	(0.0054)	(0.0048)	(0.0047)
Spring	0.0145***	0.0182***	0.0139***	0.0172***	0.0129***	0.0158***				
	(0.0012)	(0.0013)	(0.0011)	(0.0013)	(0.0011)	(0.0013)				
Availability	-0.0090	-0.0257	-0.0158	-0.0381***	0.0181***	0.0028	-0.0158	-0.0381***		
	(0.0175)	(0.0213)	(0.0101)	(0.0136)	(0.0058)	(0.0073)	(0.0101)	(0.0135)		
Month of birth	-0.0331***	-0.0340***	-0.0331***	-0.0340***	-0.0332***	-0.0341***				
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)				
Constant	0.2088***	0.2105***								
	(0.0033)	(0.0047)								
Municipality covariates					Yes	Yes				
Fixed-effects										
Department			Yes	Yes	Yes	Yes	Yes	Yes		
Month of birth							Yes	Yes	Yes	Yes
Municipality × Year									Yes	Yes
Fit statistics										
Observations	3,524,383	3,535,553	3,524,383	3,535,553	3,522,872	3,534,034	3,524,383	3,535,553	3,524,383	3,535,553
DV mean	0.00724	0.00429	0.00724	0.00429	0.00721	0.00426	0.00724	0.00429	0.00724	0.00429

Source. Authors' calculations based on DEPP administrative data, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.

Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). The first column is the baseline specification. The second column includes department fixed effect. The third column includes municipality-level controls (degree of urbanization, labor force participation for men and women aged 25-54 in the 2013 census, percentage of occupational categories (self-employed, manual workers, managers, middle managers) in the 2013 census, percentage of employed in different industries every year and the percentage of homeowners and vacant houses in the 2013 census, mean income in the municipality in 2013, number of libraries and child-parent drop-in center). The fourth column includes month fixed effects instead of the linear month control. The fifth column, along with the month fixed effect, included municipality × year fixed effects. Standard errors are heteroskedasticity robust and clustered at the municipality level are reported in parentheses.

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 7.4: Baseline first-stage regression, standard errors clustered at the municipality level.

Dependent Variable:	Daycare				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Spring × Availability	0.0750**	0.0763**	0.0769**	0.0768**	0.1137**
	(0.0377)	(0.0362)	(0.0358)	(0.0360)	(0.0451)
Spring	0.0136**	0.0128**	0.0130**		
	(0.0059)	(0.0057)	(0.0057)		
Availability	0.2874***	0.1870***	0.1254***	0.1863***	
	(0.0526)	(0.0374)	(0.0277)	(0.0375)	
Month of birth	-0.0034***	-0.0035***	-0.0035***		
	(0.0007)	(0.0007)	(0.0007)		
(Intercept)	0.1004***				
	(0.0088)				
Municipality covariates		Yes			
Fixed-effects					
Department		Yes	Yes	Yes	
Month of birth				Yes	Yes
Municipality × Year					Yes
Fit statistics					
Observations	45,480	45,480	44,429	45,480	45,480
F-test	9.4274	16.001	29.293	29.567	30.569
Mean DV:	0.1201	0.1201	0.1201	0.1201	0.1201

Source. Authors' calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.
Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). Standard errors are heteroskedasticity robust and clustered at the municipality level are reported in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

7.5.1 Descriptive statistics

Table 7.6: Descriptive statistics of the FL survey

Statistic	N	Mean	St. Dev.	Min	Max
Daycare attendance	45,533	0.120	0.325	0	1
Daycare availability	45,480	0.131	0.178	0.000	16.500
Individual characteristics					
Female	45,286	0.490	0.500	0	1
Month of birth	45,533	6.488	3.470	1	12
Age	45,533	1.523	1.147	0	4
Foreign born	45,533	0.049	0.216	0	1
Migrant	45,533	0.009	0.093	0	1
Birth order	45,157	1.933	1.067	1	14
Born in Spring	45,533	0.246	0.430	0	1
Born before June	45,533	0.415	0.493	0	1
Family characteristics					
Number of cohabiting siblings	45,316	2.036	1.020	0	10
Single parent	45,316	0.071	0.257	0	1
Married	45,533	0.630	0.483	0	1
Father IPS	41,494	103.587	31.711	54	160

Continued on next page

Table 7.6 – continued from previous page

Statistic	N	Mean	St. Dev.	Min	Max
Mother's characteristics					
Mother's year of birth	45,356	1,977.592	6.428	1,947	1,992
Mother's IPS	44,555	102.859	30.411	58	168
Mother's nationality: Born French	45,533	0.842	0.365	0	1
Mother's nationality: Foreigner	45,533	0.092	0.289	0	1
Mother's natioanlity: Naturalized French	45,533	0.062	0.241	0	1
Mother migrant status	45,533	0.139	0.346	0	1
Mother's contract: Apprentice	30,673	0.002	0.045	0	1
Mother's contract: Caregiver	30,673	0.006	0.078	0	1
Mother's contract: Employer	30,673	0.027	0.161	0	1
Mother's contract: Interim worker	30,673	0.011	0.103	0	1
Mother's contract: Internship	30,673	0.001	0.035	0	1
Mother's contract: Permanent	30,673	0.814	0.389	0	1
Mother's contract: Self-employed	30,673	0.047	0.212	0	1
Mother's contract: Temporary	30,673	0.085	0.279	0	1
Mother's employment status: Apprentice or intern	44,722	0.003	0.054	0	1
Mother's employment status: Employed	44,722	0.634	0.482	0	1
Mother's employment status: Homemaker or housewife	44,722	0.191	0.393	0	1
Mother's employment status: Other	44,722	0.067	0.249	0	1
Mother's employment status: Retired	44,722	0.005	0.067	0	1
Mother's employment status: Student	44,722	0.007	0.085	0	1
Mother's employment status: Unemployed	44,722	0.089	0.285	0	1
Municipality characteristics					
% homeowners	44,725	59.835	19.033	19.400	100.000
% overcrowded houses	44,725	8.504	8.751	0.000	50.000
% vacant houses	44,725	8.251	3.677	0.000	33.500
% manual workers pct	44,680	23.285	11.520	0.000	100.000
% managers pct	44,680	13.093	9.331	0.000	100.000
% self-employed pct	44,680	8.250	6.509	0.000	100.000
LFP (Women 25-54)	44,725	86.567	5.861	28.600	100.000
LFP (Men 25-54)	44,725	94.536	3.376	46.700	100.000
% workers in secondary sector	44,604	0.049	0.113	0.000	2.623
% workers in construction	44,604	0.022	0.023	0.000	0.298
% workers in sales	44,604	0.043	0.055	0.000	1.658
% workers in HoReCa	44,604	0.014	0.021	0.000	0.574
% workers in other market services	44,604	0.087	0.108	0.000	1.735
% workers in non-market services	44,604	0.031	0.033	0.000	0.466
% temporary workers	44,604	0.006	0.010	0.000	0.185
Libraries per capita	44,725	0.0003	0.001	0.000	0.013
Median income	44,539	20,588.250	3,685.057	12,933.810	37,028.890
LEAP per capita	44,725	0.00002	0.00005	0.000	0.001
Daycare availability characteristics					
Median daycare opening hours	28,928	10.593	1.216	2.500	14.100
Median hourly price paid by the family	28,928	1.535	0.357	0.509	2.870

Table 7.5: Results for the two-sample 2SLS, without coefficients of the covariates (results with the covariates coefficients are in Table 7.33 in the Appendix).

	First stage	Second stage	Second stage	Second stage capped	Second stage capped
Dependent Variables:	Daycare	Maths	French	Maths	French
$\widehat{Daycare}$		0.219***	0.123***		
		(0.012)	(0.023)		
$\widehat{Daycare}$ (capped)				0.239***	0.136***
				(0.024)	(0.017)
Spring	0.013*				
	(0.006)				
Availability	0.125***				
	(0.023)				
Month of birth	−0.004***	−0.033	−0.034	−0.032	−0.034
	(0.001)	(0.039)	(0.060)	(0.038)	(0.036)
Spring × Availability	0.077*				
	(0.043)				
Municipality covariates	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Department	Yes	Yes	Yes	Yes	Yes
Urbanization	Yes	Yes	Yes	Yes	Yes

Source. Author's calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016, birth registries (INSEE), France, 2012-2016 and DEPP EvalAide data, 2018-2023.
Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). The first column is the first stage regression. The second and third column report TS2SLS estimates for Maths and French, respectively, using the non-capped generated daycare availability. The fourth and fifth columns report TS2SLS estimates for Maths and French, respectively, using the capped generated daycare availability. Standard errors are bootstrapped with K = 100 repetitions.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 7.7: Descriptive statistics of the FL survey, divided by the type of childcare arrangement

	Crèche	SD	Childmindler	SD	Parents	SD	Grandparents, family	SD	Other	SD
Individual characteristics										
Month of birth	6.04	(3.323)	6.48	(3.386)	6.63	(3.52)	6.39	(3.496)	6.41	(3.492)
Spring	0.30	(0.458)	0.25	(0.433)	0.23	(0.422)	0.25	(0.434)	0.23	(0.421)
Female	0.48	(0.499)	0.50	(0.5)	0.49	(0.5)	0.49	(0.5)	0.54	(0.499)
Birth order	1.74	(0.885)	1.65	(0.793)	2.18	(1.23)	1.64	(0.817)	2.02	(1.114)
Twin	0.04	(0.187)	0.02	(0.143)	0.04	(0.197)	0.02	(0.142)	0.05	(0.209)
Age of the kid	1.41	(0.923)	1.41	(1.057)	1.54	(1.214)	1.86	(1.155)	2.20	(1.127)
Mother characteristics										
Mother IPS	116.04	(28.795)	117.82	(27.306)	90.36	(27.1)	104.37	(26.244)	118.91	(32.433)
Mother is employed	0.81	(0.39)	0.92	(0.276)	0.38	(0.477)	0.83	(0.37)	0.82	(0.378)
Mother is migrant	0.15	(0.357)	0.06	(0.229)	0.24	(0.425)	0.13	(0.34)	0.21	(0.404)
Mother age	34.37	(6.188)	33.45	(5.632)	33.70	(7.399)	34.93	(8.396)	35.51	(6.068)
Municipality characteristics										
% of homeowners	52.90	(17.444)	64.40	(17.865)	56.01	(18.186)	59.96	(18.05)	51.78	(17.832)
% of overcrowded	12.59	(9.636)	7.02	(7.502)	9.99	(8.55)	9.22	(8.649)	15.08	(10.642)
vacant houses	7.81	(3.104)	7.70	(3.441)	8.24	(3.592)	7.85	(3.44)	7.46	(2.858)
% manual workers	19.56	(9.521)	24.03	(11.648)	22.26	(10.374)	22.70	(11.306)	17.85	(9.717)
% managers	17.79	(10.215)	12.27	(8.985)	14.10	(8.659)	13.55	(9.672)	20.62	(11.597)
% self employed	7.21	(5.319)	8.70	(6.466)	7.79	(6.011)	8.46	(6.546)	6.67	(4.37)
LFP (Women 25-54)	86.72	(5.068)	88.21	(5.354)	85.28	(6.108)	86.20	(6.002)	87.55	(4.489)
LFP (Men 25-54)	94.14	(3.151)	95.30	(3.83)	94.05	(3.538)	94.57	(3.483)	94.48	(3.374)
Rural	0.12	(0.33)	0.35	(0.473)	0.21	(0.407)	0.27	(0.442)	0.14	(0.342)
% secondary sector workers	0.04	(0.071)	0.04	(0.104)	0.05	(0.093)	0.04	(0.094)	0.04	(0.065)
% workers in construction	0.02	(0.023)	0.02	(0.024)	0.02	(0.021)	0.02	(0.023)	0.02	(0.018)
% workers in sales	0.06	(0.096)	0.04	(0.045)	0.04	(0.058)	0.04	(0.061)	0.05	(0.036)
% workers in HoReCa	0.02	(0.025)	0.01	(0.016)	0.01	(0.02)	0.01	(0.025)	0.02	(0.021)
% workers in other market services	0.13	(0.155)	0.07	(0.097)	0.09	(0.105)	0.09	(0.126)	0.15	(0.154)
% workers in non-market services p	0.04	(0.03)	0.03	(0.032)	0.03	(0.031)	0.03	(0.035)	0.04	(0.032)
% workers temporary workers	0.01	(0.013)	0.00	(0.009)	0.01	(0.011)	0.00	(0.009)	0.01	(0.009)
Libraries per capita	0.00	(0)	0.00	(0.001)	0.00	(0)	0.00	(0)	0.00	(0)
Median income	21562.28	(4415.563)	20996.59	(3355.932)	20023.30	(3624.488)	20609.03	(3677.69)	22756.33	(4821.913)
LEAP per capita	0.00	(0)	0.00	(0)	0.00	(0)	0.00	(0)	0.00	(0)
Availability	0.21	(0.26)	0.11	(0.139)	0.14	(0.144)	0.13	(0.137)	0.19	(0.158)

Table 7.8: Descriptive statistics of the FL survey, divided by children born in spring or not.

Variable	Mean Spring	SD Spring	Mean no Spring	SD no Spring	Diff. in means
Birth order	1.9529	1.1188	1.9528	1.0430	0.0065
Age child	1.5399	1.1583	1.4973	1.1129	-0.0375
Mother IPS	102.1142	30.5346	102.7964	30.8614	0.0224
Mother age	33.7809	6.9403	34.0538	6.8118	0.0427
% homeowners	57.8864	18.5971	57.7477	18.4895	-0.0073
% overcrowded houses	9.6742	8.8077	9.6764	8.7930	
% vacant houses	8.0017	3.4970	8.0005	3.5040	-0.0003
% manual workers	22.2782	10.8692	22.1965	10.7387	-0.0071
% managers	14.2246	9.3362	14.4116	9.5615	0.0199
% selfemployed	7.9816	6.0805	7.8697	6.1945	-0.0171
LFP Women 25-54	86.3094	5.7954	86.3931	5.6696	0.0143
LFP Men 25-54	94.4153	3.3329	94.4493	3.2527	0.0100
% secondary sector	0.0453	0.0943	0.0461	0.0913	0.0073
% construction	0.0231	0.0227	0.0233	0.0219	0.0092
% sales	0.0443	0.0614	0.0451	0.0615	0.0146
% HoReCa	0.0140	0.0200	0.0141	0.0211	0.0053
% other tertiary	0.0922	0.1157	0.0949	0.1178	0.0250
% non-market services	0.0319	0.0317	0.0322	0.0312	0.0086
Median income	20579.2243	3789.4448	20601.0047	3791.5745	0.0059
% temporary workers	0.0062	0.0106	0.0063	0.0106	0.0073
Libraries per capita	0.0002	0.0005	0.0002	0.0005	-0.0037
LEAP per capita	0.0000	0.0000	0.0000	0.0000	0.0097
Daycare availability	0.1416	0.1642	0.1428	0.1657	0.0065
Weight	98.2947	63.6186	98.1929	62.8446	-0.0023

Table 7.9: Descriptive statistics of the DEPP sample

Statistic	N	Mean	St. Dev.	Min	Max
Tests					
Maths standardized test scores	3,653,288	−0.007	0.665	−8.370	1.544
French standardized test scores	3,665,489	−0.013	0.713	−5.556	1.721
Maths ranks	3,653,288	0.324	0.119	0.000	0.906
French ranks	3,665,489	0.421	0.173	0.000	0.938
At least 1 insufficient item in maths	3,665,489	0.315	0.464	0	1
At least 1 insufficient item in French	3,665,489	0.262	0.439	0	1
Individual characteristics					
Spring	3,668,543	0.242	0.428	0	1
In time students (aged 6 in CP)	3,668,543	0.965	0.185	0	1
Female	3,668,543	0.489	0.500	0	1
School IPS	2,857,302	103.650	17.809	52.500	156.500
Municipality characteristics					
Availability (municipality)	3,644,839	0.160	0.174	0.000	20.000
Parental care (municipality)	2,989,939	0.409	0.211	0.000	1.000
Rural	3,644,950	0.203	0.403	0	1
Urban	3,644,950	0.309	0.462	0	1
Suburban	3,644,950	0.403	0.491	0	1
% homeowners	3,645,461	58.316	17.664	13.700	97.600
% vacant houses	3,645,461	7.957	3.487	0.000	39.100
LFP (Women 25-54)	3,645,326	86.772	5.698	45.200	100.000
LFP (Men 25-54)	3,645,326	94.318	3.727	25.900	100.000
% manual workers	3,645,213	22.209	10.167	0.000	100.000
% self employed	3,645,213	8.044	5.609	0.000	100.000
% managers	3,645,213	14.185	8.987	0.000	100.000
% workers in construction	3,644,583	0.024	0.026	0.000	0.835
% workers in sales	3,644,583	0.048	0.054	0.000	2.910
% workers in HoReCa	3,644,583	0.014	0.028	0.000	2.709
% workers in other market services	3,644,583	0.096	0.166	0.000	17.770
% workers temporary workers	3,644,583	0.006	0.013	0.000	0.800
Median income	3,644,770	20,617.300	3,744.120	10,021.250	46,250.560
Libraries per capita	3,645,326	0.0002	0.0004	0.000	0.015
LEAP per capita	3,645,461	0.00002	0.0001	0.000	0.005

7.5.2 Robustness checks to the choice of the spring instrument

Table 7.10: First-stage regression: placebo using other seasons instead of spring.

Dependent Variable:		Daycare		
Model:	(1)	(2)	(3)	(4)
Variables				
(Intercept)	0.1004***	0.1071***	0.1095***	0.1222***
	(0.0088)	(0.0077)	(0.0103)	(0.0105)
Spring	0.0136**			
	(0.0059)			
Availability	0.2874***	0.3326***	0.3088***	0.2984***
	(0.0526)	(0.0495)	(0.0701)	(0.0663)
Month of birth	-0.0034***	-0.0047***	-0.0041***	-0.0053***
	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Spring × Availability	0.0750**			
	(0.0377)			
Summer		0.0164*		
		(0.0093)		
Summer × Availability		-0.0833		
		(0.0616)		
Fall			-0.0066	
			(0.0098)	
Fall × Availability			-0.0128	
			(0.0649)	
Winter				-0.0252***
				(0.0086)
Winter × Availability				0.0345
				(0.0566)
Fit statistics				
DV mean	0.12016	0.12016	0.12016	0.12016
F-test	9.4274	9.1807	9.0644	9.2910

Source. Author's calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.

Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1).
Standard errors are heteroskedasticity robust and clustered at the municipality level are reported in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 7.11: Reduced form results, robustness of the daycare availability instrument: excluding Paris, using the availability defined at the EPCI level, using the availability at the EPCI level for rural municipalities, at the municipality level for urban and suburban ones. Back

Dependent Variables:	Maths	French	Maths	French	Maths	French
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Spring	0.0140***	0.0173***	0.0158***	0.0193***	0.0150***	0.0181***
	(0.0011)	(0.0013)	(0.0008)	(0.0010)	(0.0013)	(0.0014)
Availability	-0.0172*	-0.0446***				
	(0.0095)	(0.0129)				
Month birth	-0.0326***	-0.0336***	-0.0326***	-0.0336***	-0.0326***	-0.0336***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Spring × Availability	0.0136***	0.0143***				
	(0.0048)	(0.0053)				
Daycare avail. (EPCI)			-0.0002	-0.0011***		
			(0.0001)	(0.0002)		
Spring × Daycare avail. (EPCI)			0.0006***	0.0005***		
			(5.2×10^{-5})	(5.2×10^{-5})		
Diff. availability rur. and urb.					0.0249*	-0.0069
					(0.0147)	(0.0200)
Spring × Diff. availability rur. and urb.					0.0071	0.0091
					(0.0062)	(0.0067)
Fixed-effects						
Department	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,524,383	3,535,553	3,518,387	3,529,478	3,524,006	3,535,172
Dependent variable mean	0.00724	0.00429	0.00738	0.00406	0.00720	0.00424

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Clustered (municipality level) standard-errors in parentheses

Table 7.12: Reduced form results, robustness of the daycare availability instrument: division bias, controlling for the number of commuters from another municipality in the school, robustness to transformations of the right-skewed daycare availability

Dependent Variables:	Maths	French	Maths	French	Maths	French	Maths	French
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Spring	0.0140***	0.0174***	0.0138***	0.0171***	0.0125***	0.0158***	0.0132***	0.0165***
	(0.0011)	(0.0013)	(0.0011)	(0.0012)	(0.0012)	(0.0013)	(0.0012)	(0.0013)
Availability	-0.0111	-0.0365***	0.0031	-0.0173				
	(0.0083)	(0.0113)	(0.0084)	(0.0112)				
Month of birth	-0.0326***	-0.0336***	-0.0326***	-0.0336***	-0.0326***	-0.0336***	-0.0326***	-0.0336***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Kids born in municipality	$-6.16 \times 10^{-6***}$	$-8.18 \times 10^{-6***}$						
	(2.05×10^{-6})	(2.72×10^{-6})						
Spring × Availability	0.0135***	0.0141***	0.0132***	0.0137***				
	(0.0048)	(0.0052)	(0.0046)	(0.0050)				
% commuters from outside municipality			0.2794***	0.3759***				
			(0.0109)	(0.0146)				
log(Availability+1)					-0.0742***	-0.1340***		
					(0.0158)	(0.0212)		
Spring × log(Availability+1)					0.0264***	0.0276***		
					(0.0069)	(0.0073)		
asinh(Availability)							-0.0382***	-0.0795***
							(0.0129)	(0.0174)
Spring × asinh(Availability)							0.0192***	0.0203***
							(0.0057)	(0.0060)
Fixed-effects								
Department	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	3,524,383	3,535,553	3,523,960	3,535,130	3,524,383	3,535,553	3,524,383	3,535,553
DV mean	0.00724	0.00429	0.00721	0.00428	0.00724	0.00429	0.00724	0.00429

Clustered (municipality level) standard-errors in parentheses

Table 7.13: Reduced form results: robustness to the choice of only using children that are 6 years old ("in time") in the main specification.

Dependent Variables:	Maths	French	Maths	French	Maths	French	Maths	French
Model:	(1) Baseline	(2) Baseline	(3) "Late"	(4) "Late"	(5) "In advance"	(6) "In advance"	(7) All	(8) All
Variables								
Spring	0.0140***	0.0173***	0.0183	0.0046	0.0588***	0.0678***	0.0143***	0.0169***
	(0.0011)	(0.0013)	(0.0126)	(0.0117)	(0.0096)	(0.0107)	(0.0011)	(0.0013)
Availability	-0.0172*	-0.0446***	-0.0369	-0.0964**	-0.0048	-0.0024	-0.0198**	-0.0483***
	(0.0095)	(0.0129)	(0.0280)	(0.0383)	(0.0087)	(0.0132)	(0.0096)	(0.0132)
Month of birth	-0.0326***	-0.0336***	-0.0038***	-0.0009	-0.0199***	-0.0175***	-0.0333***	-0.0348***
	(0.0002)	(0.0002)	(0.0011)	(0.0009)	(0.0021)	(0.0021)	(0.0002)	(0.0002)
Spring × Availability	0.0136***	0.0143***	-0.0628	-0.0322	0.0298	-0.0222	0.0122**	0.0131**
	(0.0048)	(0.0053)	(0.0447)	(0.0491)	(0.0364)	(0.0394)	(0.0049)	(0.0055)
Fixed-effects								
Department	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	3,524,383	3,535,553	89,066	89,545	16,869	16,905	3,630,318	3,642,003
DV mean	0.00724	0.00429	-0.51406	-0.70038	0.26251	0.40504	-0.00437	-0.01117

Clustered (municipality level) standard-errors in parentheses

Table 7.14: Reduced form results: robustness to the measure of cognitive skills: baseline using standardized test scores, using the probability of having no insufficient items, using the ranks.

Dependent Variables:	Maths	French	> 1 insuff. Maths	> 1 insuff. French	French (ranks)	French (ranks)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Spring	0.0140***	0.0173***	-0.0083***	-0.0067***	0.0027***	0.0043***
	(0.0011)	(0.0013)	(0.0008)	(0.0007)	(0.0002)	(0.0003)
Availability	-0.0172*	-0.0446***	0.0191***	0.0229***	0.0016	-0.0065**
	(0.0095)	(0.0129)	(0.0058)	(0.0057)	(0.0018)	(0.0030)
Month birth	-0.0326***	-0.0336***	0.0164***	0.0138***	-0.0068***	-0.0090***
	(0.0002)	(0.0002)	(9.64×10^{-5})	(0.0001)	(2.1×10^{-5})	(3.05×10^{-5})
Spring × Availability	0.0136***	0.0143***	-0.0007	-0.0061**	0.0023***	0.0035***
	(0.0048)	(0.0053)	(0.0036)	(0.0030)	(0.0008)	(0.0013)
Fixed-effects						
Department	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,524,383	3,535,553	3,620,398	3,620,398	3,524,383	3,535,553
Dependent variable mean	0.00724	0.00429	0.30889	0.25404	0.32619	0.42524

Clustered (municipality level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Clustered (municipality level) standard-errors in parentheses

Table 7.15: Reduced form results, placebo using the interaction of different seasons from Spring

Dependent Variables:	Maths	French	Maths	French	Maths	French	Maths	French
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Constant	0.2188***	0.2240***						
	(0.0032)	(0.0046)						
Spring	0.0146***	0.0182***						
	(0.0011)	(0.0013)						
Availability	-0.0047	-0.0217	-0.0095	-0.0380***	-0.0144	-0.0426***	-0.0140	-0.0389***
	(0.0168)	(0.0205)	(0.0090)	(0.0126)	(0.0093)	(0.0128)	(0.0093)	(0.0128)
Month of birth	-0.0327***	-0.0336***	-0.0332***	-0.0344***	-0.0337***	-0.0348***	-0.0344***	-0.0355***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Spring × Availability	0.0132***	0.0140***						
	(0.0047)	(0.0051)						
Fall			-0.0020	-0.0009				
			(0.0013)	(0.0014)				
Fall × Availability			-0.0169***	-0.0119**				
			(0.0048)	(0.0052)				
Summer					0.0161***	0.0114***		
					(0.0010)	(0.0012)		
Summer × Availability					0.0023	0.0059		
					(0.0042)	(0.0053)		
Winter							-0.0291***	-0.0274***
							(0.0011)	(0.0012)
Winter × Availability							0.0008	-0.0091*
							(0.0041)	(0.0047)
Fixed-effects								
Department			Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	3,524,383	3,535,553	3,524,383	3,535,553	3,524,383	3,535,553	3,524,383	3,535,553
DV mean	0.00724	0.00429	0.00724	0.00429	0.00724	0.00429	0.00724	0.00429

Clustered (municipality level) standard-errors in parentheses

Table 7.16: Robustness of the first stage results to the inclusion of February and June to the definition of spring and to the exclusion of mothers who are teachers (and potentially more likely to time their birth). Back

Dependent Variable:	Daycare		
Model:	(1)	(2)	(3)
Variables			
(Intercept)	0.1004***	0.0956***	0.1017***
	(0.0088)	(0.0093)	(0.0091)
Spring	0.0136**		
	(0.0059)		
Availability	0.2874***	0.2823***	0.2796***
	(0.0526)	(0.0519)	(0.0523)
Month of birth	-0.0034***	-0.0028***	-0.0036***
	(0.0007)	(0.0007)	(0.0007)
Spring × Availability	0.0750**		
	(0.0377)		
(Spring + February)		0.0136**	
		(0.0067)	
(Spring + February) × Availability		0.0684	
		(0.0420)	
(Spring + June)			0.0080
			(0.0054)
(Spring + June) × Availability			0.0867**
			(0.0362)
Fit statistics			
DV mean	0.12016	0.12016	0.12016
F-test	9.4274	9.3845	9.4292

Source. Author's calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.
Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). Standard errors are heteroskedasticity robust and clustered at the municipality level are reported in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 7.17: Reduced form results, robustness of the Spring instrument to the exclusion of the linear month control, to the inclusion of February or June

Dependent Variables:	Maths		French		Maths	French	Maths	French	Maths	French
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables										
Constant	0.0561***	0.2979***	0.0815***	0.3304***						
	(0.0020)	(0.0021)	(0.0027)	(0.0027)						
Spring	0.1153***	0.0045***	0.1221***	0.0081***						
	(0.0013)	(0.0014)	(0.0015)	(0.0015)						
Availability > 0	-0.1118***	-0.1118***	-0.1538***	-0.1537***						
	(0.0056)	(0.0056)	(0.0074)	(0.0075)						
Spring × Availability > 0	0.0171***	0.0171***	0.0173***	0.0174***						
	(0.0018)	(0.0018)	(0.0020)	(0.0020)						
Month birth		-0.0327***		-0.0336***	-0.0326***	-0.0333***	-0.0326***	-0.0333***		
		(0.0002)		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)		
(Spring + Feb.)					0.0094***	0.0152***	0.0094***	0.0152***		
					(0.0011)	(0.0013)	(0.0011)	(0.0013)		
Availability					-0.0180*	-0.0438***	-0.0180*	-0.0438***	-0.0187*	-0.0457***
					(0.0097)	(0.0131)	(0.0097)	(0.0131)	(0.0096)	(0.0130)
(Spring + Feb.) × Availability					0.0131***	0.0086*	0.0131***	0.0086*		
					(0.0047)	(0.0051)	(0.0047)	(0.0051)		
(Spring + June)									0.1164***	0.1207***
									(0.0010)	(0.0011)
(Spring + June) × Availability									0.0157***	0.0152***
									(0.0040)	(0.0044)
Fixed-effects										
Department					Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics										
Observations	3,524,383	3,524,383	3,535,553	3,535,553	3,524,383	3,535,553	3,524,383	3,535,553	3,524,383	3,535,553
Dependent variable mean	0.00724	0.00724	0.00429	0.00429	0.00724	0.00429	0.00724	0.00429	0.00724	0.00429

Clustered (municipality level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Clustered (municipality level) standard-errors in parentheses

7.5.3 Robustness checks to the measure of daycare availability

Table 7.18: Definition of the availability at the municipal level, at the EPCI level and at the municipal level for urban and suburban municipalities but at the EPCI level for rural municipalities

Dependent Variable:	Daycare		
Model:	(1) Municipality	(2) EPCI	(3)
Variables			
(Intercept)	0.1004***	0.0607***	0.0748***
	(0.0088)	(0.0066)	(0.0063)
Spring	0.0136**	-0.0143**	-0.0030
	(0.0059)	(0.0073)	(0.0076)
Availability	0.2874***		
	(0.0526)		
Month of birth	-0.0034***	-0.0031***	-0.0035***
	(0.0007)	(0.0007)	(0.0007)
Spring × Availability	0.0750**		
	(0.0377)		
Availability (EPCI)		0.5781***	
		(0.0397)	
Spring × Availability (EPCI)		0.2760***	
		(0.0603)	
Diff. availability rur. and urb.			0.4634***
			(0.0366)
Spring × Diff. availability rur. and urb.			0.1851***
			(0.0553)
Fit statistics			
Standard-Errors	Municipality	EPCI level	Municipality
DV mean	0.12016	0.11148	0.12145
F-test	9.4274	8.2238	12.780

Source. Author's calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.
Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). Standard errors are heteroskedasticity robust and clustered at the municipality level are reported in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 7.19: Robustness checks to the availability specification

Dependent Variable:	Daycare			
Model:	Baseline	Division bias	No Paris	Binary
Variables				
(Intercept)	0.1004***	0.0974***	0.0979***	0.0815***
	(0.0088)	(0.0078)	(0.0081)	(0.0115)
Spring	0.0136**	0.0136**	0.0144***	0.0054
	(0.0059)	(0.0058)	(0.0055)	(0.0052)
Availability	0.2874***	0.2541***	0.2675***	
	(0.0526)	(0.0452)	(0.0470)	
Month of birth	-0.0034***	-0.0034***	-0.0031***	-0.0035
	(0.0007)	(0.0007)	(0.0006)	(0.0016)
Spring × Availability	0.0750**	0.0749**	0.0514*	
	(0.0377)	(0.0368)	(0.0280)	
Kids born in municipality		1.42×10^{-6}***		
		(1.53×10^{-7})		
$\mathbb{1}(Availability > 0)$				0.0877***
				(1.94×10^{-5})
Spring × $\mathbb{1}(Availability > 0)$				0.0272***
				(1.14×10^{-5})
Fit statistics				
Standard-Errors	Municipality	Municipality	Municipality	groups
DV mean	0.12016	0.12016	0.11149	0.12016
F-test	9.4274	8.9582	8.0290	0.01622

Source. Author's calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.

Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). Standard errors are heteroskedasticity robust and clustered at the municipality level are reported in parentheses.

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 7.21: First-stage regression: falsification test

Dependent Variables:	Mother is employed	Mother has university education	Grandfather was a manager
Model:	(1)	(2)	(3)
Variables			
(Intercept)	0.6292***	0.3993***	0.0746***
	(0.0107)	(0.0118)	(0.0056)
Spring	0.0017	0.0060	-0.0006
	(0.0083)	(0.0081)	(0.0065)
Availability	-0.0448	0.2263***	0.1688***
	(0.0364)	(0.0634)	(0.0430)
Month of birth	-0.0021**	-0.0007	0.0002
	(0.0009)	(0.0010)	(0.0005)
Spring × Availability	0.0460	0.0127	0.0168
	(0.0333)	(0.0339)	(0.0422)
Fit statistics			
DV mean	0.63441	0.44288	0.09752
F-test	0.18128	2.0404	3.1019

Source. Author's calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.

Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). Standard errors are heteroskedasticity robust and clustered at the municipality level are reported in parentheses.

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

7.5.4 Robustness checks using different first stage samples

Table 7.23: Robustness checks of the first-stage regression.

Dependent Variable:	Daycare			
Model:	Baseline (FL)	Elfe 1 year	Elfe 2 years	FL Probit
Variables				
(Intercept)	0.0967***	0.0835***	0.1395***	-1.289***
	(0.0043)	(0.0128)	(0.0153)	(0.0025)
Spring	0.0094*	0.0130	0.0021	0.066***
	(0.0051)	(0.0126)	(0.0151)	(0.0032)
Availability	0.3047***	0.3401***	0.4339***	1.333***
	(0.0112)	(0.0219)	(0.0261)	(0.0067)
Month of birth	-0.0035***	-0.0005	-0.0036	-0.018***
	(0.0005)	(0.0040)	(0.0048)	(0.0002)
Spring $\times$ Availability	0.1026**	0.1492***	0.1562***	0.2764***
	(0.0227)	(0.0476)	(0.0563)	(0.0136)
Fit statistics				
Standard-Errors	Clustered	Het.-robust	Het.-robust	Clustered
Observations	45,533	13,669	12,723	45,533
Mean DV:	0.1201	0.1379	0.1967	0.1201
F-test	9.4274	100.6	108.4	-

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

7.5.5 Robustness checks to the choice of the standard errors

Table 7.24: Robustness to different assumptions on the standard errors

Dependent Variable:		Daycare	
Model:	(1) Clustered	(2) Het. robust	(3) IID
Variables			
(Intercept)	0.1004***	0.1004***	0.1004***
	(0.0088)	(0.0073)	(0.0042)
Spring	0.0136**	0.0136	0.0136***
	(0.0059)	(0.0092)	(0.0050)
Availability	0.2874***	0.2874***	0.2874***
	(0.0526)	(0.0416)	(0.0107)
Month of birth	-0.0034***	-0.0034***	-0.0034***
	(0.0007)	(0.0006)	(0.0005)
Spring × Availability	0.0750**	0.0750	0.0750***
	(0.0377)	(0.0610)	(0.0215)
Fit statistics			
Standard-Errors	Municipality	Het.-robust	Standard
DV mean	0.12016	0.12016	0.12016
F-test	9.4274	312.93	312.93

Source. Author's calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.

Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). Standard errors are heteroskedasticity robust and clustered at the municipality level are reported in parentheses.

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

7.5.6 Further robustness checks

Table 7.25: First-stage regression: adding municipality covariates one by one.

Dependent Variable:	Daycare							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
(Intercept)	0.1004***	0.0949***	0.0628**	0.0323	0.0246	0.0444	0.1142	
	(0.0088)	(0.0241)	(0.0248)	(0.0802)	(0.0805)	(0.0848)	(0.0768)	
Spring	0.0136**	0.0184***	0.0133**	0.0130**	0.0130**	0.0111**	0.0092*	0.0130**
	(0.0059)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0057)
Availability	0.2874***	0.1976***	0.2003***	0.1937***	0.1905***	0.1536***	0.1416***	0.1254***
	(0.0526)	(0.0317)	(0.0375)	(0.0363)	(0.0354)	(0.0241)	(0.0224)	(0.0277)
Month of birth	-0.0034***	-0.0033***	-0.0034***	-0.0034***	-0.0034***	-0.0036***	-0.0039***	-0.0035***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Spring × Availability	0.0750**	0.0672**	0.0495*	0.0511*	0.0505*	0.0563**	0.0578**	0.0769**
	(0.0377)	(0.0279)	(0.0293)	(0.0294)	(0.0294)	(0.0276)	(0.0277)	(0.0358)
% of homeowners		-6.3×10^{-5}	0.0001	-0.0003	-6.94×10^{-5}	-1.91×10^{-5}	-0.0007*	-0.0006*
		(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
% of overcrowded		0.0040***	0.0025***	0.0023***	0.0023***	0.0020**	0.0016*	0.0003
		(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
vacant houses		-0.0019**	-0.0013	-0.0011	-0.0006	-0.0004	8.47×10^{-5}	-0.0004
		(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0008)
% manual workers			-0.0002	-0.0001	-5.59×10^{-5}	0.0001	0.0002	0.0001
			(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
% managers			0.0023***	0.0019***	0.0018***	0.0015**	0.0006	0.0004
			(0.0007)	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0005)
% selfemployed			0.0006	0.0007*	0.0009**	0.0012***	0.0009**	-0.0001
			(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
LFP (Women 25-54)				0.0023***	0.0024***	0.0023***	0.0010	0.0018***
				(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0007)
LFP (Men 25-54)				-0.0016	-0.0016*	-0.0018*	-0.0020**	-0.0026***
				(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0008)
urbanization 9 catBV NR MP					-0.0380***	-0.0578***	-0.0444***	-0.0637***
					(0.0131)	(0.0125)	(0.0114)	(0.0156)
urbanization 9 catBV NR PER					-0.0242	-0.0231	-0.0304*	-0.0319**
					(0.0157)	(0.0159)	(0.0165)	(0.0140)
urbanization 9 catBV NR PP					-0.0176**	-0.0097	-0.0364***	-0.0206
					(0.0084)	(0.0088)	(0.0099)	(0.0191)
urbanization 9 catBV RU AUT					-0.0071	-0.0110	-0.0085	-0.0104
					(0.0121)	(0.0126)	(0.0134)	(0.0124)
urbanization 9 catBV RU GPU					-0.0037	-0.0127	-0.0047	-0.0180*
					(0.0098)	(0.0099)	(0.0098)	(0.0101)
urbanization 9 catBV RU MP					-0.0405***	-0.0469***	-0.0389***	-0.0390***
					(0.0097)	(0.0093)	(0.0100)	(0.0108)
urbanization 9 catBV RU PER					-0.0280***	-0.0295***	-0.0256***	-0.0200**
					(0.0086)	(0.0085)	(0.0084)	(0.0078)
urbanization 9 catBV RU PP					-0.0134	-0.0231**	-0.0148	-0.0087
					(0.0097)	(0.0098)	(0.0099)	(0.0090)
% secondary sector workers						-0.0176	-0.0107	0.0027
						(0.0173)	(0.0140)	(0.0162)
% workers in construction						0.0265	0.0882	0.1149
						(0.1292)	(0.1393)	(0.1271)
% workers in sales						0.0374	0.0044	-0.0449
						(0.0607)	(0.0580)	(0.0490)
% workers in HoReCa						0.4308*	0.2917	0.1803*
						(0.2323)	(0.1840)	(0.1018)
% workers in other market services						0.0380	0.0384	0.0410
						(0.0492)	(0.0455)	(0.0404)
% workers in non-market services p						0.0746	0.0192	0.0360
						(0.0910)	(0.0821)	(0.0828)
% workers temporary workers						-0.3012	-0.0260	0.2927
						(0.3769)	(0.3644)	(0.3327)
Median income							$5.74 \times 10^{-6***}$	$5.67 \times 10^{-6***}$
							(1.59×10^{-6})	(1.66×10^{-6})
Libraries per capita								1.489
								(3.981)
LEAP per capita								36.87
								(58.25)
Fixed-effects								
Department								Yes
Fit statistics								
DV mean	0.12016	0.12147	0.12155	0.12155	0.12155	0.12170	0.12188	0.12188
F-test	9.4274	6.4072	4.7546	4.0492	2.5133	1.8661	1.8094	0.51306

Source. Author's calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.
Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). Standard errors are heteroskedasticity robust and clustered at the municipality level are reported in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 7.26: Reduced form regression adding municipality covariates one by one, for numeracy skills.

Dependent Variable:	Maths							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Spring	0.0140***	0.0139***	0.0134***	0.0129***	0.0140***	0.0140***	0.0132***	0.0129***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Availability	-0.0172*	0.0564***	0.0969***	-0.0031	0.0488***	0.0071	-0.0457***	0.0156***
	(0.0095)	(0.0082)	(0.0086)	(0.0066)	(0.0081)	(0.0091)	(0.0072)	(0.0054)
Month of birth	-0.0326***	-0.0327***	-0.0327***	-0.0327***	-0.0327***	-0.0326***	-0.0327***	-0.0328***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Spring × Availability	0.0136***	0.0130***	0.0131***	0.0145***	0.0132***	0.0133***	0.0113**	0.0126***
	(0.0048)	(0.0045)	(0.0048)	(0.0046)	(0.0045)	(0.0046)	(0.0051)	(0.0044)
Urban		-0.0757***						
		(0.0058)						
Isolated city		0.0205***						
		(0.0057)						
Rural		0.0848***						
		(0.0042)						
% of homeowners			0.0050***					0.0021***
			(0.0001)					(0.0002)
vacant houses			-0.0054***					-0.0022***
			(0.0005)					(0.0004)
LFP (Women 25-54)				0.0168***				0.0070***
				(0.0007)				(0.0006)
LFP (Men 25-54)				0.0061***				-0.0003
				(0.0009)				(0.0006)
% manual workers					0.0013***			-0.0001
					(0.0002)			(0.0001)
% selfemployed					0.0082***			0.0009***
					(0.0003)			(0.0002)
% managers					1.69×10^{-5}			0.0006***
					(0.0004)			(0.0002)
% workers in construction						0.2660***		-0.0490
						(0.0788)		(0.0382)
% workers in sales						-0.1767***		-0.0642***
						(0.0602)		(0.0218)
% workers in HoReCa						0.0625		0.1616***
						(0.0646)		(0.0539)
% workers in other market services						0.0387*		0.0060
						(0.0206)		(0.0109)
% workers temporary workers						-2.177***		0.1687*
						(0.2612)		(0.0920)
Median income							$2.88 \times 10^{-5***}$	$1.54 \times 10^{-5***}$
							(8.41×10^{-7})	(7.73×10^{-7})
Libraries per capita							51.76***	16.89***
							(2.239)	(1.806)
LEAP per capita							-99.04***	-17.96
							(19.79)	(14.10)
urbanization 9 catBV NR MP								0.0219**
								(0.0094)
urbanization 9 catBV NR PER								0.0158***
								(0.0050)
urbanization 9 catBV NR PP								-0.0046
								(0.0161)
urbanization 9 catBV RU AUT								0.0296***
								(0.0051)
urbanization 9 catBV RU GPU								0.0122**
								(0.0057)
urbanization 9 catBV RU MP								0.0148***
								(0.0054)
urbanization 9 catBV RU PER								0.0246***
								(0.0033)
urbanization 9 catBV RU PP								0.0185***
								(0.0041)
Fixed-effects								
Department	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	3,524,383	3,524,306	3,524,276	3,524,276	3,524,168	3,523,577	3,523,717	3,522,872
DV mean	0.00724	0.00723	0.00723	0.00723	0.00723	0.00723	0.00722	0.00721

Clustered (municipality level) standard-errors in parentheses

Table 7.27: Reduced form regression adding municipality covariates one by one, for literacy skills.

Dependent Variables:	Maths			French			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Spring	0.0140***	0.0173***	0.0171***	0.0165***	0.0158***	0.0172***	0.0173***
	(0.0011)	(0.0013)	(0.0012)	(0.0013)	(0.0013)	(0.0012)	(0.0012)
Availability	-0.0172*	-0.0446***	0.0562***	0.1113***	-0.0257***	0.0430***	-0.0127
	(0.0095)	(0.0129)	(0.0106)	(0.0111)	(0.0088)	(0.0106)	(0.0125)
Month of birth	-0.0326***	-0.0336***	-0.0336***	-0.0337***	-0.0337***	-0.0336***	-0.0336***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Spring × Availability	0.0136***	0.0143***	0.0137***	0.0137***	0.0158***	0.0138***	0.0139***
	(0.0048)	(0.0053)	(0.0048)	(0.0052)	(0.0049)	(0.0048)	(0.0050)
Urban			-0.1052***				
			(0.0079)				
Isolated city			0.0268***				
			(0.0076)				
Rural			0.1153***				
			(0.0056)				
% of homeowners				0.0068***			
				(0.0002)			
vacant houses				-0.0071***			
				(0.0007)			
LFP (Women 25-54)					0.0233***		
					(0.0009)		
LFP (Men 25-54)					0.0077***		
					(0.0011)		
% manual workers						0.0015***	
						(0.0002)	
% selfemployed						0.0114***	
						(0.0004)	
% managers						9.55×10^{-5}	
						(0.0006)	
% workers in construction							0.5191***
							(0.1090)
% workers in sales							-0.2341***
							(0.0839)
% workers in HoReCa							0.0703
							(0.0874)
% workers in other market services							0.0662**
							(0.0303)
% workers temporary workers							-3.190***
							(0.3672)
Fixed-effects							
Department	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	3,524,383	3,535,553	3,535,476	3,535,446	3,535,446	3,535,336	3,534,744
DV mean	0.00724	0.00429	0.00429	0.00429	0.00429	0.00429	0.00429

Clustered (municipality level) standard-errors in parentheses

Table 7.28: Baseline reduced form adding school-level covariates, Maths

Dependent Variable:	Maths				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Spring	0.0139***	0.0139***	0.0138***	0.0129***	0.0112***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0013)
Availability	-0.0168*	-0.0168*	-0.0295***	-0.0316***	-0.0736***
	(0.0094)	(0.0094)	(0.0098)	(0.0076)	(0.0077)
Month of birth	-0.0323***	-0.0323***	-0.0323***	-0.0324***	-0.0324***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Spring $\times$ Availability	0.0135***	0.0134***	0.0130***	0.0126**	0.0128**
	(0.0048)	(0.0048)	(0.0050)	(0.0050)	(0.0060)
Female		0.0184***	0.0186***	0.0188***	0.0181***
		(0.0008)	(0.0008)	(0.0008)	(0.0009)
School status = Private			0.1142***	0.0760***	-0.0139***
			(0.0071)	(0.0049)	(0.0027)
School priority = REP				-0.2088***	-0.0163***
				(0.0050)	(0.0045)
School priority = REP+				-0.2958***	-0.0335***
				(0.0101)	(0.0087)
School IPS					0.0078***
					(0.0001)
Fixed-effects					
Department	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	3,524,383	3,524,383	3,522,263	3,522,263	2,747,876
R^2	0.04040	0.04061	0.04393	0.06056	0.08386
Within R^2	0.03200	0.03220	0.03555	0.05232	0.07471

Clustered (municipality level) standard-errors in parentheses

Table 7.29: Baseline reduced form adding school-level covariates, French

Dependent Variable:	French				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Spring	0.0172***	0.0174***	0.0172***	0.0159***	0.0120***
	(0.0013)	(0.0013)	(0.0013)	(0.0012)	(0.0014)
Availability	-0.0443***	-0.0442***	-0.0612***	-0.0643***	-0.0992***
	(0.0129)	(0.0129)	(0.0136)	(0.0103)	(0.0102)
Month of birth	-0.0334***	-0.0334***	-0.0334***	-0.0335***	-0.0330***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Spring × Availability	0.0142***	0.0137***	0.0131**	0.0125**	0.0123**
	(0.0053)	(0.0053)	(0.0055)	(0.0056)	(0.0063)
Female		0.1230***	0.1232***	0.1235***	0.1187***
		(0.0009)	(0.0009)	(0.0009)	(0.0010)
school status = Privé			0.1523***	0.0966***	-0.0186***
			(0.0092)	(0.0062)	(0.0033)
school priority = REP				-0.3020***	-0.0394***
				(0.0068)	(0.0061)
school priority = REP+				-0.4327***	-0.0775***
				(0.0126)	(0.0097)
school ips					0.0106***
					(0.0001)
Fixed-effects					
Department	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	3,535,553	3,535,553	3,533,404	3,533,404	2,752,948
R^2	0.04896	0.05679	0.06177	0.09161	0.12841
Within R^2	0.02953	0.03752	0.04259	0.07305	0.11075

Clustered (municipality level) standard-errors in parentheses

Table 7.30: Reduced form regression: robustness to the inclusion of school × year fixed effects, inclusion of year fixed effects, exclusion of tests administered in September 2020.

Dependent Variables:	Maths	French	Maths	French	Maths	French
Model:	(1)	(2)	(3)	(4)	(5) No 2020	(6) No 2020
Variables						
Spring × Availability	0.0082*	0.0113**	0.0138***	0.0150***	0.0129**	0.0147**
	(0.0046)	(0.0045)	(0.0049)	(0.0050)	(0.0055)	(0.0060)
Spring			0.0142***	0.0165***	0.0139***	0.0169***
			(0.0011)	(0.0012)	(0.0012)	(0.0014)
Availability			-0.0211**	-0.0258**	-0.0177*	-0.0506***
			(0.0096)	(0.0125)	(0.0092)	(0.0127)
Month of birth			-0.0326***	-0.0336***	-0.0324***	-0.0339***
			(0.0002)	(0.0002)	(0.0002)	(0.0002)
Fixed-effects						
School×year	Yes	Yes				
Month of birth	Yes	Yes				
Year			Yes	Yes		
Department			Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,524,383	3,535,553	3,524,383	3,535,553	2,782,854	2,791,704
DV mean	0.00724	0.00429	0.00724	0.00429	0.01527	0.03361

Clustered (municipality level) standard-errors in parentheses

Table 7.31: Reduced form regression: using more granular skills for Maths.

Dependent Variables:	Maths	Number recognition	Number comparison	Problem solving and counting	Geometry
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Spring	0.0140***	0.0096***	0.0148***	0.0163***	0.0173***
	(0.0011)	(0.0014)	(0.0015)	(0.0014)	(0.0019)
Availability	-0.0172*	-0.0429***	-0.0069	-0.0227**	0.0365***
	(0.0095)	(0.0084)	(0.0116)	(0.0110)	(0.0098)
Month of birth	-0.0326***	-0.0213***	-0.0420***	-0.0329***	-0.0367***
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Spring × Availability	0.0136***	0.0164***	0.0146**	0.0117*	0.0105
	(0.0048)	(0.0060)	(0.0057)	(0.0060)	(0.0076)
Fixed-effects					
Department	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	3,524,383	3,522,917	3,521,117	3,522,604	2,865,474
DV mean	0.00724	0.01150	0.00738	0.00921	0.01414

Clustered (municipality level) standard-errors in parentheses

Table 7.32: Reduced form regression: using more granular skills for French.

Dependent Variables:	French	Letters recognition	Phonology	Oral comprehension
Model:	(1)	(2)	(3)	(4)
Variables				
Spring	0.0173***	0.0140***	0.0181***	0.0182***
	(0.0013)	(0.0015)	(0.0015)	(0.0015)
Availability	-0.0446***	-0.0739***	-0.0076	-0.0650***
	(0.0129)	(0.0115)	(0.0126)	(0.0167)
Month of birth	-0.0336***	-0.0326***	-0.0367***	-0.0314***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Spring × Availability	0.0143***	0.0129**	0.0146**	0.0150**
	(0.0053)	(0.0064)	(0.0059)	(0.0060)
Fixed-effects				
Department	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,535,553	3,521,204	3,534,574	3,534,637
DV mean	0.00429	-0.00365	0.01213	0.01005

Clustered (municipality level) standard-errors in parentheses

Table 7.33: Results for the two-sample 2SLS, with coefficients of the covariates.

	First stage	Second stage maths	Second stage French	Second stage maths, capped	Second stage French, capped
Spring	0.013*				
	(0.006)				
Availability	0.125***				
	(0.023)				
Month of birth	−0.004***	−0.033	−0.034	−0.032	−0.034
	(0.001)	(0.039)	(0.060)	(0.038)	(0.036)
Female	−0.007*	0.021***	0.125***	0.021***	0.125***
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
% homeowners	−0.001*	0.003**	0.003***	0.003***	0.003***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
% overcrowded houses	0.000	0.001***	0.001***	0.001***	0.001***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
% vacant houses	0.000	−0.002***	−0.002***	−0.002***	−0.002***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
% manual workers	0.000	0.000	−0.001***	0.000	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% managers	0.000	0.000***	0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% self employed	0.000	0.001***	0.002***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LFP Women 25-54	0.002***	0.006***	0.010***	0.006***	0.009***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
LFP Men 25-54	−0.003*	0.000*	−0.001***	0.000*	−0.001***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
% secondary sector	0.003	0.005	0.012*	0.005	0.012**
	(0.016)	(0.003)	(0.005)	(0.005)	(0.004)
% construction	0.113	−0.087***	0.107***	−0.090***	0.106***
	(0.099)	(0.022)	(0.014)	(0.024)	(0.020)
% sales	−0.044	−0.050***	−0.070***	−0.050***	−0.070***
	(0.056)	(0.009)	(0.010)	(0.007)	(0.007)
% HoReCa	0.181	0.105***	0.147***	0.102***	0.145***
	(0.154)	(0.020)	(0.026)	(0.023)	(0.032)
% other tertiary	0.040+	−0.005	0.013+	−0.005***	0.013***
	(0.024)	(0.006)	(0.007)	(0.001)	(0.003)
% non-market tertiary	0.037	0.108***	0.134***	0.107***	0.133***
	(0.082)	(0.014)	(0.017)	(0.013)	(0.019)
% temporary workers	0.302	0.079*	−0.111*	0.074	−0.115**
	(0.276)	(0.038)	(0.057)	(0.045)	(0.039)
Median income	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Libraries per capita	1.582	17.908***	27.189***	17.912***	27.191***
	(2.328)	(0.822)	(0.781)	(0.766)	(1.021)
LEAP per capita	36.725	−26.668***	−29.149***	−27.799***	−29.853***
	(28.661)	(5.204)	(7.541)	(6.300)	(5.879)
Spring × Availability	0.077*				
	(0.043)				
$\widehat{Daycare}$		0.219***	0.123***		
		(0.012)	(0.023)		
$\widehat{Daycare}$ (capped)				0.239***	0.136***
				(0.024)	(0.017)
Fixed-effects					
Department	Yes	Yes	Yes	Yes	Yes
Urbanization	Yes	Yes	Yes	Yes	Yes

Source. Author's calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016, birth registries (INSEE), France, 2012-2016.

Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). The first column is the first stage regression. The second and third column report TS2SLS estimates for Maths and French, respectively, using the non-capped generated daycare availability. The fourth and fifth columns report TS2SLS estimates for Maths and French, respectively, using the capped generated daycare availability. Standard errors are heteroskedasticity robust and clustered at the municipality level are reported in parentheses.

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

7.5.7 Quantile regressions

Table 7.34: Reduced form regression: results defining the local daycare availability as a binary variable.

Dependent Variables:	Maths		French		Maths		French	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Constant	0.0561***	0.2979***	0.0815***	0.3304***	0.0561***	0.2979***	0.0815***	0.3304***
	(0.0020)	(0.0021)	(0.0027)	(0.0027)	(2.36×10^{-15})	(0.0086)	(2.7×10^{-14})	(0.0067)
Spring	0.1153***	0.0045***	0.1221***	0.0081***	0.1153***	0.0045	0.1221***	0.0081*
	(0.0013)	(0.0014)	(0.0015)	(0.0015)	(6.2×10^{-14})	(0.0039)	(7.87×10^{-14})	(0.0031)
av binary numeric	-0.1118***	-0.1118***	-0.1538***	-0.1537***	-0.1118***	-0.1118***	-0.1538***	-0.1537***
	(0.0056)	(0.0056)	(0.0074)	(0.0075)	(4.19×10^{-15})	(1.13×10^{-6})	(2.87×10^{-14})	(1.13×10^{-6})
Spring × av binary numeric	0.0171***	0.0171***	0.0173***	0.0174***	0.0171***	0.0171***	0.0173***	0.0174***
	(0.0018)	(0.0018)	(0.0020)	(0.0020)	(6.22×10^{-14})	(2.26×10^{-6})	(7.93×10^{-14})	(1.45×10^{-6})
Month of birth		-0.0327***		-0.0336***		-0.0327***		-0.0336***
		(0.0002)		(0.0002)		(0.0012)		(0.0009)
Fit statistics								
Standard-Errors	Municipality	Municipality	Municipality	Municipality	Group	Group	Group	Group
DV mean	0.00724	0.00724	0.00429	0.00429	0.00724	0.00724	0.00429	0.00429

The first four columns have clustered standard-errors at the municipality level in parentheses, while the last columns cluster the error at the group level: following Bertrand et al. (2004), this accounts for autocorrelation. While the number of clusters (4) is too low to credibly apply asymptotics, it shows that the significance of the coefficient of interest (Spring × av binary numeric) is not biased downward.

Table 7.36: Reduced form regression: quantile regression using the binary definition of availability (Equation 6) for Maths.

Quantile	QTE	Std. Error
0.05	0.049	0.004
0.1	0.032	0.003
0.15	0.024	0.002
0.2	0.020	0.003
0.25	0.019	0.003
0.3	0.018	0.002
0.35	0.017	0.002
0.4	0.018	0.002
0.45	0.016	0.001
0.5	0.016	0.001
0.55	0.014	0.001
0.6	0.013	0.001
0.65	0.012	0.001
0.7	0.011	0.001
0.75	0.010	0.001
0.8	0.008	0.001
0.85	0.007	0.001
0.9	0.011	0.002
0.95	-0.003	0.002

Table 7.37: Reduced form regression: quantile regression using the binary definition of availability (Equation 6) for French.

Quantile	QTE	Std. Error
0.05	0.049	0.004
0.1	0.032	0.003
0.15	0.024	0.002
0.2	0.020	0.003
0.25	0.019	0.003
0.3	0.018	0.002
0.35	0.017	0.002
0.4	0.018	0.002
0.45	0.016	0.001
0.5	0.016	0.001
0.55	0.014	0.001
0.6	0.013	0.001
0.65	0.012	0.001
0.7	0.011	0.001
0.75	0.010	0.001
0.8	0.008	0.001
0.85	0.007	0.001
0.9	0.011	0.002
0.95	-0.003	0.002

Table 7.38: Reduced form regression: robustness to the choice of standard errors.

Dependent Variables:	Maths	French	Maths	French	Maths	French	Maths	French
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Spring	0.0140***	0.0173***	0.0140***	0.0173***	0.0140***	0.0174***	0.0140***	0.0173***
	(0.0011)	(0.0013)	(0.0010)	(0.0011)	(0.0012)	(0.0012)	(0.0011)	(0.0013)
Availability	-0.0172*	-0.0446***	-0.0172***	-0.0446***	-0.0170	-0.0445*	-0.0172	-0.0446
	(0.0095)	(0.0129)	(0.0022)	(0.0025)	(0.0203)	(0.0247)	(0.0217)	(0.0283)
Month birth	-0.0326***	-0.0336***	-0.0326***	-0.0336***	-0.0326***	-0.0336***	-0.0326***	-0.0336***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Spring × Availability	0.0136***	0.0143***	0.0136***	0.0143***	0.0136***	0.0143***	0.0136***	0.0143***
	(0.0048)	(0.0053)	(0.0040)	(0.0045)	(0.0048)	(0.0052)	(0.0042)	(0.0046)
Fixed-effects								
Department	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	3,524,383	3,535,553	3,524,383	3,535,553	3,524,065	3,535,235	3,524,383	3,535,553
Dependent variable mean	0.00724	0.00429	0.00724	0.00429	0.00724	0.00428	0.00724	0.00429

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Clustered (municipality level) standard-errors in parentheses

Table 7.20: First stage regression: dividing the sample between those who move in the last 6 months and those who do not in the FL survey, those who moved and not in the last 2 years in the Elfe sample, and those who expressed a preference for daycare or not in the 2-month Elfe wave.

	Moved in last 6 months	Did not move	Moved in last 2 years	Did not move	Preference for daycare	Preference for other
	Creche					
Variables						
Constant	0.0782**	0.1002***	0.0418	0.0934***	0.5051***	0.0375***
	(0.0382)	(0.0089)	(0.0268)	(0.0171)	(0.0607)	(0.0132)
Spring	0.0136**	0.0034	0.0303	0.0086	-0.0451	0.0164
	(0.0059)	(0.0769)	(0.0352)	(0.0178)	(0.0689)	(0.0137)
Availability	0.2874***	0.0578	0.1997***	0.3773***	0.2587**	0.2702***
	(0.0526)	(0.0860)	(0.0457)	(0.0502)	(0.1092)	(0.0293)
Month of birth	-0.0034***	0.0005	0.0110	-0.0032	-0.0410**	0.0062
	(0.0007)	(0.0039)	(0.0083)	(0.0052)	(0.0179)	(0.0043)
Spring × Availability	0.0750**	0.4695	0.2812	0.1180	0.1478	0.1398*
	(0.0377)	(0.5231)	(0.1880)	(0.0967)	(0.2541)	(0.0780)
Mean DV	0.09657	0.12033	0.1379	0.1379	0.1379	0.1379
Fit statistics						
Standard-Errors	Clustered, municipality		Heteroskedasticity-robust			
Observations	321	45,480	2,634	11,035	1,971	11,303
R^2			0.02156	0.03202	0.01783	0.02389
Adjusted R^2			0.02007	0.03167	0.01584	0.02355

Source. Author's calculations based on FL survey, France, 2011, Elfe survey, France, 2011-2012, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016.
Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May in the FL survey, taking value 1 when children are born in April in the Elfe survey. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). The first and second column split the sample between families that moved in the last 6 months and not and are estimated from the FL survey. The third and fourth column split the sample between families that moved in the last 2 years and not and are estimated from the Elfe survey. The fifth and sixth columns split the sample between children whose mother said that daycare was her ideal childcare arrangement during the 2-month wave of the Elfe longitudinal survey and those who stated a different preference. Standard errors are heteroskedasticity robust in column 3, 4, 5 and 6 and clustered at the municipality level in column 1 and 2. In fact, I do not have access to the information of the municipality of birth for the Elfe sample.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 7.22: Comparison of first-stage surveys.

Name	**Source**	**N, attrition**	**Definition of childcare arrangement**	**Children born in years**	**Pro**	**Con**
Elfe	Ined	18.000, 16%	“main”	2011	Multiple surveys → intensity, descriptive variables	Attrition, sample size, only kids born in 4 months
Enquête Famille Logement	Insee (distributed with census)	45.000	“main”	2007-2011	Sample size, covariates	Too early
Enquête Mode de Garde	Drees	3000	hour per hour	2011-2013	Precision	Sample size

Table 7.35: Reduced form regression: quantile regression using the continuous definition of availability (Equation 2).

Dependent Variables: Model:	French (1) 25th p.	French (2) 50th p.	French (3) 75th p.	Maths (4) 25th p.	Maths (5) 50th p.	Maths (6) 75th p.
Variables						
Constant	0.07533***	0.45148***	0.70499***	0.07533***	0.45148***	0.70499***
	(0.00183)	(0.0016)	(0.0016)	(0.0018)	(0.0015)	(0.0017)
Spring	0.00959***	0.00748***	0.00789***	0.00959***	0.00748***	0.00789***
	(0.00238)	(0.0016)	(0.0016)	(0.0018)	(0.0015)	(0.0017)
Availability	-0.21305***	-0.12762***	-0.06909***	-0.21305***	-0.12762***	-0.06909***
	(0.00150)	(0.0132)	(0.0098)	(0.0133)	(0.0096)	(0.0131)
Month birth	-0.04401***	-0.03408***	-0.02409***	-0.04401***	-0.03408***	-0.02409***
	(0.00020)	(0.00013)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Spring × Availability	0.02277**	0.02116*	0.01264**	0.02277**	0.02116**	0.01264**
	(0.00288)	(0.00196)	(0.00148)	(0.00288)	(0.00196)	(0.00148)