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

Does early education intervention benefit children's cognitive development, and if so, why? Neurological literature[1] has reached a consensus on responsive caregiving (Gunderson et al., 2013) and language-rich interactions (Cartmill et al., 2013; Hart & Risley, 1995, 2003; Rowe & Goldin-Meadow, 2009) being associated with stronger early language development (Cartmill et al., 2013; Tamis-LeMonda, Bornstein, & Baumwell, 2001). Daycare centers may have a direct positive effect on children's early human capital accumulation, through socialization with other children and interactions with trained staff that provide explicit opportunities for skill development. There is a heated policy debate about the effectiveness of subsidized, universally accessible child care solutions on the accumulation of human capital in the US and in Europe, with specific targets on the proportion of children that should be offered a place in formal childcare under 3 years of age (The Council of the European Union, 2019).

This paper provides the first causal investigation of long-term cognitive outcomes of daycare attendance in France, in particular focusing on French and Math abilities in the first grade of primary school. We identify the reduced-form effect of the quality of childcare on cognitive outcomes, exploiting the variety of types of daycare and of management in France. Identifying this effect is a key step in the design of public childcare policies that are effective in reducing long-lasting inequality in educational outcomes.

France is an interesting setting to study childcare policies since it is a front-runner in access to formal childcare. With a 58% coverage of total formal childcare arrangements, it is well above the OECD average of 36% (OECD, 2021). Moreover, France provides an interesting context to study different childcare solutions, ranging from compensated parental leave up to 3 years to personal in-home childcare to daycare centers, all at least partly funded through public intervention. 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. While the relevance of the season of birth for daycare access builds on Le Bouteillec, Kandil, and Solaz (2014) and Berger, Panico, and Solaz (2021), this paper is the first to use the interaction of it with the local daycare availability. The identification comes from the interaction of an excluded but endogenous quasi-IV - the local daycare availability - with one exogenous but included quasi-IV - the random assignment to the month of birth (Bruneel-Zupanc & Beyhum, 2024). 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

[1]For example, Council et al. (2000); Nelson and Sheridan (2011); Noble et al. (2015); Sowell et al. (2003) show that a large proportion of the neuronal connections in the brain are formed during the first years of life.

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 & Hangartner, 2020). The main instrument we use - interaction between birth in spring and local daycare availability - seems to isolate 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 & Simonsen, 2016), or difference-in-differences using the staggered expansion of childcare reforms (Andresen, 2019; Cascio, 2009; Cornelissen, Dustmann, Raute, & Schönberg, 2018; Felfe & Lalive, 2018; Felfe, Nollenberger, & Rodríguez-Planas, 2015; Havnes & Mogstad, 2011; Jessen, Schmitz, & Waights, 2020; Noboa-Hidalgo & Urzua, 2012; Pora, 2020). Among those, the ones that do not use individual-level data on daycare attendance, but rely on reduced-form estimates (Baker, Gruber, & Milligan, 2008, 2015; Haeck, Lebihan, & Merrigan, 2018; Havnes & Mogstad, 2011, 2015) are particularly relevant, as we also do not have full-coverage administrative data on childcare attendance. The main advantage of reduced form parameters is that they measure the overall impact of subsidized child care, taking into account potential changes in parental behavior and any spill-over effects on children who were not enrolled in subsidized care. 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.

The main contributions of this paper to the literature are two. First, it fills a gap in the literature on the causal identification of long-term impact of different quality of daycare, as highlighted by European Commission (2022): most papers on the topic are either correlational (Melhuish et al., 2008; Sammons et al., 2008; Slot, Leseman, Verhagen, & Mulder, 2015) or are meta-analyses (Ulferts & Anders, 2016; van Huizen & Plantenga, 2018) 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 the class size is mandated by a national law, so we focus on different types of daycare centers (described in Section 2), of different types of management (public, private for profit, non profit) and 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 (Feller, Grindal, Miratrix, & Page, 2016; Kline & Walters, 2016; Zhai, Brooks-Gunn, & Waldfogel, 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, Hoynes, and Domina (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 the eligibility is defined - fuzzily - by being born in spring. Differently from Kottelenberg and Lehrer (2017) and Bitler et al. (2014), we can estimate the 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, Greenwood, Everingham, Houbé, and Kilburn 1998, J. J. Heckman, Moon, Pinto, Savelyev, and Yavitz 2010, J. Heckman, Pinto, and Savelyev 2013). This takeaway message is coherent with the results of Fort, Ichino, and Zanella (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 & 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[2].

Virtually all children enrol in a center-based pre-school in the year they turn 3 (INSEE, 2019):

[2]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).

in the 2012-2016 period, there is little variation in this figure, that is always above 97%[3]. 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[4].

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 7.6):

- 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.
- 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.

[3] 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 7.23.

[4] 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).

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 & Magnuson, 2013; van Huizen & 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[5], 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, Bigot, & Dajoux, 2014). In the department of Côtes-d'Armor in Brittany, where childminders are much more common 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, De Chaisemartin, Dugravier, & Gurgand, 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.

[5] There is in fact a strong association between the socio-economic status of parents and the quantity and style of spoken words (Hart & Risley, 2003), the use of child-directed speech (Rowe, 2008), and the utilization of gestures (Rowe & 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

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[6]. 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 7.15, 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 7.17 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 7.13), 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, 2016) comes to similar results through in-depth interviews: parents particularly 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 7.18), and that the time to find a spot in daycare is usually longer than for other options (Figure 7.16).

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[7].

One-fourth of children attends multiple childcare arrangements, according to the Elfe survey.

[6] 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?"

[7] 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.

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
Elfe, 1-year wave	46%	5%	32.75%	14%	1%	-	1%
Elfe, 2-year wave	38%	4%	35%	20%	1%	1%	2%
FL, age 0	60%	4%	25%	9%	-	-	2%
FL, age 1	44%	5%	31%	17%	-	-	2%
FL, age 2	45%	5%	29%	18%	-	-	2%
Mode de garde, age 0	73%	2%	16%	8%	1%	0%	0%
Mode de garde, age 1	58%	3%	22%	16%	1%	0%	0%
Mode de garde, age 2	50%	3%	13%	19%	1%	13%	1%

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.

The fact of having a complementary childcare arrangement is relatively evenly distributed among the various principal childcare arrangements (Figure 7.19). 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 7.19 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.

3 Data

3.1 Data on educational outcomes

The educational outcomes are taken from the "ÉvalAide - Évaluer pour mieux aider" standardized evaluations in first and second grade of primary school. The ÉvalAide programme is administered by the DEPP (*Direction de l'évaluation, de la prospective et de la performance*), the statistical and research branch of the French Education Ministry. It assesses the cognitive skills of all French pupils at the beginning and middle of first grade and at the beginning of the second grade, resulting in 3 tests for each pupil. The aim is to spot early the specific needs of each pupil so that teachers can better adapt their teaching. The assessments provide benchmarks for each pupil's attainment and progress in different areas of language and mathematics. This administrative dataset covers the universality of children that attend elementary school in

France between 2018 and 2023.

We use the test administered in September of the first grade for the main analysis, resulting in a cross-sectional dataset. Focusing on September of the first grade, each student fills 8 items in French and 8 items in maths. In the main specification, since each item has a different evaluation scale, we standardize the scores for each item, and we take the unweighted average for maths items and French items. The result is a dataset where the unit of observation is the student, each with a maths and a French score and a few covariates (gender, birthday, school they are attending). Results are robust to using the rank[8] of each student instead of the score (Table 7.8). To compute the rank, we first compute the rank of each item and then we take the unweighted average rank for all items for each student in maths and French. In the main specification we use the score rather than the rank as this increase the comparability with other results in the literature on universal childcare that measure cognitive skills using standard deviations (Andresen 2019; Drange and Havnes 2019; Filatriau, Fougère, and Tô 2013; Gupta and Simonsen 2016; Heim 2018 among the others). Moreover, for every item, the Ministry sets *a priori* a sufficient threshold. The great majority of students have no insufficient items (Figure 7.23), and we define as an alternative dependent variable the fact of having at least one insufficient item. Following Drange and Havnes (2019), the rationale of using this definition of cognitive skills is that, while the economic significance of test scores may be hard to assess, the thresholds are constructed in order to identify children with potential development problems, so that teachers can address those problems as early as possible (Martinot et al., 2021). In this way, we can see the impact of daycare attendance on the likelihood of reducing developmental issues.

From the total number of students in the administrative DEPP dataset, we delete those that did not take any test (2.81%), while if some single items are missing, we take the average of the ones that are present. There is no apparent pattern of missingness in the data (Figure 7.21). 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). Finally, 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 who are 7 or 5 in first grade is negligible (Figure 7.22), and they are part of two very selected populations. Children who are 7 either repeated the first grade, which is very uncommon, or the preschool teachers decided to hold them in preschool for an additional 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, that is granted on an exceptional basis. Not surprisingly, the main analysis does not hold in these two small subsamples, but it is nevertheless robust to the inclusion of these children (Table 7.7). 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

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

7.3.

We argue that these standardized test scores proxy underlining skills relatively well: they are administered equally and reasonably under the same conditions and are objectively marked. The teacher corrects them, but following a strict Ministry guideline (Ministère de l'Éducation nationale et de la Jeunesse, 2023), and all items are multiple choice, so there is small margin for the teacher's personal interpretation, as there would be in an oral exam or in grading an essay.

3.2 Data on childcare availability

To measure daycare availability, we use administrative data on the number of places provided by each daycare center, from the French Social Security system (CAF)[9]. For each year, from 2007 to 2016, we compile a new dataset by aggregating the places at the municipality level (around 35,000 units) and at the EPCI level (around 1,200 units).

We collect data on births from birth registries (Bulletin état civil, from INSEE) from 2005 to 2016. The annual statistics concern children born alive and birth declarations. The place of birth is the mother's place of residence, not the place of birth[10]. 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[11].

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. 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 3.1.

FL is a cross-sectional survey, the unit of observation are children aged 0-3 (born in 2007-2011), weighted[12] to be representative for the French population.

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

[10] 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.

[11] An easily implementable avenue for future research is to use the data at the arrondissement level, that is available in the monthly birth registries (available on the Quetelet platform).

[12] 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 - thus excluding those who live mainly in shelter houses or with grandparents or family members other than the parents. In particular, the sampling weighting process take into account the selection of the municipality, the cluster in the municipality[13], the probability of surveying a man or a woman and the sampling weights of the census. The non-response weighting process takes into account the non-response at the

Table 3.1: 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

3.3.1 Data limitations

One of the biggest limitations 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 7.6).

Another important limitation is that we cannot observe the childcare attendance for all children in the reduced form, and that the survey that we use to show the relevance of the instrument is administered on children who are born in 2008-2011, while we observe the test scores for children born in 2012-2016. Since in these two periods the number of daycare spots has increased, a potential threat could be that since in the latter period the number of daycare spots is higher and the fertility is relatively lower (INSEE, 2020), a marginal daycare spot may not be filled. However, this is extremely unlikely in the French context, where the daycare supply is extremely lower than the daycare demand. First, the supply did not increase dramatically: it moved from around 4% in 2007 to around 6% in 2019, meaning that the daycare at full capacity may only accommodate 6% of all children who are potentially eligible to attend daycare. While it increased overall, the daycare supply did not change in the greatest majority of municipalities (see maps in Figure 7.25 and 7.26). Secondly, daycare demand exceeds daycare supply: the number of families whose first choice is daycare are systematically lower than the number of families that actually manage to find a daycare slot, in both the Elfe sample and the MDG one (Figure 7.15 and section 2.1.3), which interviews 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 from a municipality to another. However, as detailed in Section

municipality level and at the individual level, by multiplying the sampling weights by the inverse of the individual probability of response.

7.1, 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, Molière, Ohnheiser, & Chazal, 2010), residency is ranked first among the allocation criteria.

For this reason, we choose the municipality as the relevant geographical level to define availability. An alternative is to measure the availability for each of the 1200 public intercommunal cooperation establishments (EPCI), administrative groups in which municipalities collaborate to jointly manage public facilities or services and plan projects on a larger scale than that of the municipality. Results are robust to the definition of availability at the EPCI level (column 2 of table 7.12 for the first stage, column 3 and 4 of table 7.5 for the reduced form). Results are also robust to defining availability at the municipality level for urban municipalities and at the EPCI level for rural ones (column 3 of table 7.12 for the first stage, column 5 and 6 of table 7.5 for the reduced form). Results are also robust to the exclusion of Île-de-France, showing that the magnitude and significance is not driven by it (column 4 of table 7.13 for the first stage, column 1 and 2 of table 7.5 for the reduced form). The rationale to show this robustness check is that mobility patterns in the Parisian region may be different - for example, it is easier to move from one municipality to another thanks to a better developed public transport system.

Since data on individual daycare attendance is not available, we cannot rule out that some parents manage to send their child to a daycare center that is located in another municipality. Thus, the actual demand for daycare may be larger than the denominator in the definition of availability, i.e. children born in the municipality in the 2 years before. There is thus a mechanical negative correlation between births and availability (similar to the hours and hourly wage in Borjas 1980) because of a type of measurement error - the division bias. Following Pora (2020), we add the sum of the births as a separate regressor in the analysis, and the results are robust (column 2 of 7.13 for the first stage, column 1 and 2 of table 7.6 for the reduced form).

Another measurement error is due to the fact that we observe newborns in municipalities, but we do not know if families moved to another municipality between the birth of the child and the moment when the child attend daycare. If parents move for reasons unrelated to childcare, this leads to an attenuation bias. If parents tend to move to municipalities with a high number of daycare places, it is another mechanism for division bias.

A further limitation of the data is that we only observe daycare center funded by CAF through the PSU benefit, while microcrèches are funded by CAF throught the CMG and some daycare centers are funded by employers. While microcrèches and company daycares are not evenly distributed and more concentrated in large cities, the dataset we use includes the great majority of daycare spots (97.9%).

Finally, some places may be used by several children on a part-time basis, and the decision to make a child attend daycare on a part-time or full-time basis may be related to other factors that have an impact on the cognitive ability of the child (e.g. whether the mother works). Unfortunately, we are unable to observe whether children attend daycare full-time or part-time in the FL survey. While possible to observe it in the MDG sample, the low number of observations make the survey unsuitable for this analysis.

4 Empirical strategy

4.1 Reduced form

We instrument the endogenous daycare attendance with the interaction between being born in Spring and the local daycare availability. The reduced-form regression is:

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

Where m indexes the municipality, i indexes the individual children, and d the department. In this cross sectional approach, we only observe each child once and we regress the daycare availability in the year in which they are born. $Spring_i$ is a dummy equal to 1 if the child is born in March, April or May. $Availability_m$ is the local daycare availability, as defined in equation 1.

The coefficient of interest is γ_1.

The rationale for using the timing of the birth as an instrument is that crèche spots are not consistently available throughout the year. The greatest majority of openings occur in September when older children leave for kindergarten (see Graph 7.11 on the month when children begin daycare from the Elfe survey). Even in the rare cases when a child leaves in the middle of the school year, the new child's age has to match the age of the child who's leaving (Fagnani, 2014), so that finding a spot in the middle of the year is even more difficult. Toddlers cannot be enrolled in daycare center before they are 3 months old (Cour des Comptes, 2013). Moreover, local authorities typically hold meetings to allocate crèche places only two or three times a year, often scheduling in May or June the last meeting to review applications from parents whose children are already born and in need of a spot for the autumn (Le Bouteillec et al., 2014). Lastly, spring months are the months with fewer births (INSEE, 2020): thus, not only more places are available, but there is also less competition.

The rationale for including the local availability is that being born in Spring is not relevant by itself if there is no daycare center where parents can apply. At the same time, local availability by itself is likely to be endogenous. In the literature, local availability is often used in a difference-in-differences specification, with the assumption that families do not choose to move to municipalities where availability is higher[14]. In a cross-sectional analysis, it is used to compare municipalities in Denmark that grant a daycare spot and those that do not (Gupta & Simonsen,

[14] More often, it is used when there is a staggered introduction of a childcare reform (Baker et al., 2008, 2015; Cascio, 2009; Felfe & Lalive, 2018; Felfe et al., 2015; Haeck et al., 2018; Havnes & Mogstad, 2011, 2015; Jessen et al., 2020; Kottelenberg & Lehrer, 2017; Noboa-Hidalgo & Urzua, 2012; Pora, 2020), and is more credible when there is a rapid increase in the number of available spots: while parents can decide to live in municipalities that have a higher daycare availability, it is less likely that they can predict which municipalities are going to increase the childcare supply.

2010, 2016).

The instrument is the interaction between the local daycare availability and the fact that the child is born in spring.

We provide evidence of the relevance of the instrument by regressing the probability of attending daycare on it, from the FL survey. While the FL survey samples children born from 2008 to 2011, and the children included in the DEPP administrative data are born from 2012 to 2016, the instrument has a strong and large effect on the probability of attending childcare (Table 5.2). Being born in Spring in a municipality with an additional daycare spot, keeping the number of births in the municipality fixed, increases the probability of attending daycare by 7.5 percentage point, a sizable effect considering that on average 12% of children attend childcare.

For the exclusion restriction to hold, the effect of being born in spring in a municipality with a certain daycare availability on cognitive skills must be only mediated by the daycare attendance. A potential violation of it would happen if municipalities that spend more on daycare also spend more on other skills-enhancing public policies, for example public libraries. However, since the month of birth in the context at hand is plausibly as good as random, there is no reason why children born in different months should benefit more from other municipality policies.

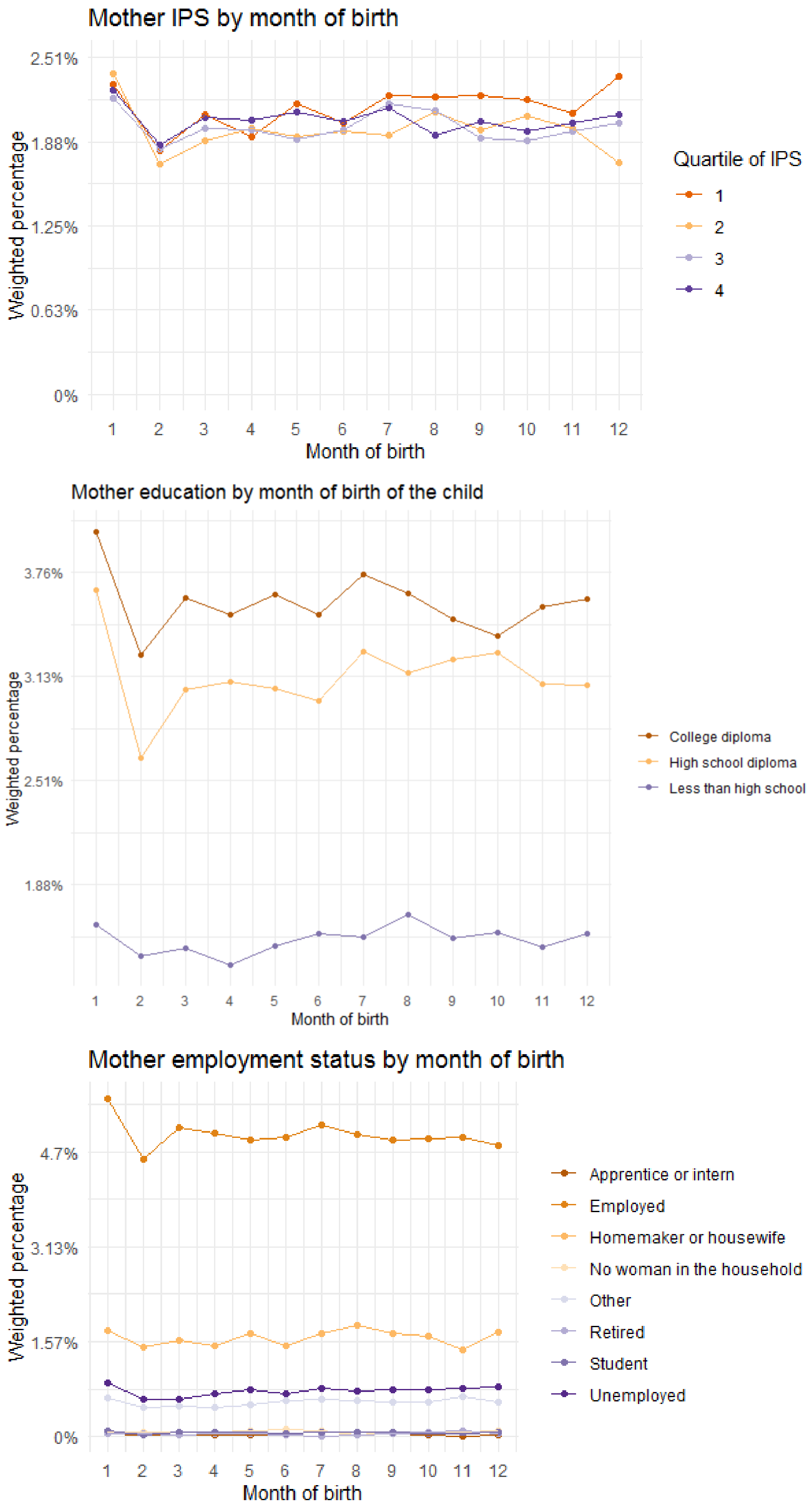
The identification comes from the interaction of an excluded but endogenous quasi-IV - the local daycare availability - with one exogenous but included quasi-IV - the random assignment to the month of birth (Bruneel-Zupanc & Beyhum, 2024).

In fact, the local daycare availability is endogenous to other characteristics of the municipality, but it is excluded, i.e. the effect on cognitive skills is mediated only through daycare attendance. On the other hand, being born in Spring is arguably exogenous to the main confounder of the analysis, the family socio-economic status, as shown in the balance table 7.2. Empirical evidence of birth timing finds that it is not particularly common in the French context (Moreau, 2023). In 2005, only 14% of people intentionally discontinue contraception in order to have a child at a particular time of the year (Régnier-Loilier & Wiles-Portier, 2010). A strong correlation between seasonality of births and the mother's occupation used to be widespread in France (Grenet, 2009), but it is a long-term decreasing trend (Régnier-Loilier & Wiles-Portier, 2010), with the exception of elementary school teachers. The first stage is however robust to the exclusion of families in which the mother is an elementary school teacher, showing that the results are not driven by birth timing by this category (column 1 in Table 7.10). While families that have children in spring may have different unobservable characteristics, they do not differ for the mother's level of education, employment status or IPS - *indice de position sociale*, a measure of the socio-economic status based on the occupation[15] (Figure 4.1).

However, being born in spring is included, i.e., without the interaction, being born in spring would have an effect on the cognitive skills of the child that is not mediated through daycare attendance. In fact, all children are tested on the same day, and there is a consensus in the

[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).

Figure 4.1: Mother characteristics by month of birth of the child. Source: FL survey.



literature that older kids perform better than younger ones[16]. This pattern is matched in DEPP data, where there is a strong linear correlation between the ranks of the test scores and the month of birth (Figure 7.3). However, reassuringly, the coefficient of the instrument is not affected by the inclusion or exclusion of the linear month control (Table 7.11). The results are robust to using month fixed effects instead of a linear control, to including Municipality $\times$ Year fixed effects instead of the daycare availability, and to the inclusion of both (Table 5.1).

As robustness checks, we run placebos with the interactions between the availability and being born in Summer, Fall and Winter, and none of the interactions in the placebo is significantly positive in the reduced form (Table 7.9), nor in the first stage (Table 7.4). We also show that the definition of spring (which we define as being born in March, April or May) is robust to the inclusion of children born in June, and to the inclusion of children born in February (Table 7.11).

The results are also robust to the inclusion of municipality covariates, 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 accessible to everyone, that often organize activities for toddlers[17] (Tables 7.19 and 7.20).

The most likely violation of this assumption is that parents decide where to live, sorting themselves into municipalities with characteristics correlated with the local daycare availability.

On the one hand, it is unlikely that parents or parents-to-be decide to live in a municipality because of the daycare availability. While the quality of schools greatly influences the decision-making process of households when choosing a location (Bayer, Ferreira, & McMillan, 2007), especially in France where all families living in the primary school catchment area are mandated to send their kids there (for example, Fack and Grenet 2010), the availability of childcare is a separate consideration. Moving residences incurs significant costs, and parents prioritize the quality of primary and secondary schools in the area over the availability of early schooling options when selecting a location. Quality of high schools, measured by value added at the Baccalaureat success, does not correlate strongly with the definition of local daycare availability (Figure 7.20). This is further attenuated by the fact that it is not easy for parents to predict the number of children that will try to enrol in daycare at the same time as their own (Filatriau et al., 2013).

On the other hand, parents or parents-to-be may decide their residence place for characteristics of the municipalities that are correlated with the daycare availability. For example, they can decide to live in an urban area, and urban areas have a higher daycare availability. However, the interaction of the endogenous local availability with the quarter of birth, that is plausibly exogenous, alleviates this concern. At the same time, controls for the municipality-level

[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] 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

characteristics (urbanization included) are included in the main specification.

It is not possible to follow the decision to move of the family before the child is born in either Elfe or FL datasets. In both, we can only noisily control for the housing sorting decision of families: using the FL dataset, we split the sample between families that moved in the last 6 months and those who did not, using the Elfe dataset, we do the same for moving in the last 2 years. The coefficient of the interaction Availability × Spring is significant and robust for the families that did not move and not significant for those who moved (Table 7.14), but clearly the decision on where to live may happen before the decision to have a child. Moreover, along with other municipality-level controls, we control for the share of vacant houses and the number of homeowners in the municipality where the school is, which are instrumental to the parents' decision to move there.

It is further reassuring that falsification tests that use an indicator variable for whether the mother has a university degree, whether she is employed and whether the grandfather was a manager show that the instrument is not significant on these outcomes (Table 7.15).

The monotonicity assumption is likely to hold: it makes little sense that parents that would have sent their child to daycare if she were not born in spring and there were no daycare in the municipality[18] decide instead not to send her when these two conditions are met. A necessary but not sufficient test is that the coefficient of the interaction in the first stage is never significantly negative in all subsamples and under all robustness checks.

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

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).

There are two samples: FL is the "first stage sample" and DEPP the "second stage sample". For the identification to be valid, they need to be two i.i.d. random vectors from the same underlying population. Both are cross-sectional data, so issues of serial correlation do not arise. The DEPP second-stage data includes all the population of children attending primary schools in France. A potential threat is that some children do not have (some) test scores, as they were probably absent the day of the test, but it is a relatively low number of children (see Data section 3) and patterns of missingness do not highlight particular selection problems (Figure 7.21). Survey data such as the FL has the inherent problem of non-response, but it is taken care of by using non-response weights. The underlying population are thus children who lived with at least one parent, and are in France when they are 6 years old and attend primary school. Since the number of children not living with at least one parent is extremely low[19], we can safely assume that the two datasets measure the same underlying population.

[18] That is, if they sent the child to a daycare in another municipality.

[19] According to DREES, around 80,000 children under 18 live in some sort of foster houses, sometimes with their parents too. The number of children aged 6 out of this population is probably negligible.

Adapting Choi, Gu, and Shen's (2018) model to this specification:

$$\begin{aligned} &\text{DEPP data} = \{(Y_{DEPP,i}, \mathbf{z}_{DEPP,i}, \mathbf{x}_{DEPP,i})\}_{i=1}^{N_{DEPP}} \\ &\text{FL data} = \{(Daycare_{FL,j}, \mathbf{z}_{FL,j}, , \mathbf{x}_{FL,j})\}_{i=1}^{N_{FL}} \end{aligned} \tag{3}$$

Where Y_{DEPP} is a $n_{DEPP} \times 1$ vector of dependent variable; $Daycare_{FL,j}$ is a $n_{FL} \times 1$ vector of endogenous variables; $\mathbf{x}_{FL}$ and $\mathbf{x}_{DEPP,i}$ are matrices of endogenous covariates (for example, municipality characteristics). $\mathbf{z}_{DEPP,i}$ and $\mathbf{z}_{FL,j}$ are $n_{DEPP} \times K$ and $n_{FL} \times K$ matrices of instruments.

$$\text{Observed first stage in FL: } Daycare_{FL,j} = \mathbf{z}_{FL,j}\Pi_{FL} + v_{FL,j} \tag{4}$$

$$\text{Observed reduced form in DEPP: } Y_{DEPP} = \mathbf{z}_{DEPPi}\Pi\beta + X_{DEPP}\gamma_{DEPP} + u_i \tag{5}$$

$$\text{Second stage with TS2SLS: } Y_{DEPP} = \mathbf{z}_{FL,i}\Pi\beta + \beta v_{FL,i} + X_{DEPP}\gamma_{DEPP} + \epsilon_i \tag{6}$$

Where β is the causal effect of $Daycare_i$ on Y_i, our parameter of interest.

The main assumptions for the TS2SLS to be consistent are:

1. While Π_{DEPP} and Π_{FL} could differ in practice, we assume that $\Pi_{DEPP} = \Pi_{FL} = \Pi$, a crucial assumption to pass from line (6) to (7) in the above model. In practice, the coefficient of the instrument on the probability of attending daycare needs to be the same in the two samples.

2. $E(\mathbf{z}_{DEPP,i}Daycare_{DEPP,i})$ and $E(\mathbf{z}_{FL,j}Daycare_{FL,j})$ have rank K and are equal and $E(\mathbf{z}_{DEPP,i}\mathbf{z}_{DEPP,i})$ and $E(\mathbf{z}_{FL,j}\mathbf{z}_{FL,j})$ are non-singular and equal (assumption of equal moments). Those assumptions are needed as a basis to combine the two samples. In practice, 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 7.16) are reassuring.

3. The exclusion restriction of the instrument holds in both samples: $E(\mathbf{z}_{DEPP,i}u_{DEPP,i}) = 0$, $E(\mathbf{z}_{DEPP,i}v_{DEPP,i}) = 0$, and $E(\mathbf{z}_{FL,j}v_{FL,j}) = 0$. We argued in favor of the exclusion restriction in the previous section, and if the DEPP and the FL sample do measure the same population, there is no reason why it should not hold in both samples.

In practice, the estimation of TS2SLS estimator boils down to (Khawand & Lin, 2015):

1. Generating an estimate of the first stage parameter Π using the FL sample to compute $\hat{\Pi}_{FL}$, the coefficients of the instrument and of individual- and municipality-level covariates.

2. Computing N_{DEPP} cross-sample fitted values using $\hat{\Pi}_{FL}$, i.e. $\hat{w}_{DEPP,i} = \mathbf{z}_{DEPP,i}\widehat{\Pi_{FL}}$.

3. Regressing $Y_{DEPP,i}$ - the literacy and numeracy scores - on $\hat{w}_{DEPP,i}$ to estimate β, i.e. 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 & 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).

$$\begin{aligned} \text{Test scores}_{im} = \delta_1 Spring_i \times \mathbf{1}\{Availability_m > 0\} + \delta_2 \mathbf{1}\{Availability_m > 0\} \\ + \delta_3 Spring_i + \mathbf{X}_{im} + \alpha_{d(m)} + \epsilon_{im} \end{aligned} \tag{7}$$

Where the dummy $\mathbf{1}\{Availability_m > 0\}$ takes value 1 when there is at least one daycare center in the municipality, and $Spring_i$ takes value 1 when the child is born in March, April or May. γ_1 is the coefficient of interest. The results of this specification of the main regression are in the fourth column of Table 7.13. With this binary specification, $Daycare(Interaction)$ can take value $Daycare(1)$ or $Daycare(0)$.

In order to identify the characteristics of compliers, 3 assumptions are needed (Marbach & Hangartner, 2020):

- Independence of the instrument: $Daycare(1), Daycare(0), X \perp Interaction$. The instrument is assigned independently of a unit's compliance. The covariate X is independent of the instrument.
- Monotonicity: $Daycare(1) > Daycare(0)$, to rule out defiers.
- Relevance, otherwise the share of compliers is 0.

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

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

Thanks to monotonicity, we can rule out defiers.

$$
\begin{aligned}
\mathbb{E}[X] = & \ \mathbb{E}[X|D(1)=1, D(0)=0]\mathbb{P}[D(1)=1, D(0)=0] \ \textit{(Compliers)} \\
& + \mathbb{E}[X|D=1, Interaction=0]\mathbb{P}[D=1, Interaction=0] \ \textit{(Always-takers)} \\
& + \mathbb{E}[X|D=0, Interaction=1]\mathbb{P}[D=0, Interaction=1] \ \textit{(Never-takers)}
\end{aligned} \tag{9}
$$

This is the formula we use.

$$
\begin{aligned}
\mathbb{E}[X|D(1)=1, D(0)=0] = & \frac{1}{\mathbb{P}[D(1)=1, D(0)=0]}\Big(\mathbb{E}[X]- \\
& \mathbb{E}[X|D=1, Interaction=0]\mathbb{P}[D=1, Interaction=0]- \\
& \mathbb{E}[X|D=0, Interaction=1]\mathbb{P}[D=0, Interaction=1]\Big)
\end{aligned} \tag{10}
$$

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

$$
\begin{aligned}
\bar{X}_{compliers} = & \frac{1}{\text{Share of compliers}}\Big(\bar{X}_{sample} - \bar{X}_{always-takers} \times P(always-takers)- \\
& \bar{X}_{never-takers} \times P(never-takers)\Big)
\end{aligned} \tag{11}
$$

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 $K = 500$.

Then, we 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).

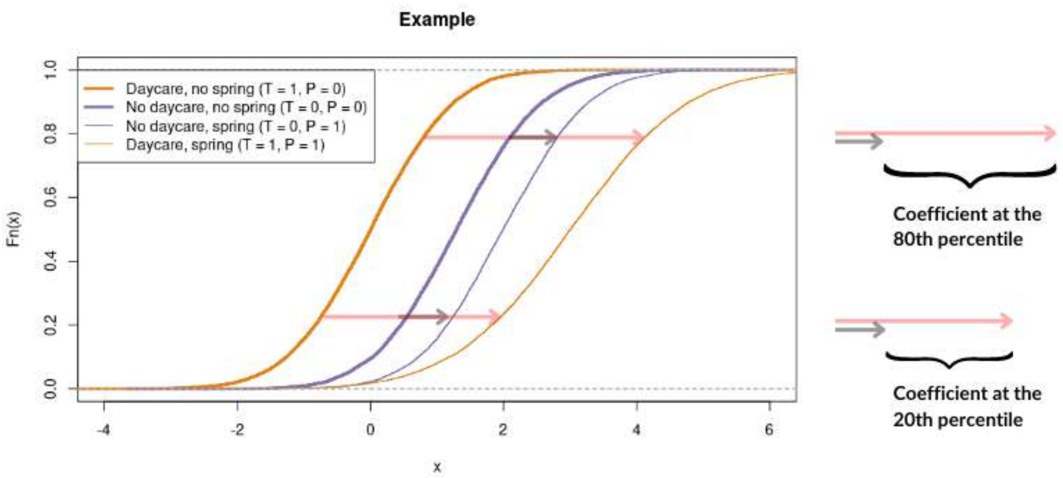
4.4 Quantile regression

This section focuses on the effect of childcare attendance along the distribution of cognitive skills. The rationale 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, Heckman, & Schennach, 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 & Heckman, 2007)[20]. This is closely related to what is the counterfactual type of care for children at different points of the skills distribution.

To do it, as for the compliers analysis, we discretize the availability measure into municipalities

[20] Most of the literature on universal childcare for children aged 0-2 (for example, all papers summarized in Table **??**) find evidence in favor of the compensatory hypothesis. However, there is also some evidence finding greater gains for more advantaged children (Deming, 2009; Gormley Jr, Gayer, Phillips, & Dawson, 2005; J. Heckman et al., 2013), 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 & Rizzica, 2018).

Figure 4.2: Example of the binary quantile regression.



that have no daycare facilities in the year when the child is born and those that have at least 1 daycare spot and run a quantile regression. Results are robust to using the continuous definition of availability (Figures 7.5 and Table 7.28).

This coefficient has the same estimation as a difference-in-differences estimator, however, the context lacks credibility in the assumptions needed to identify this estimator as an ATT, for reasons that we detail in Appendix 7.4. It 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. Results estimating this binary specification with OLS for the first stage are reported in Table 7.27, while evidence of the relevance of the instrument is reported in column 4 in Table 7.13. The coefficient of the interaction is virtually unchanged.

However, we are primarily interested in estimating equation 7 for each quantile of the distribution. Figure 4.2 uses randomly generated data to illustrate it: the coefficient δ_1 of the binary instrument at quantile τ is:

$$\begin{aligned}\delta_1(\tau) =& F^{-1}(Score_\tau|Spring_i = 1, Av = 1) - F^{-1}(Score_\tau|Spring_i = 0, Av = 1) - \\ & [F^{-1}(Score_\tau|Spring_i = 1, Av = 0) - F^{-1}(Score_\tau|Spring_i = 0, Av = 0)]\end{aligned} \tag{12}$$

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. Adding covariates in the quantile regression is often not straightforward, as the rank of $y|\mathbf{x}$ needs to be invariant to changes in the other covariates. In this setting, we have few covariates, and the results are virtually unchanged when we include those (column 3 of Table 5.1). For the quantile coefficient to be interpreted as individual effect, the rank invariance assumption needs to hold (J. J. Heckman, Smith, & Clements, 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 he 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 do not interpret the coefficients as individual childcare effects, but rather we use the quantile regression to identify the child care effect on the skills distribution. In particular, if the quantile coefficients are larger for children at the top of the distribution than for ones at the bottom, the distributional impact of childcare is to increase inequality, if the opposite is true, the inequality decreases.

4.5 Effect of quality of childcare

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

In the first specification, 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:

$$\begin{aligned}\text{Test score}_{im} =&\gamma_1 Spring_i \times \text{Availability in public}_m + \gamma_2 Spring_i \times \text{Availability in private}_m + \\ &\gamma_3 Spring_i \times \text{Availability in non-profit}_m + \gamma_4 \text{Availability in public}_m + \\ &\gamma_5 \text{Availability in private}_m + \gamma_6 \text{Availability in non-profit}_m + \gamma_7 Spring_i + \\ &\alpha_d + \epsilon_{im}\end{aligned} \tag{13}$$

Where the reference category is composed of municipalities without a daycare center.

To test if having a daycare center of one type or another makes a difference, we restrict the sample to municipalities with only one daycare center and estimate the following equation. For example, in the case of opening hours:

$$\begin{aligned}\text{Test score}_{im} =&\gamma_1 Spring_i \times \text{Availability with long opening hours}_m \\ &+\gamma_2 \text{Availability with long opening hours}_m + \gamma_3 Spring_i \\ &+\alpha_d + \epsilon_{im}\end{aligned} \tag{14}$$

In this case, the reference category are municipalities with a daycare center with short opening hours, i.e. below the median hours.

5 Results

5.1 Reduced form

Table 5.1: 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										
Constant	0.2188***	0.2240***								
	(0.0032)	(0.0046)								
Spring	0.0146***	0.0182***	0.0140***	0.0173***	0.0129***	0.0158***				
	(0.0011)	(0.0013)	(0.0011)	(0.0013)	(0.0011)	(0.0012)				
Availability	-0.0047	-0.0217	-0.0172*	-0.0446***	0.0156***	-0.0050	-0.0172*	-0.0446***		
	(0.0168)	(0.0205)	(0.0095)	(0.0129)	(0.0054)	(0.0073)	(0.0095)	(0.0129)		
Spring × Availability	0.0132***	0.0140***	0.0136***	0.0143***	0.0126***	0.0130***	0.0136***	0.0143***	0.0115**	0.0144***
	(0.0047)	(0.0051)	(0.0048)	(0.0053)	(0.0044)	(0.0047)	(0.0048)	(0.0053)	(0.0046)	(0.0046)
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

The reduced form coefficient of the instrument on cognitive skills is significant and positive, with a magnitude of 1.5% of a SD (Table 5.1). 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 are robust to the inclusion of department fixed effects (columns 3 and 4 of table 5.1) and of municipality-level covariates (columns 5 and 6 of table 5.1). We also add month of birth fixed effects instead of an indicator variable for being born in Spring and results are virtually unchanged (columns 7 and 8 of table 5.1). Results are robust to including month fixed effects and Municipality × Year fixed effects (columns 9 and 10 of table 5.1). Since the daycare availability varies along the geographical and time dimension, these fixed effects absorb the variation in local daycare availability, but also all possible shocks that varies at the Municipality × Year dimension. Finally, we add School × Year fixed effects, to account for the self-selection of more advantaged students attending the same schools (column 1 and 2 of 7.23), and results are robust.

Results are also robust to using heteroskedasticity-robust standard errors instead of errors clustered at the municipality level (Table 7.31) or adding school-level characteristics to the reduced form regression (Table 7.21 for maths and 7.22 for French). Finally, a potential problem is that we include tests administered in September 2020: those children did not attend their last 3 months of kindergarten, as schools have been closed from the 14th March 2020 to the 14th June 2020. They may thus be a different population, not comparable with the other years. However, the results are robust to the exclusion of tests administered in September 2020, and to adding year fixed effects (Table 7.23).

The magnitudes of the reduced form coefficients are statistically different for French and maths at the 5% threshold[21]. While the context and the age when cognitive skills are tested change, this is in line with Drange and Havnes (2019), Ludwig and Phillips (2007) and (Gupta & Simonsen, 2016), among others.

Results are robust to using a more granular definition of skills[22]. Results are also robust to using ranks instead of standardized 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 7.8). When using the probability of having at least one insufficient item in French or maths as an alternative dependent variable, the instrument decreases the probability of having at least one insufficient item in French, while the effect is not significant in maths. This is further evidence that daycare may have a differential impact on different types of skills.

[21]This holds true in all the main specifications, except the one without fixed effects (column 1 and 2 of Table 5.1), where they are different at the 10% level (p-value = 0.058).

[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.

Table 5.2: Baseline first-stage regression, heteroskedasticity-robust standard errors.

Dependent Variable:	Daycare				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
(Intercept)	0.1004***				
	(0.0088)				
Spring	0.0136**	0.0128*	0.0130**		
	(0.0059)	(0.0070)	(0.0061)		
Availability	0.2874***	0.1870***	0.1254***	0.1863***	
	(0.0526)	(0.0307)	(0.0233)	(0.0308)	
Month of birth	-0.0034***	-0.0035***	-0.0035***		
	(0.0007)	(0.0006)	(0.0006)		
Spring $\times$ Availability	0.0750**	0.0763*	0.0769**	0.0768*	0.1137***
	(0.0377)	(0.0432)	(0.0344)	(0.0432)	(0.0332)
Municipality covariates		Yes			
Fixed-effects					
Department		Yes	Yes	Yes	
Month of birth				Yes	Yes
Municipality $\times$ 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

Table 5.2 provides the first stage results, estimated on the FL database. 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.

The interaction between local daycare availability and being born in spring has a significant and large magnitude of 7.5 p.p. on the probability of attending daycare. Considering that on average 12% of children attend childcare, the effect is economically important.

Reassuringly, the magnitude of the coefficients is similar across the FL and Elfe surveys (Table

7.16): in the Elfe survey, an additional daycare place in the municipality, keeping the number of births fixed, increases the probability of attending childcare for a child born in spring by 10 p.p.

This allows us to do some back-of-the-envelope calculations of the rescaled effect of daycare attendance for compliers with the instrument.

$$LATE_{Maths} = \frac{E(\text{Test scores}|Interaction_{im} > 0) - E(\text{Test scores}|Interaction_{im} = 0)}{E(Daycare_i|Interaction_{im} > 0) - E(Daycare_i|Interaction_{im} = 0)} = \frac{0.0136}{0.0763} = 0.1782 \tag{15}$$

$$LATE_{French} = \frac{0.0143}{0.0763} = 0.1874$$

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

5.2 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 & Angrist, 1994). Using the two-sample two stage least square (TS2SLS) estimator allows to rescale more accurately the two coefficients, taking into account the covariates and the fact that the observations in the two samples are different.

First, it is reassuring to see that the generated daycare attendance distribution is mostly between 0 and 1, and that the average of the generated daycare attendance matches the 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. Thus, we also show results capping the probability at 0 and 1. Imputing that individuals with a predicted probability below 0 have a 0 probability and that those above 1 have a 1 probability does not change the average of the distribution. Moreover, we include results using both the capped and not generated daycare attendance: coefficients of the covariates are virtually unchanged, while the coefficient of the generated regressor is larger when using the capped probability, showing that results are not driven by the few observations in the right tail of the non-capped distribution of the generated crèche attendance.

Results for the first stage are the same as column 3 in Table 5.2, and reassuringly, bootstrapped standard errors are not particularly different from the clustered ones.

The TS2SLS coefficient on the daycare attendance ranges between 0.12 and 0.24 SD, and is not far from the simple LATE rescaling the reduced-form and first-stage coefficients (equation 15).

Those coefficients are in line with evidence from universal daycare in comparable countries.

Table 5.3: Results for the two-sample 2SLS, without coefficients of the covariates (results with the covariates coefficients are in Table 7.26 in the Appendix).

	First stage	Second stage	Second stage	Second stage capped	Second stage capped
Dependent Variables:	Daycare	Maths	French	Maths	French
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)				
$\widehat{Daycare}$		0.219***	0.123***		
		(0.012)	(0.023)		
$\widehat{Daycare}$ (capped)				0.239***	0.136***
				(0.024)	(0.017)
Municipality covariates	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Department	Yes	Yes	Yes	Yes	Yes
Urbanization	Yes	Yes	Yes	Yes	Yes

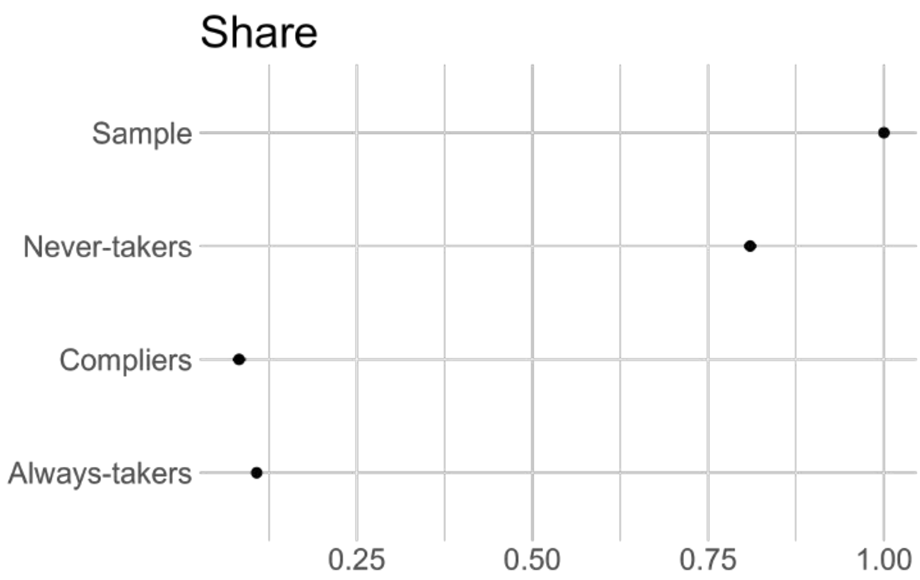
Source. Author's calculations based on FL survey, France, 2011, CAF daycare availability data, France, 2012-2016, birth registries (INSEE), France, 2012-2016 and DEPP EvalAide data, 2018-2023.
Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in 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

Meta-analysis (Camilli, Vargas, Ryan, & Barnett, 2010; Magnuson et al., 2016; Shager et al., 2013; van Huizen & Plantenga, 2018) suggest that results range between 0.14 to 0.28 SD. Studies that follow similar strategies, in particular using the local availability and eligibility as an instrument for daycare attendance, find comparable results: 0.144 SD for preschool attendance in the US (Cascio, 2009), 0.15 on reading scores in Spain (Felfe et al., 2015), 0.149 on school entry examination data in Germany (Felfe & Lalive, 2018). This is also in line with the 0.19 SD effect on the number of words known at 2 in the French context (Berger et al., 2021): since the instrumental variable method is similar (although they do not interact the local availability and use and a small and selected sample) this suggests no important decline over time of the positive effect of daycare attendance on cognitive skills. In contrast, literature focusing on the US often do not observe medium-run significant impacts (Currie & Thomas, 1995; Ludwig & Phillips, 2007), for example, at the end of first grade (US Department of Health, 2012), or when the children are 8 (Chetty et al., 2011; Schweinhart, 2005).

5.3 Compliers analysis

The estimated share of compliers, always-takers and never-takers are shown in Figure 5.1. The share of compliers with the instrument is low, which is coherent with the conservative way we defined the instrument, particularly in the binary specification: being born in spring in a municipality with at least one daycare center is enough to be considered "treated", while clearly there may be not enough daycare spots for all children.

Figure 5.1: Shares of compliers, never-takers and always-takers, following Marbach and Hangartner (2020) method



In terms of key characteristics of compliers, at the child level, children who comply with the instrument are not different from the rest of the sample. The mothers of those children, 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 have an employment. Families are more likely to be biparental and to live in rural municipalities.

In Table 5.4, we regress the main cross-sectional first-stage specification (equation **??**) on an indicator variable equal to 1 if the child is cared for by a childminder (column 2), a parent (column 3) or a grandparent (column 4). The coefficient of the instrument is negative, large and significant for the parental care, hinting at the fact that compliers' main counterfactual type of care is home care. This is in line with evidence from Maurin, Roy, 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 5.4: Margins of adjustment of changes in daycare availability and changes in the instrument

Dependent Variables:	Daycare	Childminder	Parents	Grandparents
Model:	(1)	(2)	(3)	(4)
(Intercept)	0.1004***	0.2949***	0.5096***	0.0689***
	(0.0088)	(0.0121)	(0.0102)	(0.0043)
Spring	0.0136**	0.0095	-0.0153*	-0.0055
	(0.0059)	(0.0070)	(0.0082)	(0.0047)
Availability	0.2874***	-0.2770***	-0.0300	-0.0432***
	(0.0526)	(0.0610)	(0.0327)	(0.0117)
Month of birth	-0.0034***	-0.0001	0.0045***	-0.0005
	(0.0007)	(0.0008)	(0.0010)	(0.0005)
Spring × Availability	0.0750**	-0.0295	-0.0703*	0.0390*
	(0.0377)	(0.0284)	(0.0367)	(0.0207)
Fit statistics				
DV mean	0.12016	0.28026	0.51515	0.05657
F-test	9.4274	3.9996	0.81738	0.25225

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

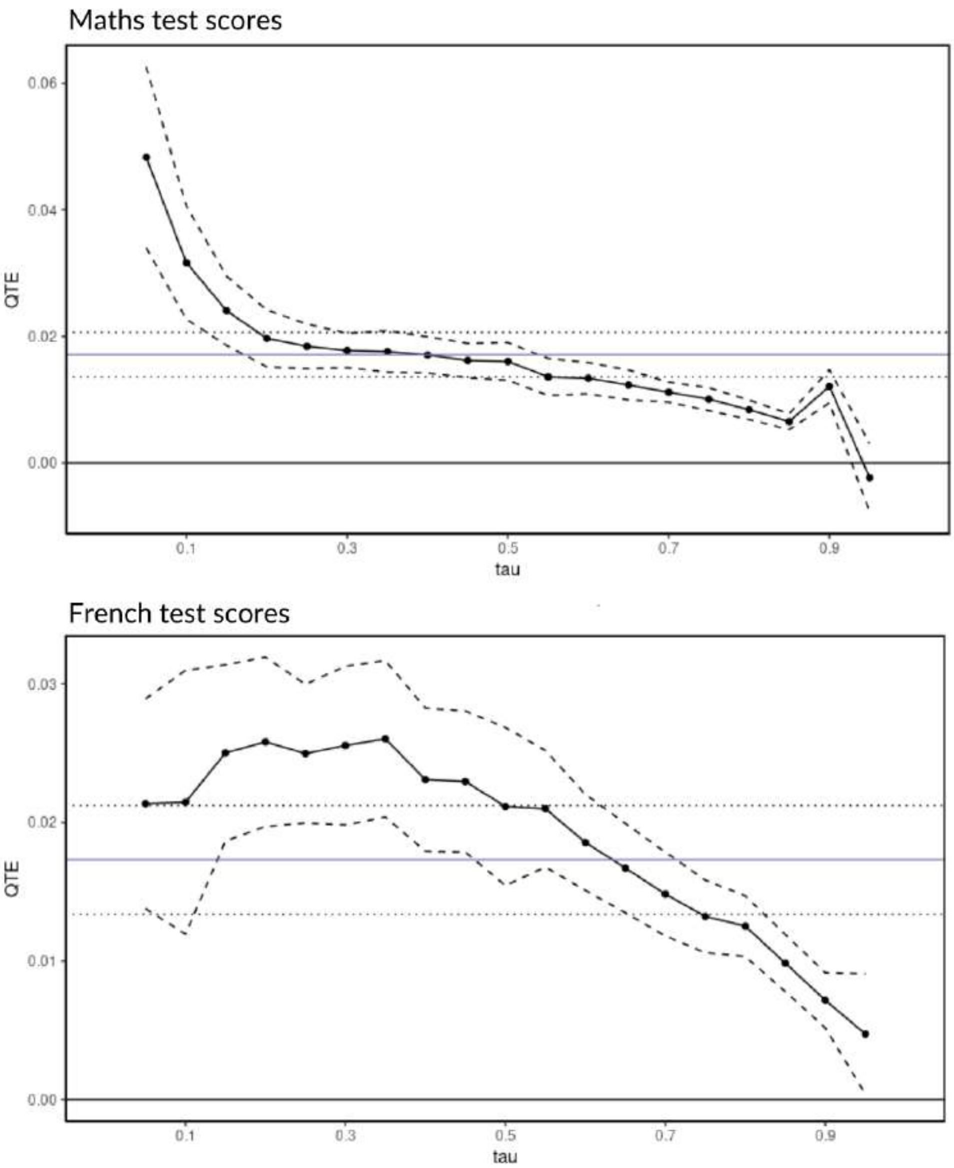
Notes. All estimates are based on OLS estimation. Spring is a dummy taking value 1 when children are born in March, April or May. Availability is defined as the number of daycare slots in the municipality divided by the number of children aged 0-2 born in the municipality (see equation 1). The first column is the baseline specification. The other columns estimate the same specification on different outcomes: respectively, the likelihood of being cared by a chilminder (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 Quantile regression

The results of the quantile regression (equation 7) are reported in Figure 5.2, where the solid black line is the point estimate of the quantile regression, the dashed lines are the confidence bounds of it. OLS results on the binary specification (Table 7.27) are also reported. Coherently with the specification with the continuous availability (Figure 7.5), the effect are significantly positive for the whole distribution, with the exception of the very top of the distibution (95th percentile), where they are not significant. The coefficient is larger for low percentiles: in particular, up to the 15th percentile in maths, they are statistically different from the average

Figure 5.2: Results of the quantile regression defining the daycare availability as a binary variable (Equation 7) 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.



coefficient computed on the whole distribution. They are lower for high percentile: in particular, children from the 85th percentile on in the French test distribution have a coefficient that, while still significantly positive, is statistically lower the one estimated on all children. Results are robust to the exclusion of the Ile-de-France region (Figure 7.24).

These results are in line with other non-linear difference-in-differences from Norway (Havnes & Mogstad, 2015), Canada (Kottelenberg & Lehrer, 2017) and the US (Bitler, Gelbach, & Hoynes, 2006). However, the reduced-form coefficient is positive for the whole distribution in France, while it is significantly negative for quantiles above the 80th percentile in Norway (Havnes & Mogstad, 2015). While this entails that daycare is potentially beneficial for all children in France, it also means that the distributional effects are somewhat more reduced than in the Norwegian context. Results are also in line with the single-parent families observed in (Kottelenberg & Lehrer, 2017), although their results are more volatile for single quantiles. Bitler et al. (2014) reports reduced-form results on that are qualitatively similar to ours, with a stronger effect at the bottom of the distribution and a positive but smaller effect for the top of the distribution for test administered before the beginning of the elementary school (PPVT, a test on vocabulary), but not significant results in the tests in first grade of elementary school. We argue that the larger effect at the bottom of the distribution is mainly given by the different counterfactual type of care shown above.

5.5 Effect of quality of childcare

We find that childcare centers managed by local authorities and other public bodies have a much higher positive impact on cognitive development than those managed by private firms or non-profit associations (Table 5.5). The collective type of daycare seems to have more positive effect than other types, but results are less strong (Table 5.6). Finally, longer opening hours seem to make a significant and positive difference compared to daycares with shorter opening hours (Table 5.7). Overall, results suggest 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.

Table 5.5: Reduced-form results for different daycare management in all municipalities.

Dependent Variables:	Maths	French	Maths	French
Model:	(1)	(2)	(3)	(4)
Variables				
Spring	0.1261***	0.1276***		
	(0.0016)	(0.0018)		
Public av.	-0.0511***	-0.0683***		
	(0.0140)	(0.0180)		
Private av.	0.1303***	0.1891***		
	(0.0345)	(0.0444)		
Non-profit av.	0.0249	0.0354*		
	(0.0152)	(0.0197)		
Spring × Public av.	0.0268***	0.0262***	0.0172**	0.0176**
	(0.0086)	(0.0092)	(0.0073)	(0.0073)
Spring × Private av.	0.0139	0.0115	0.0072	0.0051
	(0.0178)	(0.0196)	(0.0182)	(0.0187)
Spring × Non-profit av.	0.0043	0.0056	0.0031	0.0003
	(0.0088)	(0.0087)	(0.0090)	(0.0094)
Fixed-effects				
Dept. FE	Yes	Yes		
Birth month FE			Yes	Yes
Municipality × Year FE			Yes	Yes
Fit statistics				
Observations	2,188,110	2,192,351	2,188,110	2,192,351
Dependent variable mean	-0.00666	-0.08319	-0.00666	-0.08319

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

Table 5.6: Reduced-form results for different daycare types in all municipalities.

Dependent Variables:	Maths	French	Maths	French
Model:	(1)	(2)	(3)	(4)
Variables				
Spring	0.1261***	0.1277***		
	(0.0029)	(0.0032)		
Multi accueil av.	0.0964***	0.1326***		
	(0.0150)	(0.0210)		
Temporary av.	0.1134***	0.1548***		
	(0.0215)	(0.0273)		
Crèche collective av.	0.1127***	0.1464***		
	(0.0246)	(0.0314)		
Crèche familiale av.	0.0750**	0.1454***		
	(0.0382)	(0.0503)		
Other av.	0.1319***	0.1829***		
	(0.0251)	(0.0327)		
Spring × Multi accueil av.	-0.0097	-0.0184	-0.0004	-0.0075
	(0.0101)	(0.0120)	(0.0081)	(0.0081)
Spring × Temporary av.	-0.0154	-0.0106	0.0094	0.0160
	(0.0171)	(0.0181)	(0.0130)	(0.0158)
Spring × Crèche collective av.	0.0426*	0.0494**	0.0192	0.0246*
	(0.0225)	(0.0223)	(0.0150)	(0.0136)
Spring × Crèche familiale av.	0.0126	0.0302	0.0367*	0.0413*
	(0.0423)	(0.0336)	(0.0215)	(0.0226)
Spring × Other av.	0.0166	0.0034	0.0163	0.0128
	(0.0161)	(0.0173)	(0.0156)	(0.0154)
Fixed-effects				
Dept. FE	Yes	Yes		
Birth month FE			Yes	Yes
Municipality × Year FE			Yes	Yes
Fit statistics				
Observations	445,429	446,217	2,188,110	2,192,351
Dependent variable mean	0.03073	-0.03035	-0.00666	-0.08319

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

Table 5.7: Reduced-form results for opening hours above and below the median, in municipalities with one daycare center

Dependent Variables:	Maths	French	Maths	French
Model:	(1)	(2)	(3)	(4)
Variables				
Spring	0.1291***	0.1327***		
	(0.0019)	(0.0023)		
Long opening h.	-0.0385***	-0.0528***		
	(0.0065)	(0.0088)		
Spring × Long opening h.	0.0056*	0.0045	0.0055*	0.0045
	(0.0029)	(0.0033)	(0.0029)	(0.0034)
Fixed-effects				
Dept. FE	Yes	Yes		
Birth month FE			Yes	Yes
Municipality × Year FE			Yes	Yes
Fit statistics				
Observations	1,595,153	1,598,820	1,595,153	1,598,820
Dependent variable mean	-0.02851	-0.09716	-0.02851	-0.09716

Clustered (municipality) standard-errors 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 results are rescaled by the strong and significant first stage, the results 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 the distribution of skills: while these are not individual treatment effects, this uncovers the potential equalizing effect of daycare attendance, also in a context where formal childcare is widespread such as France. Shedding some light on the counterfactual type of childcare, when children do not attend daycare, is crucial to evaluate the impact of public policies that expand daycare coverage, and we find that the compliers' main alternative type of care is parental care.

Among the directions for future research, having access to standardized tests in the first grade of middle school would allow to estimate the long-term effects of daycare attendance, and especially to link elementary and middle school scores. The dataset reports the municipality of residence of individual children, and the IPS of the mother and the father. This would allow to estimate heterogeneity results based on the family-level IPS, whereas we now rely on the school-level average IPS. Moreover, individual adresses of single children would enable to measure the distance with the closest daycare center, since we have the daycare center addresses in the CAF data for most years. Another enhancement would be to use the data on test scores in January of the first year of elementary school and in September of the second year. While the reduced-form results on these outcomes are inconclusive, defining a measure of progress for each child and seeing the impact of the instrument on it may be a way forward.

Finally, it would be interesting to use the generated daycare attendance to estimate an IV-QTE, as done in the context of Head Start by Bitler et al. (2014). It would also be interesting to divide the sample, at least by gender, and see if the quantile regression uncovers heterogeneity effects: for example, the effect for boys at the bottom of the distribution may be different from the one for girls at the bottom of the distribution.

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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 7.17). However, it may marginally affect the quality of teacher/students interactions[23]. 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, 2016), accounting for around 15.000€ per year for each child attending daycare full-time (De Bodman et al., 2017; ONAPE, 2016). This cost is higher than the expenditures for comparable programs in Norway in the 1970s (Havnes & Mogstad, 2015), Denmark (Gupta & 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.

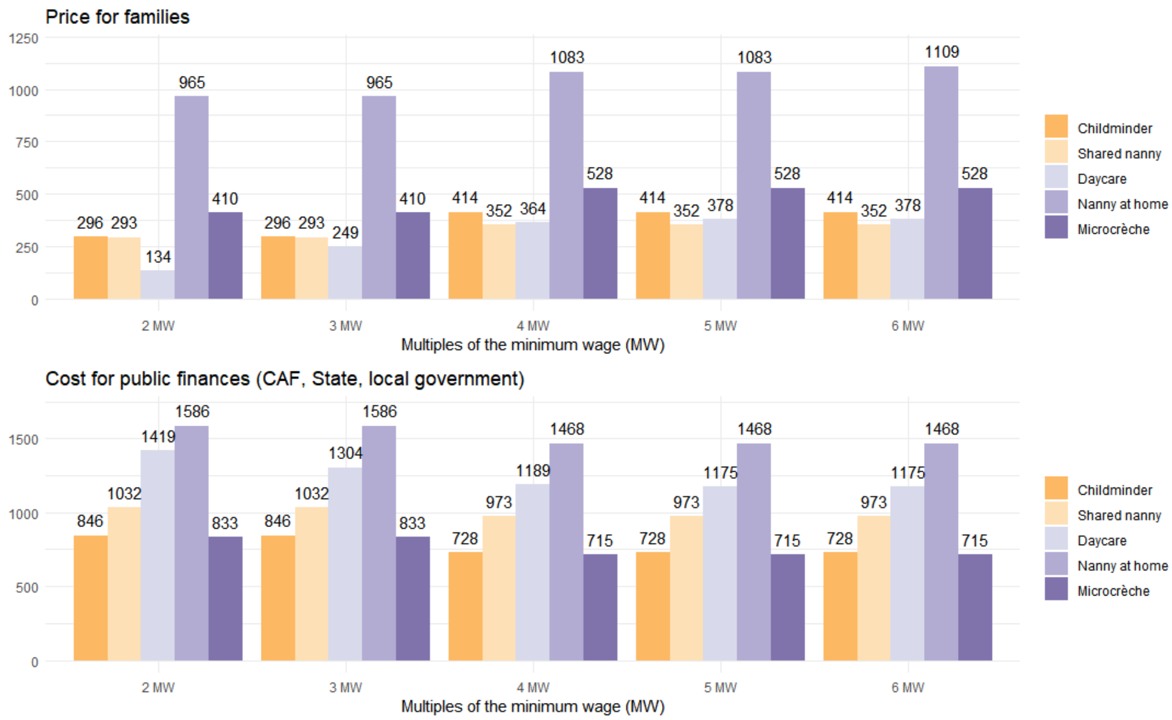
Families pay a part of this amount that varies according to their resources and the number of children, except for kindergarten at 2, that is free. For example, in 2016, a family earning twice the minimum wage paid 5% of the total cost (134€ per month), and a family earning six times the minimum wage paid 30% of the total cost, 378€ per month (Figure 7.9). On average, families pay around 20% of the total cost (ONAPE, 2016), 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

[23] 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.



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, 2016).

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[24]. 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 7.9. An

[24]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.

overview of how many families receive CMG and for which childcare arrangement is reported in Figure 7.14 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, 2016). Clearly, this causes the characteristics of families choosing different options to be different (Table 7.1, 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:

$$\begin{aligned}\text{Test score}_{im} =& \beta_1 Spring_i \times \frac{\text{Places in daycare centers}_{m,t}}{\text{Births}_{m,t-2} + \text{Births}_{m,t-1} + \text{Births}_{m,t}} + \\ & \beta_2 \frac{\text{Places in daycare centers}_{m,t}}{\text{Births}_{m,t-2} + \text{Births}_{m,t-1} + \text{Births}_{m,t}} + \beta_3 Spring_i + \\ & \beta_4 \text{Month of birth}_i + \mathbf{X}_{im} + \alpha_d + \eta_{im}\end{aligned} \tag{16}$$

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

$$\frac{\partial \text{Test score}_{im}}{\partial \text{Places}_m} = \beta_1 Spring_i \times \frac{1}{\text{Births}_m} + \beta_2 \frac{1}{\text{Births}_m} \tag{17}$$

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[25]. 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.

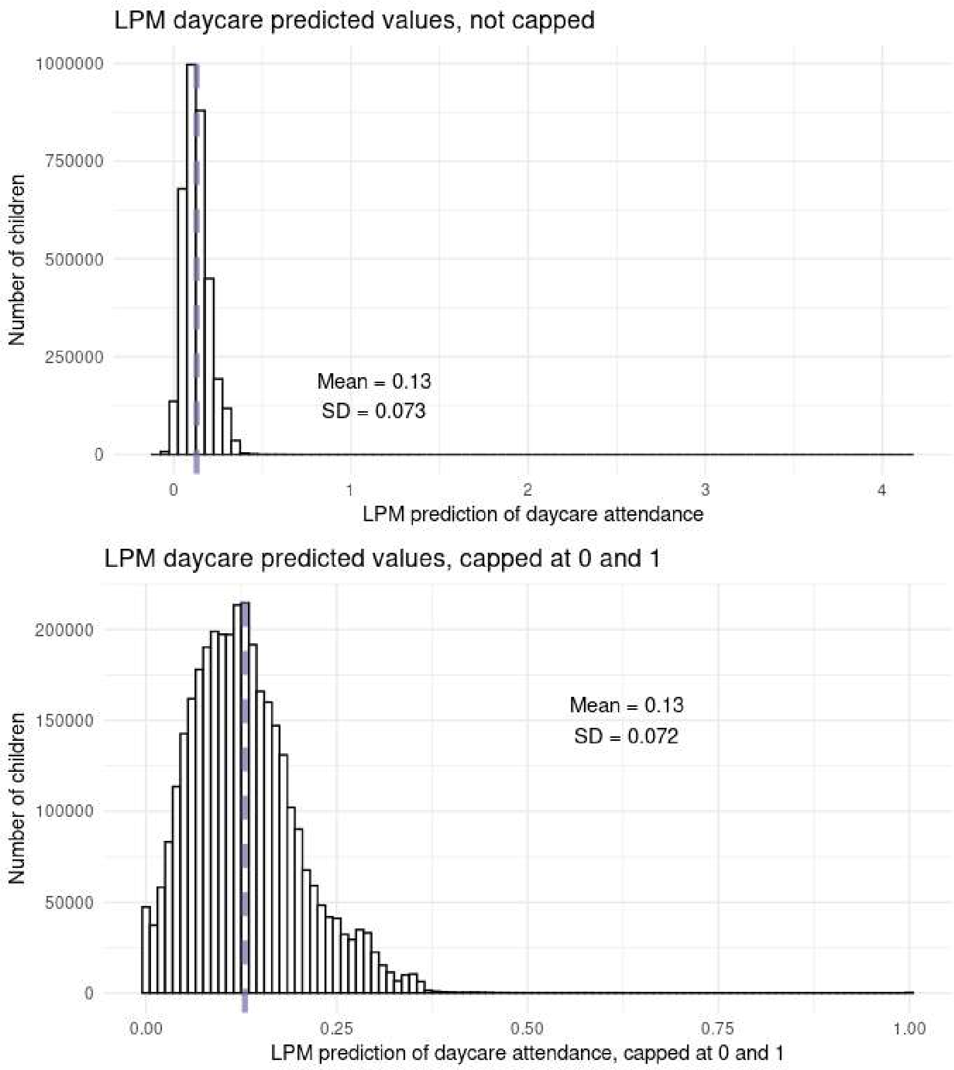
7.3 Two-sample 2SLS

7.4 Why the coefficient of the interaction with the binary availability is not a difference in difference estimator?

Following the seminal paper of Duflo (2001), let's first nest the standard before-after treatment-control DD framework into a more general framework, where geographical units may be treated ($G = 1$) or not ($G = 0$). In all geographical units, a part of the population is eligible for

[25] 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 $E(\text{marginal effect assuming births do not depend on places} - \text{marginal effect assuming they do}) = (\beta_1 Spring_i + \beta_2) \frac{Places_m \frac{\partial \text{Births}_m}{\partial \text{Places}_m}}{\text{Births}_m^2}$. 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 $\widehat{Daycare}$.



the treatment ($E = 1$), a part is not ($E = 0$). In the standard before-after treatment, the population is eligible after the treatment, so $E = 1$ corresponds to $After = 1$.

Using the standard Rubin Causal Model framework, we define daycare attendance as the treatment, and the observed outcomes are: Test scores$_i$ = $Daycare_i$ × Test scores$_i$($Daycare_i$ = 1) + (1 − $Daycare_i$) × Test scores$_i$($Daycare_i$ = 1). In this case, treated geographical units are municipalities with at least one daycare center ($G = 1 \rightarrow Availability_m > 0$), control ones those without daycare centers ($G = 0 \rightarrow Availability_m = 0$). Eligible individuals are those born in spring ($E = 1 \rightarrow Spring = 1$), non-eligible ones are those born in other seasons ($E = 0 \rightarrow Spring = 0$).

In the most straightforward DD design all units that have $E = 1$ and $G = 1$ are treated. An example is Card and Krueger (1994): the whole population of fast food workers in New Jersey ($G = 1$) after the 1992 increase of the minimum wage ($E = 1$) are treated. In this case, the difference-in-differences estimator is simply:

$$\begin{aligned}\gamma_{DD} = & E[Y_i(1)|G_i = 1, E_i = 1] - E[Y_i(0)|G_i = 1, E_i = 0] \\ & - (E[Y_i(0)|G_i = 0, E_i = 1] - E[Y_i(0)|G_i = 0, E_i = 0])\end{aligned} \tag{18}$$

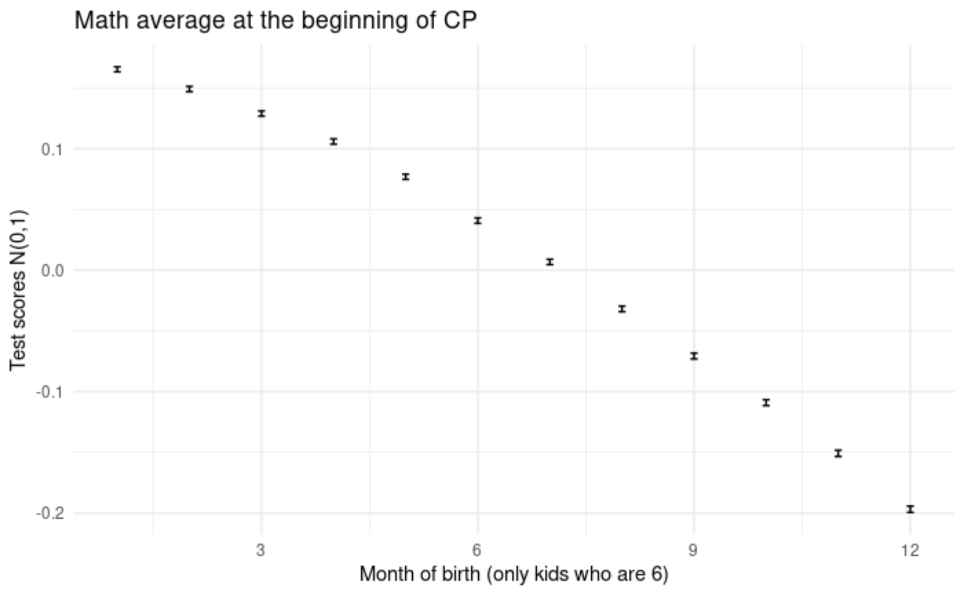
This is clearly not the case, as far from all children born in spring in a municipality with at least a daycare center attend daycare. In fact, even if $E = 1$ and $G = 1$, parents may still decide not to send their children to a daycare center. Let's denote by $T(1)$ the treatment status when a child is born in spring in a municipality with at least a daycare center: it takes value $T(1) = 1$ if the child goes to crèche (i.e. is treated), $T(1) = 0$ if not. The difference-in-differences estimator becomes:

$$\begin{aligned}\gamma_{DD} = & \{E[Y_i(1)|T(1) = 1, G_i = 1, E_i = 1] - E[Y_i(0)|T(1) = 1, G_i = 1, E_i = 0] - \\ & (E[Y_i(0)|T(1) = 1, G_i = 0, E_i = 1] - E[Y_i(0)|T(1) = 1, G_i = 0, E_i = 0])\} \\ & \times P[T(1) = 1|G_i = 1, E_i = 1]\end{aligned} \tag{19}$$

The γ_{DD} estimator becomes a sort of LATE estimator: having $G = 1$ and $E = 1$ no longer affects everybody as in the Card and Krueger (1994) case, but only the compliers, the formula from above needs to be rescaled by the percentage of compliers ($P[T(1) = 1|G_i = 1, E_i = 1]$). It is no longer possible to recover the ATT on the whole population (in this case, children aged 0 to 2).

However, at least two further problems hinder the identification of a DD parameter in this context. First, children not born in Spring still attend daycare (fortunately), so the group with $E = 0$ and $G = 1$ is partly treated. In the absence of a clear-cut reform (e.g. random assignment of daycare spots, as in Drange and Havnes 2019), the "eligibility" indicator, $Spring_i$, only affects the probability of attending daycare marginally. Second, G_i is easily manipulable: families may try to apply to daycares outside of the municipality if their municipality has no

Figure 7.3: Unconditional maths test scores by month of birth. Source: DEPP.



daycares, leading to a voilation of the SUTVA assumption. This is somewhat equivalent to moving from Pennsylvania to New Jersey after the minimum wage reform: while finding a new workplace in another state is costly, applications to daycares outside of the municipalities are more likely to happen. This issue may be partly tackled by defining the geographical units as EPCIs instead of municipalities.

Note also that we are not in the case of a fuzzy DD, as in Duflo (2001): in the Indonesian context, the treatment is a reform increasing schooling construction, that affects primarily children born in treatment regions (high school construction, $G = 1$) in the eligible cohort ($E = 1$). In her case, school attendance (measured by years of education) is an outcome, and the reduced-form impact of the reform on wages are rescaled by the first-stage DD estimate on years of education. In this case, however, in the absence of a significant reform, daycare attendance is considered the treatment, and not an outcome.

7.5 Graphs

7.5.1 Daycare availability (Main source: CAF)

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

7.5.3 Descriptive graphs from DEPP

7.5.4 Maps

Figure 7.4: Maths test scores by month of birth, residuals after fitting an OLS regression with a linear month variable. Source: DEPP.

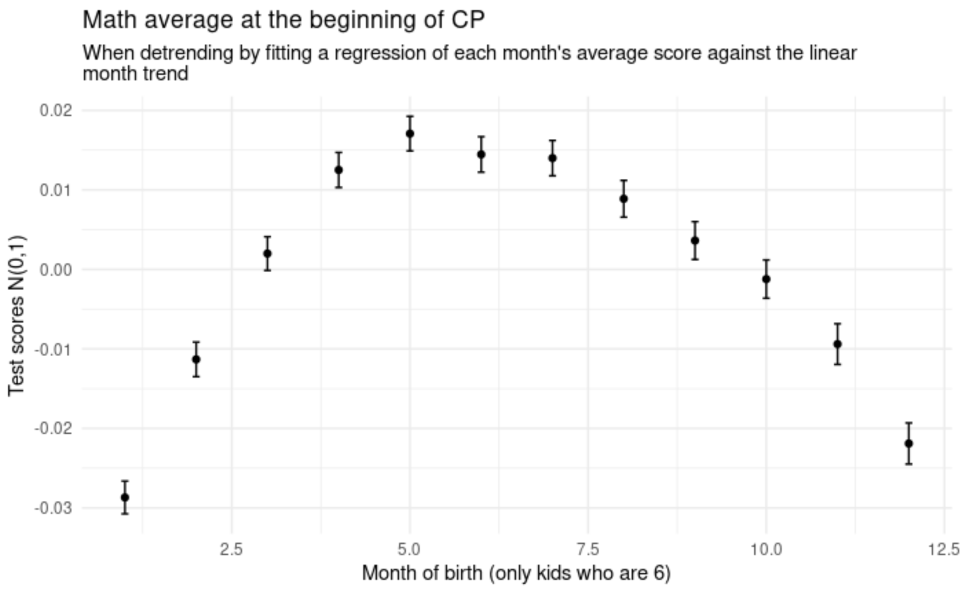
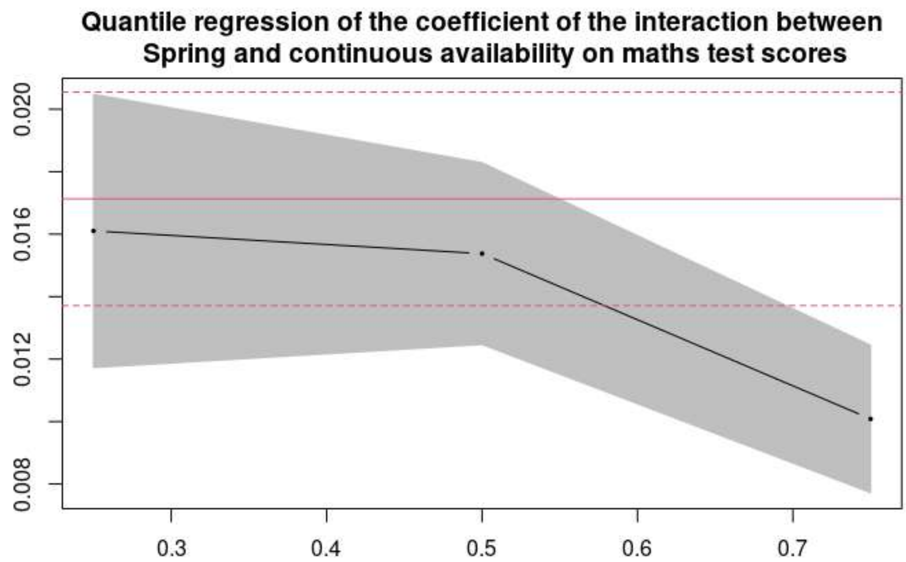


Figure 7.5: Results of the quantile regression using the main specification (Equation 2) for French and maths test scores. The red line is the OLS coefficient for the whole sample.



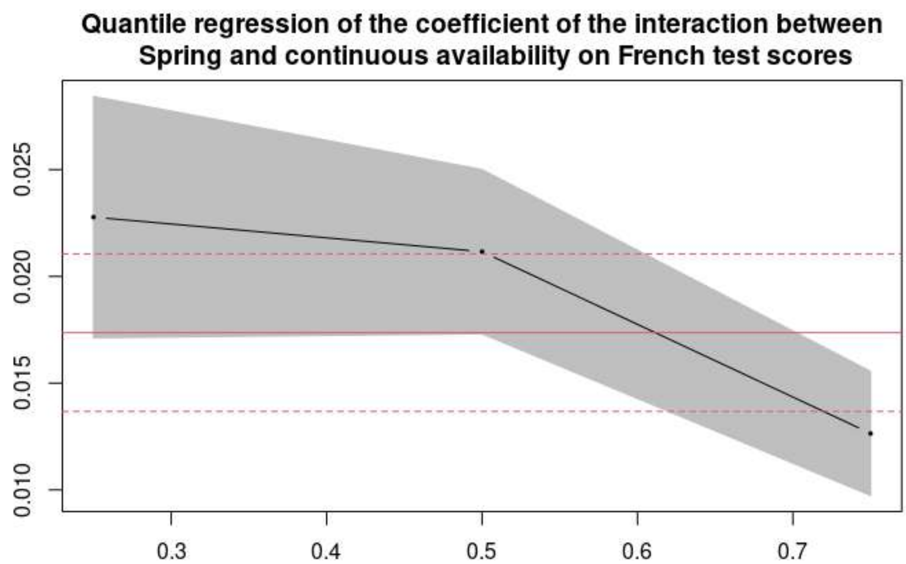


Figure 7.6: Childcare facilities financed by PSU, disaggregated by type and management. Source: CAF

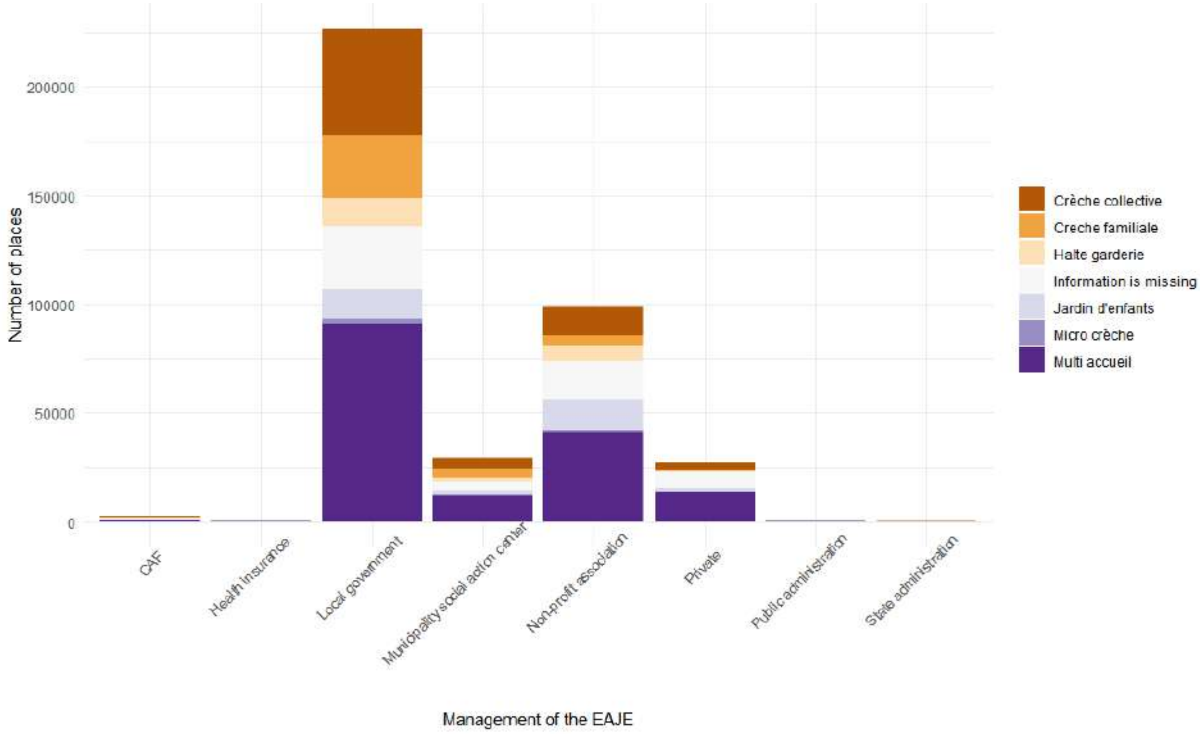


Figure 7.7: Distribution of daycare operating hours. Source: CAF

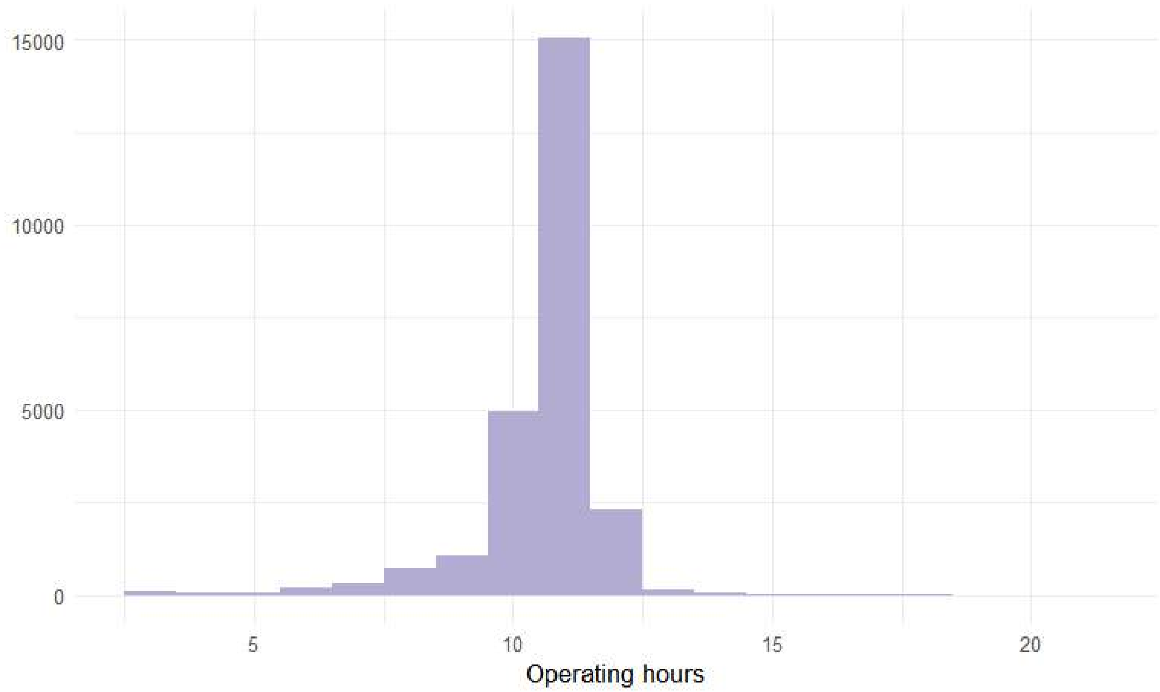


Figure 7.8: Evolution of the distribution of the number of days daycare centers are open in France. Source ONAPE (2016).

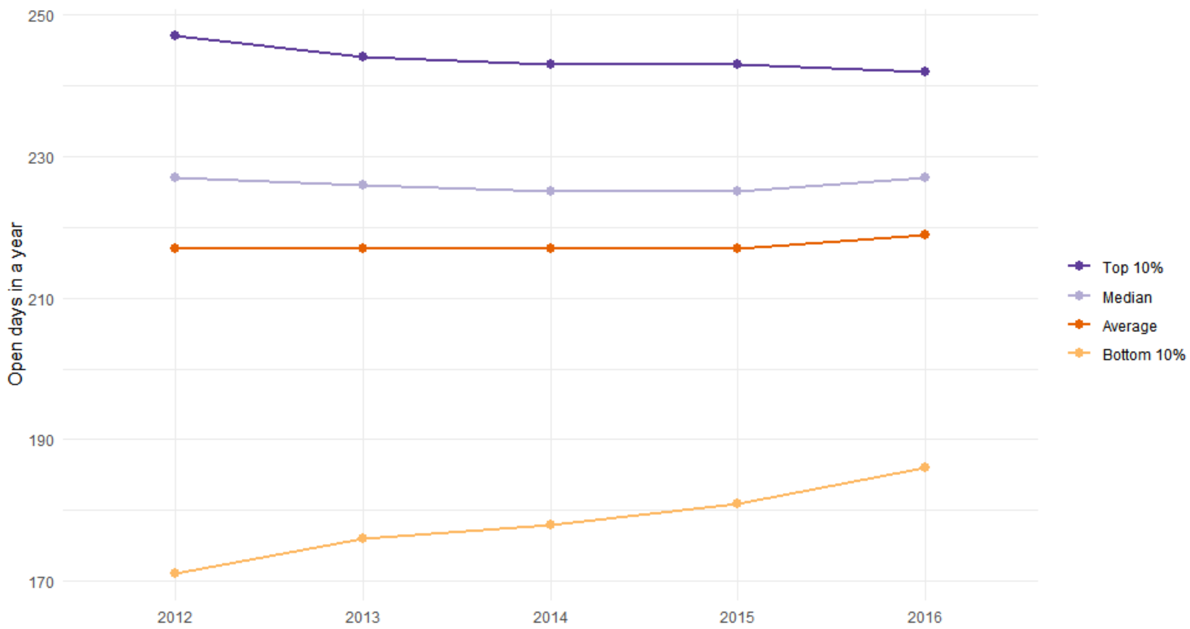


Figure 7.9: Price for families and costs for the public finances. Source: ONAPE (2016).

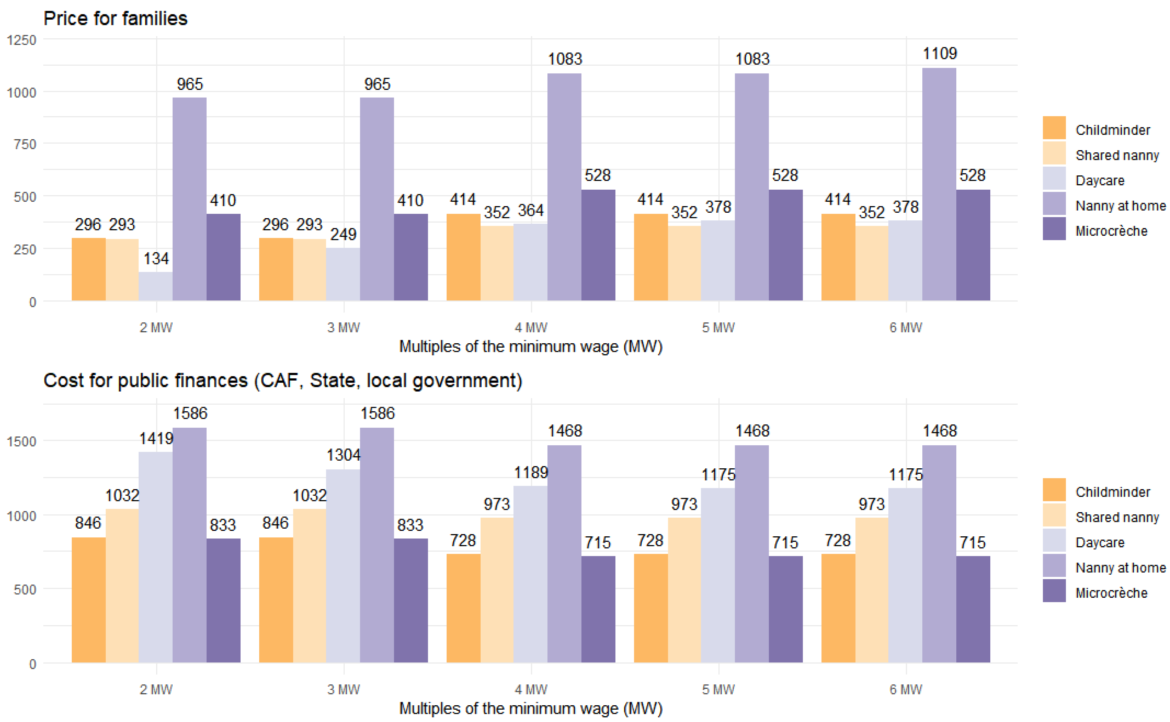


Figure 7.10: Regional variation in daycare and childminders availability in 2012. Source: ONAPE (2016).

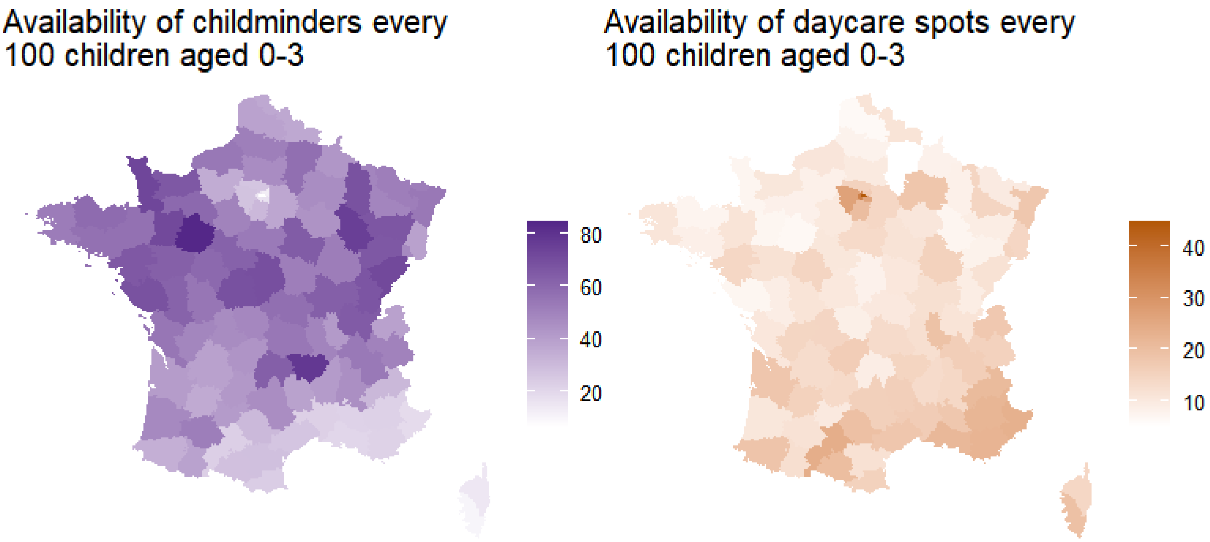


Figure 7.11: Months when the child begins daycare, based on month of birth. Source: Elfe.

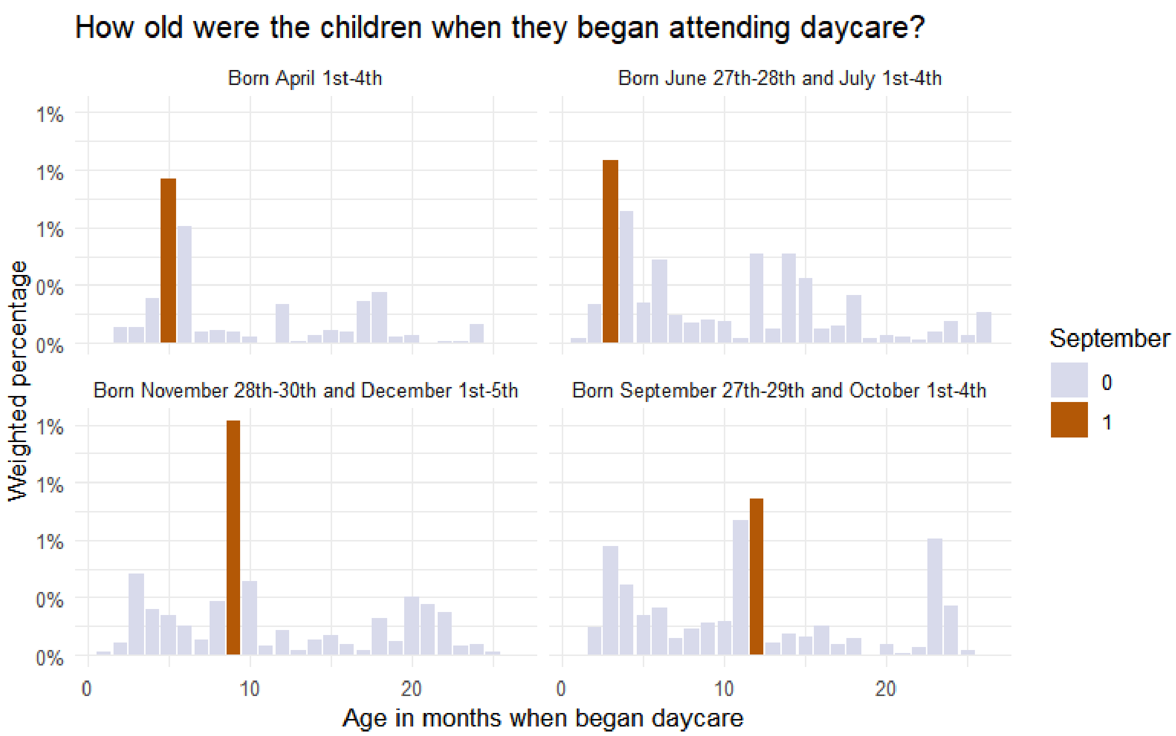


Figure 7.12: Distribution of days and hours spent in childcare by type of childcare arrangement. Source Elfe.

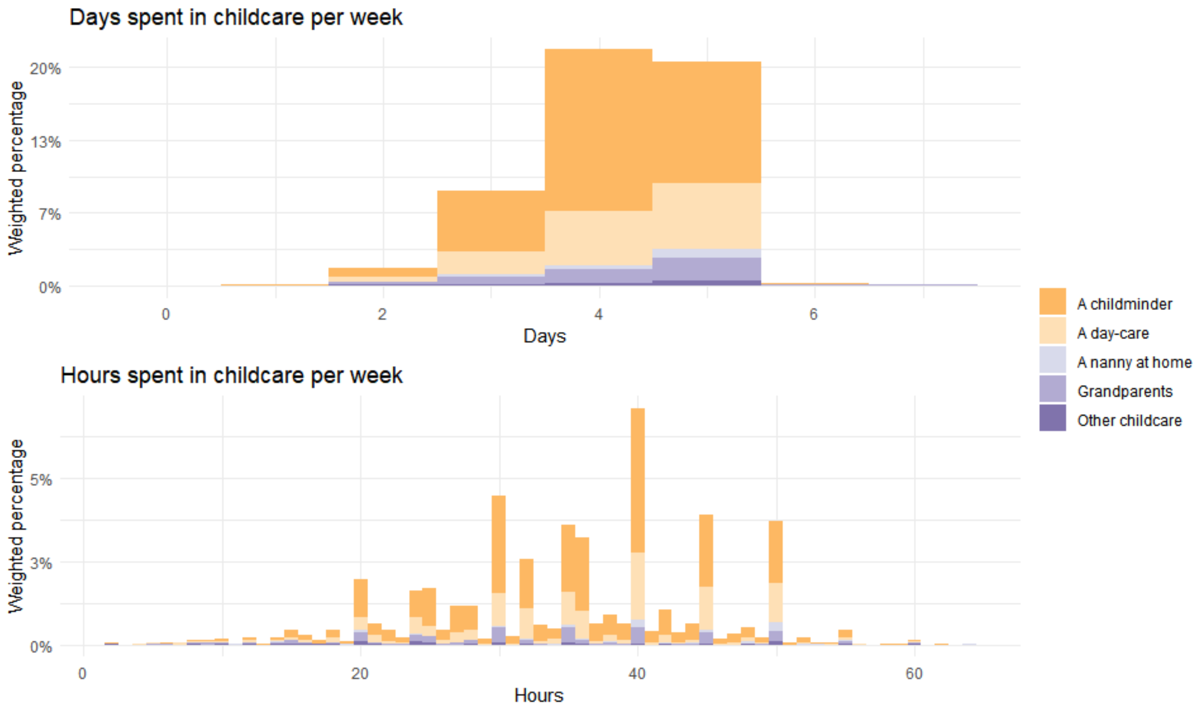


Figure 7.13: Satisfaction with the opening hours by type of childcare arrangement. Source: MDG.

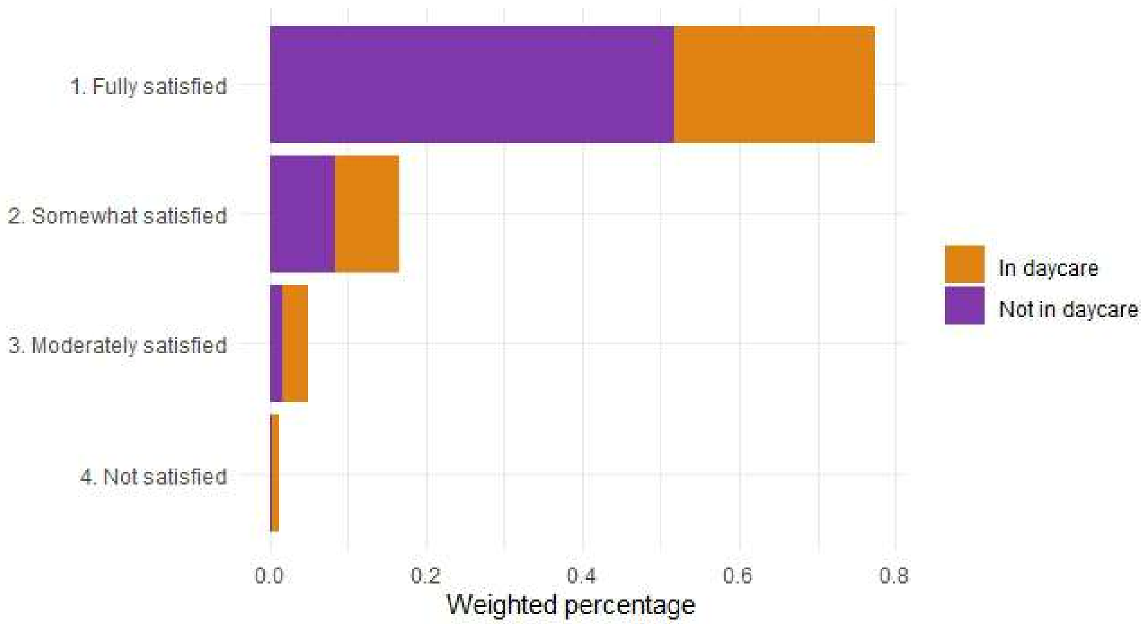
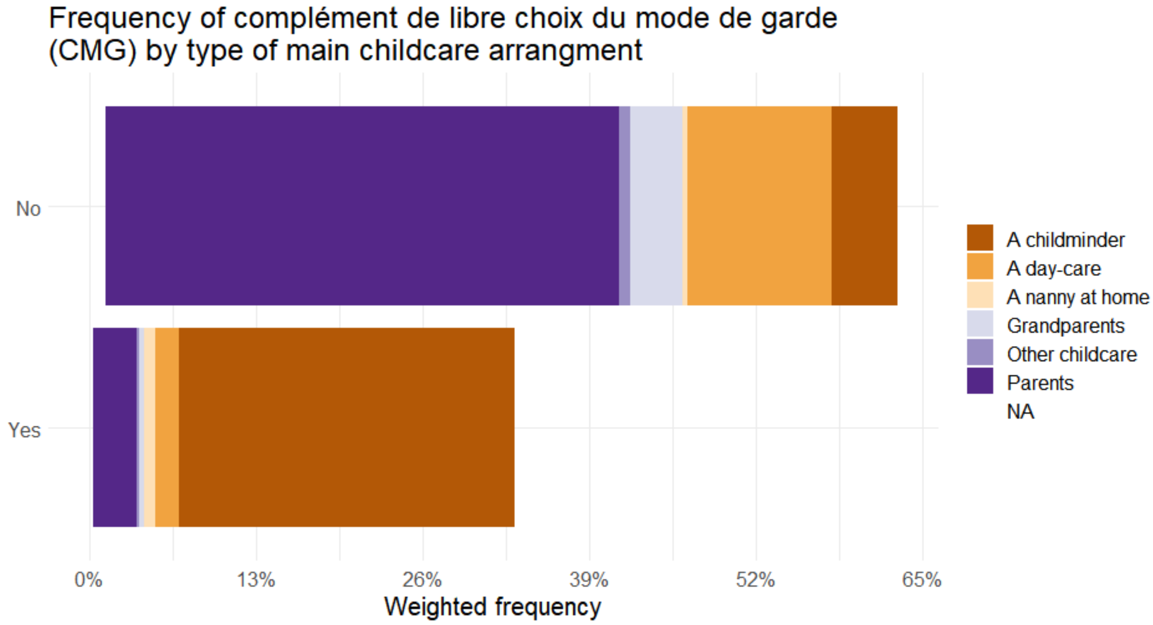


Figure 7.14: CMG when the child is 1 year old. Source: Elfe.



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 7.15: Ideal childcare arrangement according to mothers. Source: Elfe.

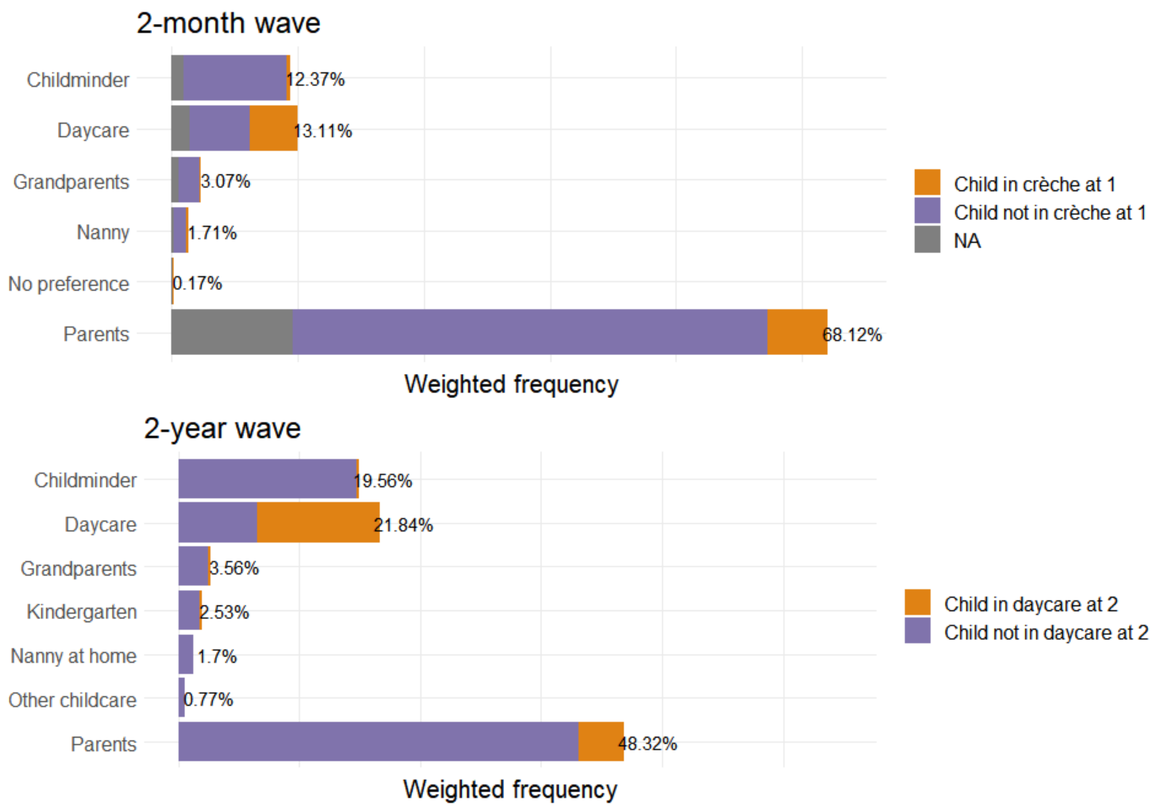


Figure 7.16: Months of research before finding the first paid childcare arrangment. Source: MDG.

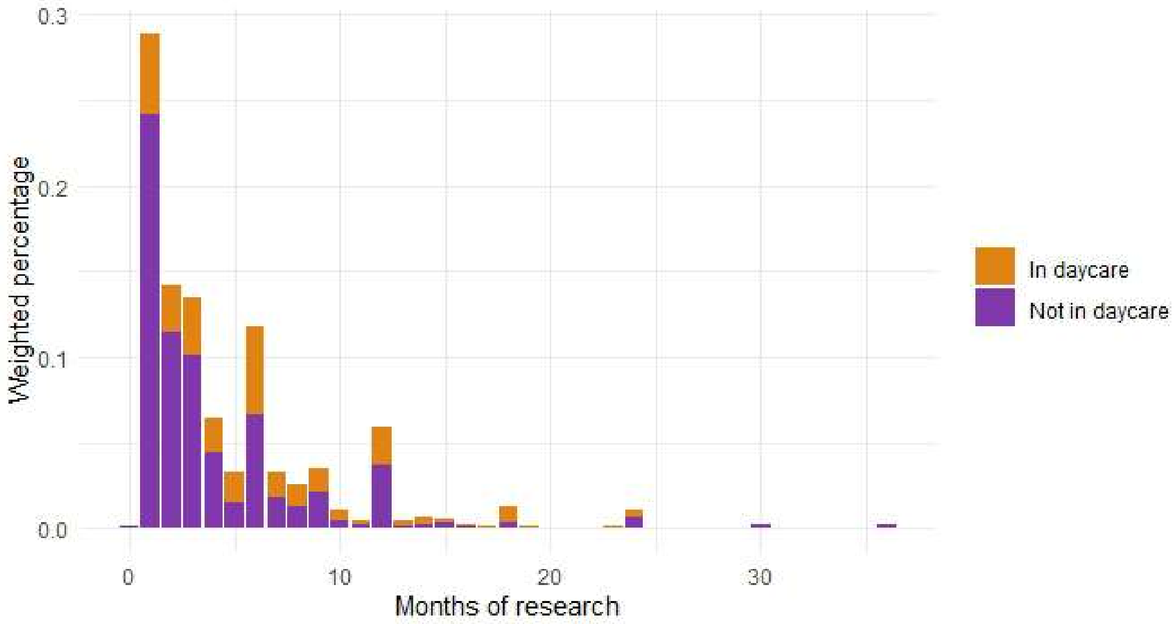


Figure 7.17: Reasons for the choice of daycare or a licensed childminder as preferred childcare arrangement. Source: own elaboration based on Enquête Mode de garde 2013.

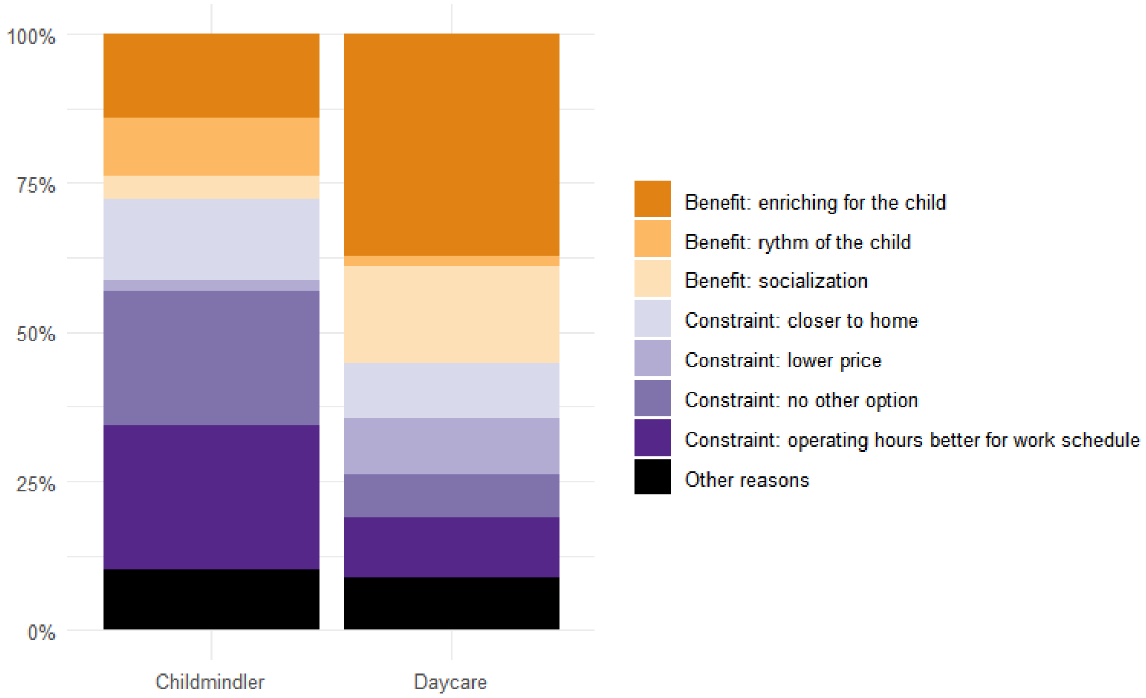


Figure 7.18: Alluvial diagram of the changes in childcare arrangement of children between 1 and 2 years of age. Source: Elfe survey

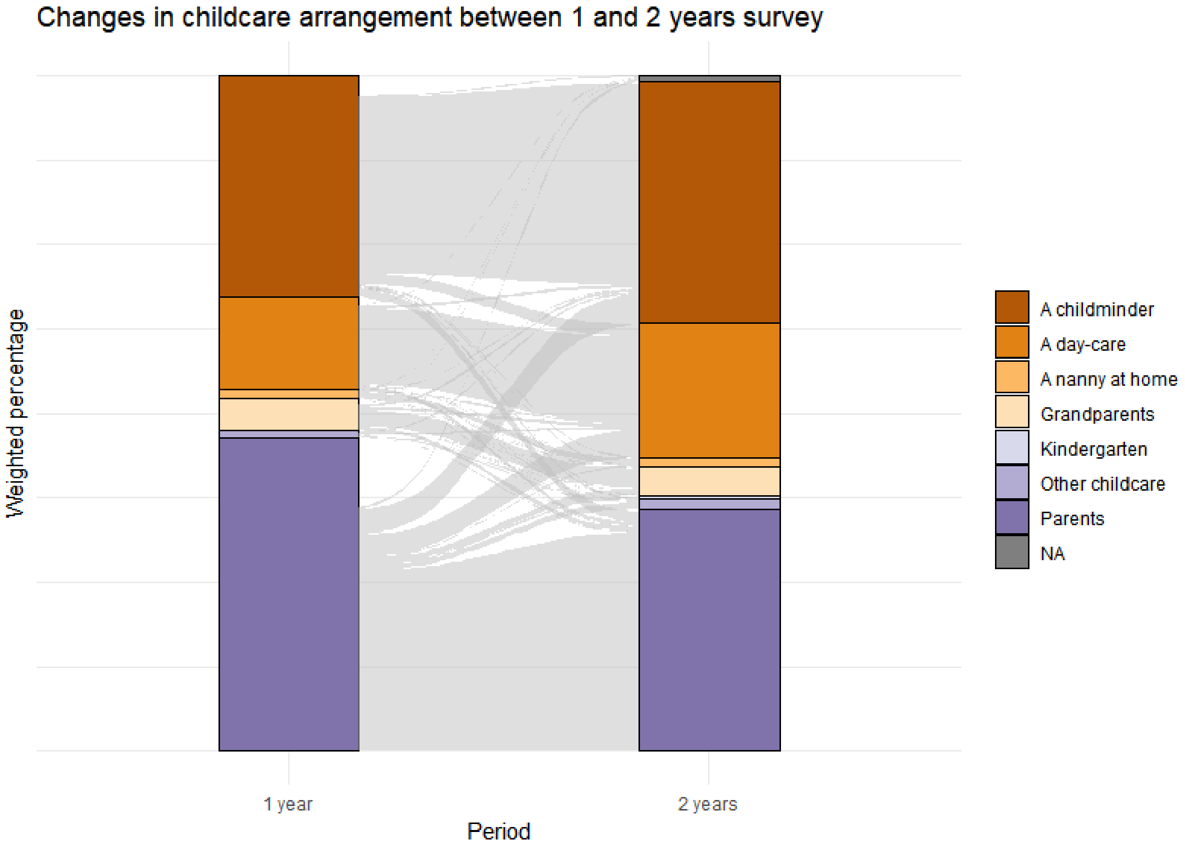


Figure 7.19: Frequency and type of complementary childcare method by type of main childcare method. Source: Elfe survey

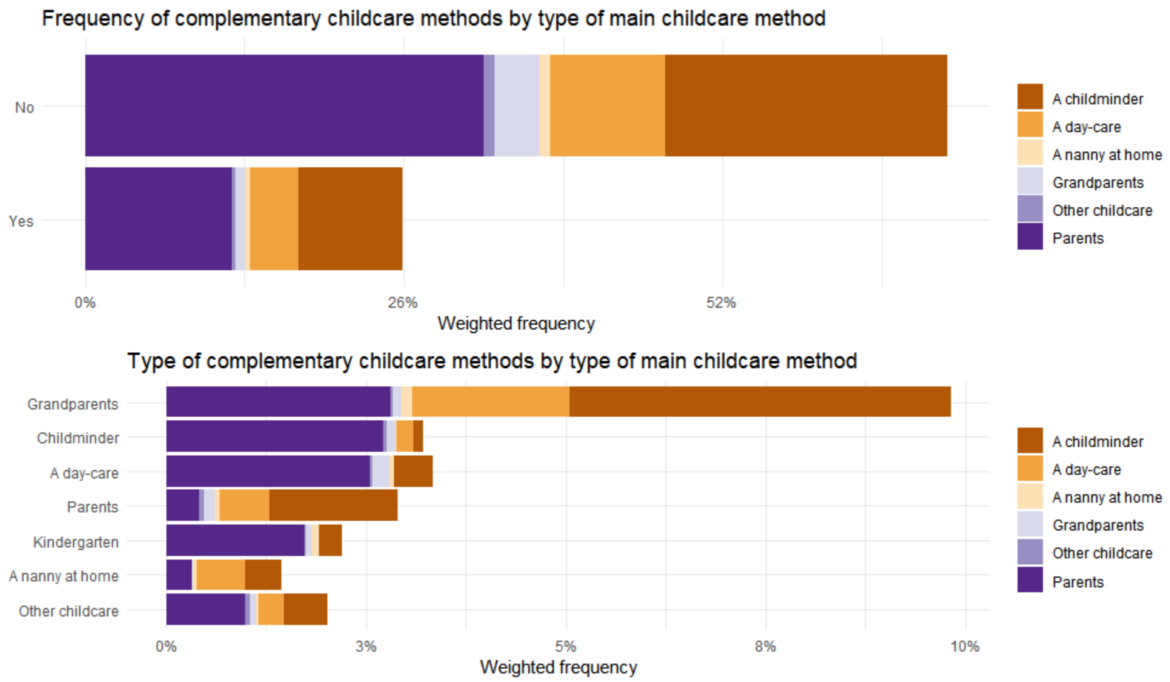


Figure 7.20: Correlation between daycare availability and average value added at the municipality level in 2012. Source: DEPP High school value-added indicators, CAF, birth registries (INSEE).

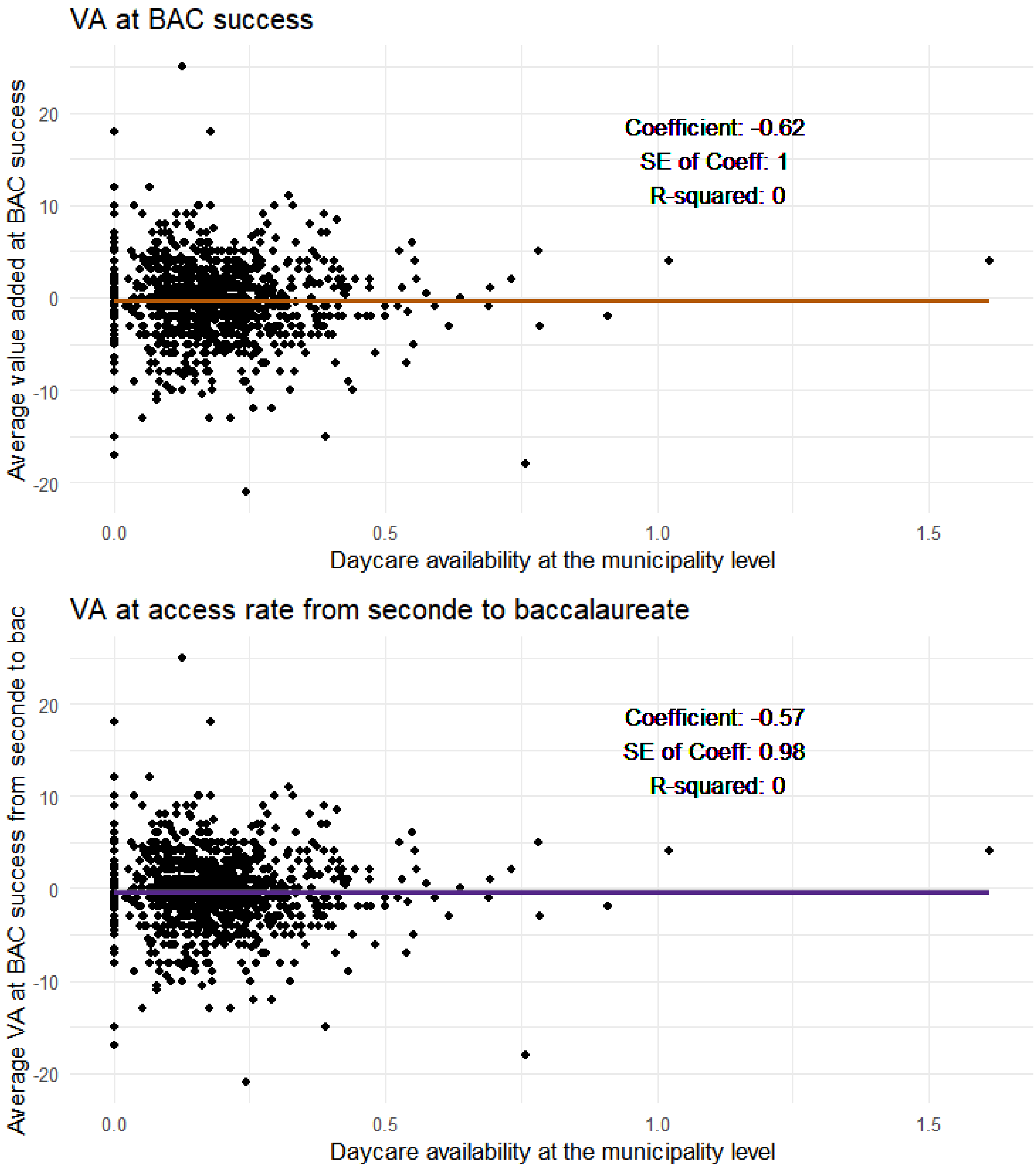


Figure 7.21: Patterns of missingness in DEPP data.

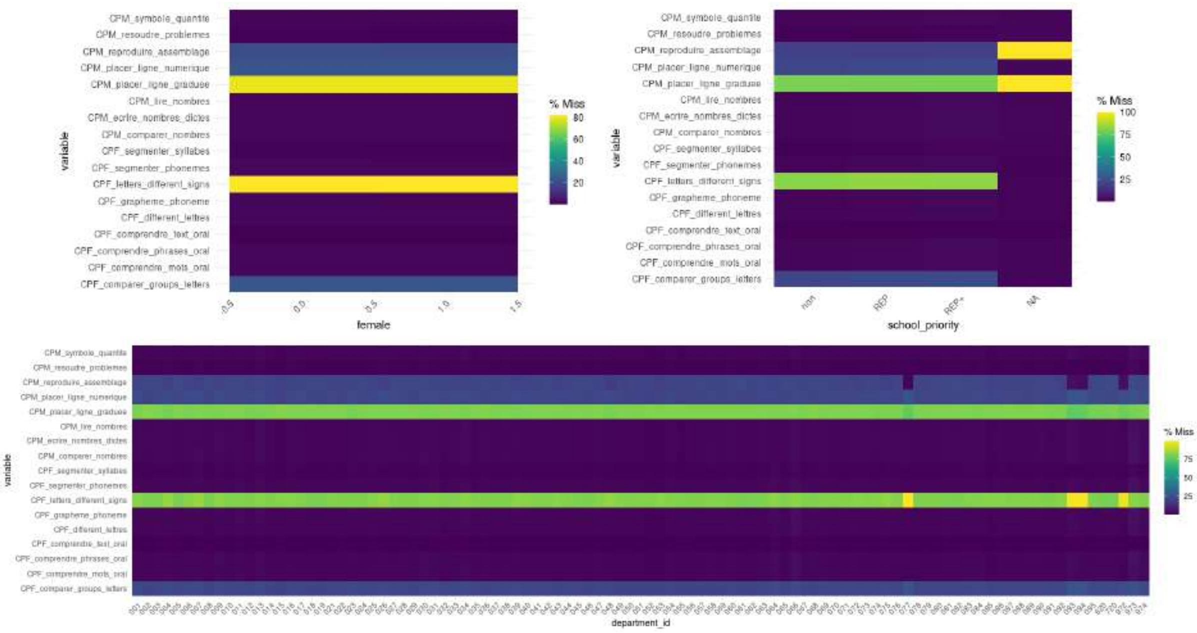


Figure 7.22: Distribution of children that are belated by one year or one year in advance. Source: DEPP.

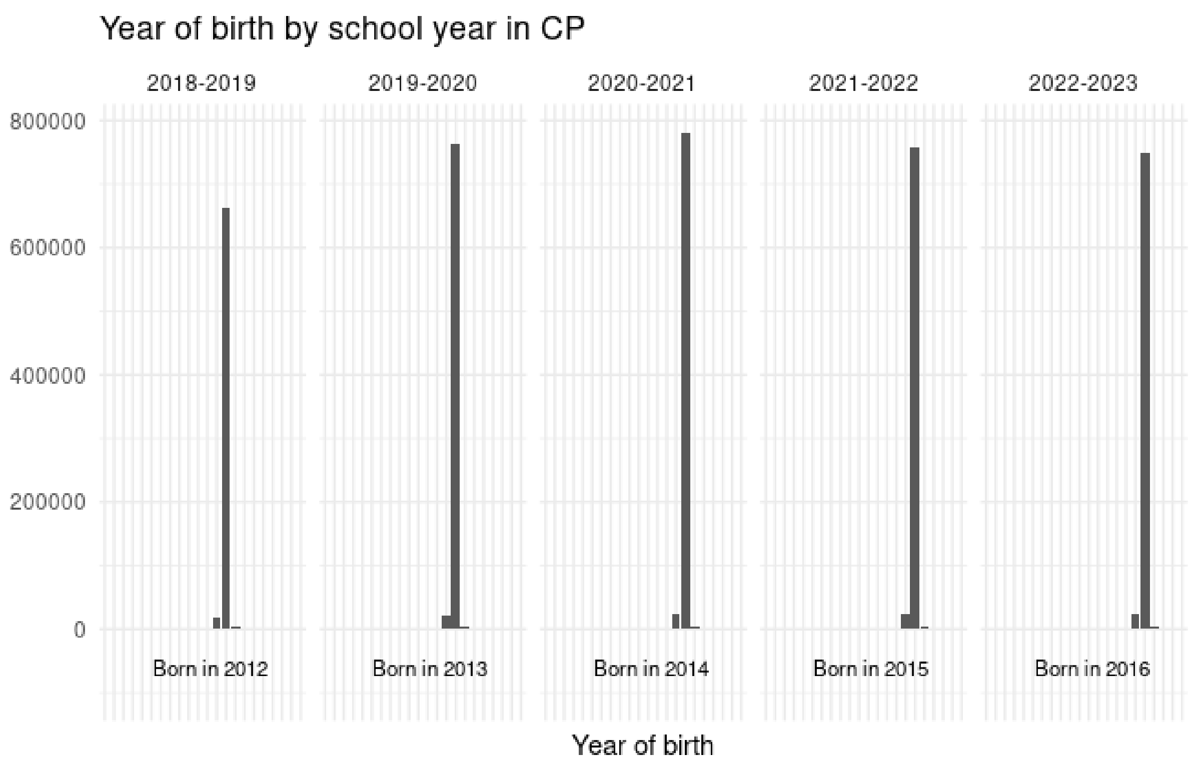


Figure 7.23: Distribution of number of children by number of insufficient items in Maths (left) and French (right). Source: DEPP.

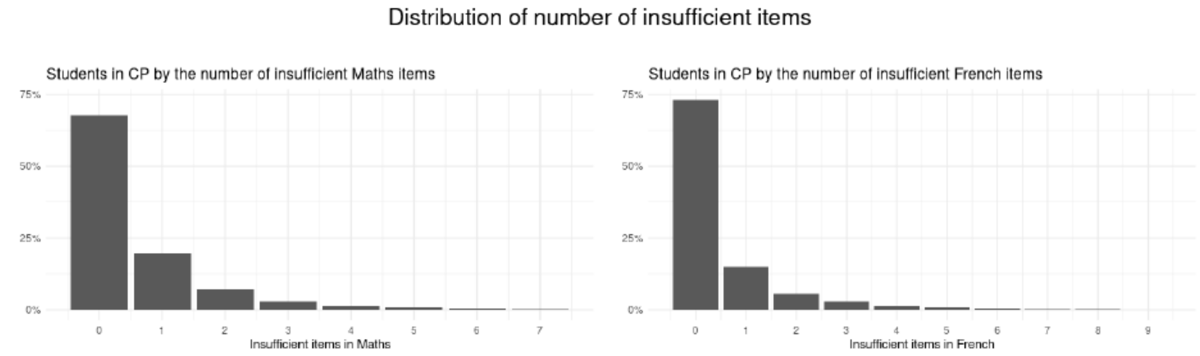


Figure 7.24: Results from the quantile regression with the binary definition of daycare availability, excluding Ile-de-France. Source: DEPP.

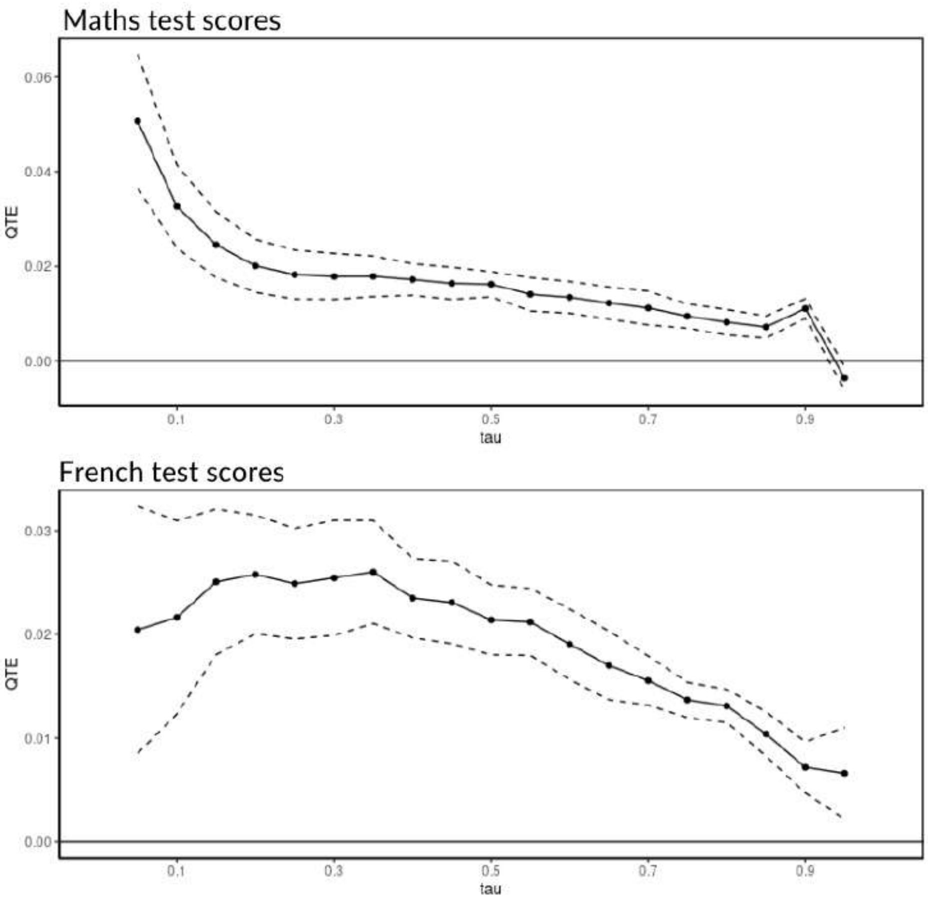


Figure 7.25: Change in daycare availability from 2011 to 2016 per French region. Source: CAF and birth registries (INSEE).

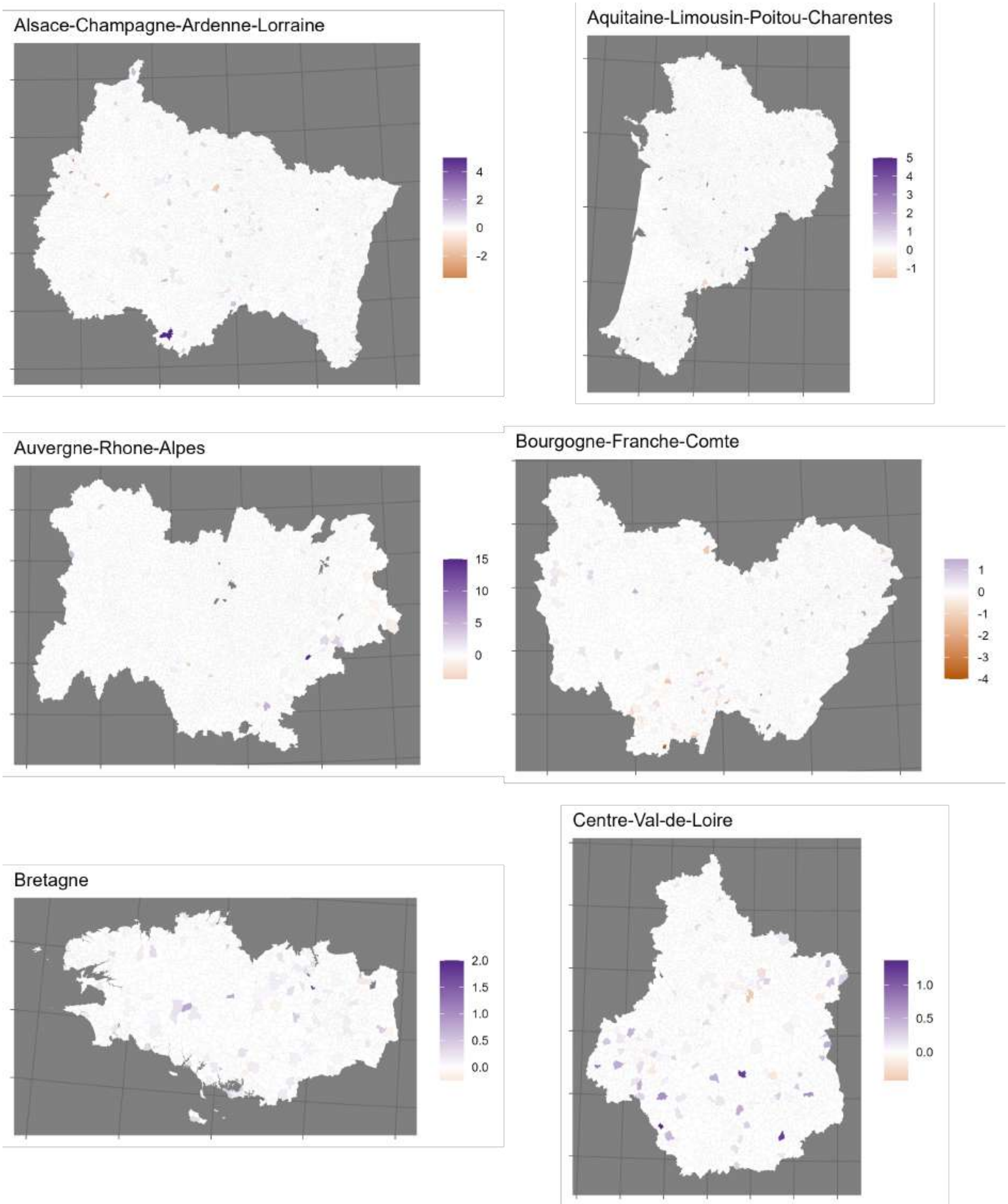
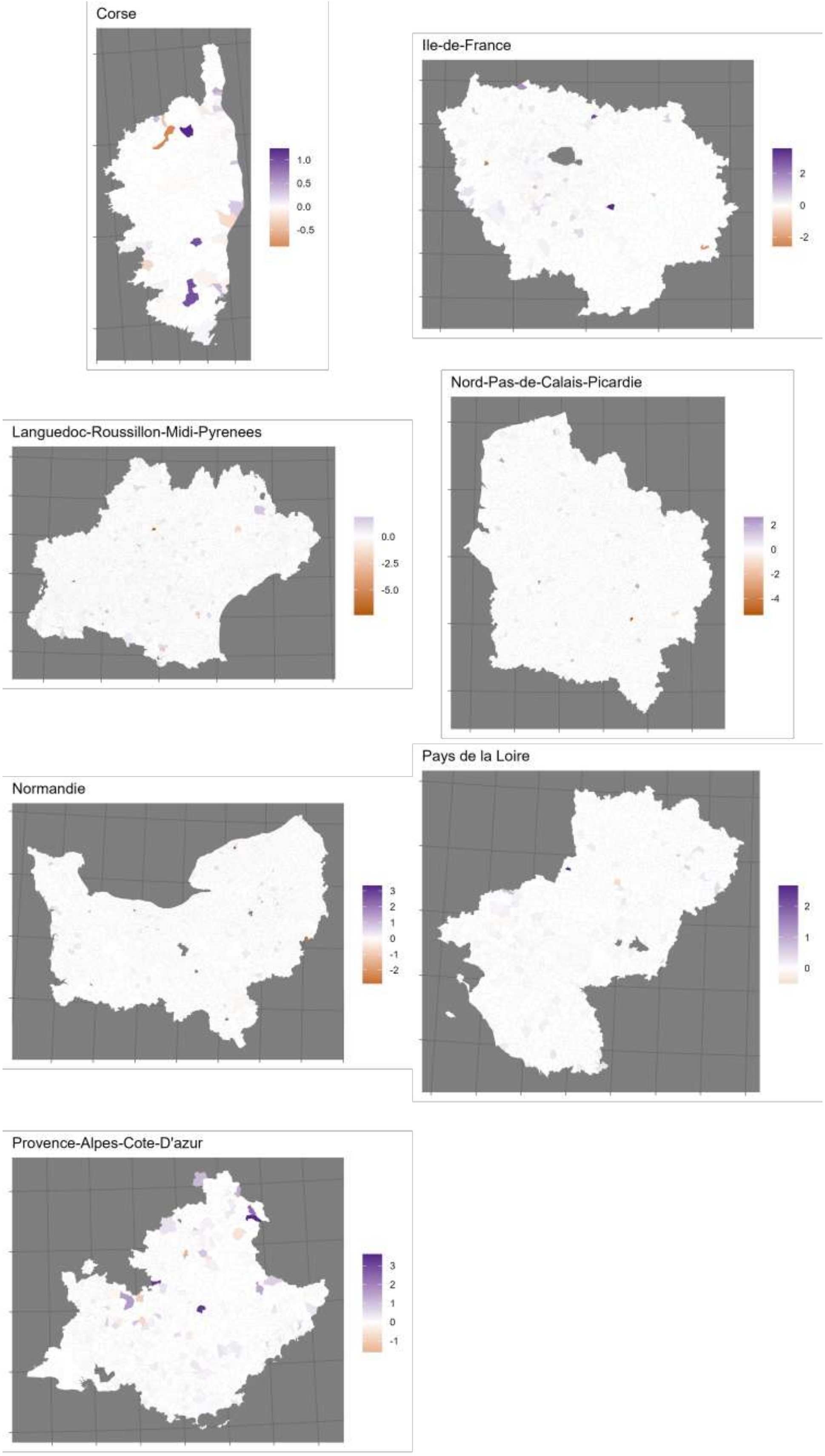


Figure 7.26: Change in daycare availability from 2011 to 2016 per French region. Source: CAF and birth registries (INSEE).



7.6 Tables

7.6.1 Descriptive statistics

Table 7.1: Descriptive statistics of the FL sample, 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 7.2: Descriptive statistics of the FL sample, 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 7.3: 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

7.6.2 Robustness checks to the choice of the spring instrument

Table 7.4: 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 7.5: 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 7.6: 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 7.7: 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 7.8: 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 7.9: 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 7.10: 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 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 7.11: 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 $\times$ 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.) $\times$ 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) $\times$ 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

7.6.3 Robustness checks to the measure of daycare availability

Table 7.12: 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 7.13: Robustness checks to the availability specification

Dependent Variable:	Daycare				
Model:	Baseline	Division bias	Commuters	No Paris	Binary
Variables					
(Intercept)	0.1004***	0.0974***	0.0631***	0.0979***	0.0815***
	(0.0088)	(0.0078)	(0.0167)	(0.0081)	(0.0115)
Spring	0.0136**	0.0136**	-0.0004	0.0144***	0.0054
	(0.0059)	(0.0058)	(0.0169)	(0.0055)	(0.0052)
Availability	0.2874***	0.2541***	0.1210**	0.2675***	
	(0.0526)	(0.0452)	(0.0572)	(0.0470)	
Month of birth	-0.0034***	-0.0034***	0.0004	-0.0031***	-0.0035
	(0.0007)	(0.0007)	(0.0012)	(0.0006)	(0.0016)
Spring × Availability	0.0750**	0.0749**	0.0464	0.0514*	
	(0.0377)	(0.0368)	(0.0867)	(0.0280)	
Kids born in municipality		1.42×10^{-6}***			
		(1.53×10^{-7})			
Non-commuter			-0.0187		
			(0.0148)		
$\mathbb{1}(Availability > 0)$					0.0877***
					(1.94×10^{-5})
Spring × $\mathbb{1}(Availability > 0)$					0.0272***
					(1.14×10^{-5})
Fit statistics					
Standard-Errors	Municipality	Municipality	Municipality	Municipality	groups
DV mean	0.12016	0.12016	0.07584	0.11149	0.12016
F-test	9.4274	8.9582	0.35988	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 7.15: 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

7.6.4 Robustness checks using different first stage samples

Table 7.16: 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*

7.6.5 Robustness checks to the choice of the standard errors

Table 7.17: 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

7.6.6 Further robustness checks in the cross-sectional specification

Table 7.18: 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							5.74×10^{-6}***	5.67×10^{-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 7.19: 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 $\times$ 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 7.20: 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 7.21: 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 × 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 7.22: 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 7.23: 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 7.24: First-stage results adding quality indicators

Dependent Variable:	Daycare					
Model:	(1) Baseline	(2) Baseline on selected N	(3)	(4)	(5) Baseline on selected N	(6)
Variables						
(Intercept)	0.1004***	0.1307***	-0.0782	0.0607***	0.0890***	0.1197
	(0.0088)	(0.0137)	(0.0780)	(0.0066)	(0.0106)	(0.1134)
Spring	0.0136**	0.0162*	0.0153	-0.0143**	-0.0272**	-0.0268**
	(0.0059)	(0.0094)	(0.0094)	(0.0073)	(0.0131)	(0.0133)
Availability	0.2874***	0.2326***	0.1828***			
	(0.0526)	(0.0591)	(0.0465)			
Month of birth	-0.0034***	-0.0048***	-0.0049***	-0.0031***	-0.0042***	-0.0042***
	(0.0007)	(0.0009)	(0.0009)	(0.0007)	(0.0009)	(0.0009)
Spring × Availability	0.0750**	0.0591	0.0623			
	(0.0377)	(0.0404)	(0.0405)			
Opening hours			0.0005			
			(0.0068)			
Financial occupancy			0.0006			
			(0.0011)			
Paid hours/day			0.0121			
			(0.0106)			
Median family price			0.0554***			
			(0.0198)			
Availability (EPCI)				0.5781***	0.4954***	0.4282***
				(0.0397)	(0.0578)	(0.0511)
Spring × Availability (EPCI)				0.2760***	0.3351***	0.3355***
				(0.0603)	(0.0868)	(0.0883)
Opening hours (EPCI)						-0.0170*
						(0.0097)
Financial occupancy (EPCI)						-0.0015
						(0.0014)
Paid hours/day (EPCI)						0.0336***
						(0.0124)
Median family price (EPCI)						0.0120
						(0.0175)
Fit statistics						
Standard-Errors	Municipality	Municipality	Municipality	EPCI level	EPCI level	EPCI level
DV mean	0.12016	0.15581	0.15581	0.11148	0.14285	0.14285
F-test	9.4274	2.6001	1.8855	8.2238	3.2049	1.2201

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 or EPCI divided by the number of children aged 0-2 born in the municipality or EPCI (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 7.25: Reduced-form results adding quality indicators

Dependent Variables:	Maths	French	Maths	French	Maths	French
Model:	(1) Baseline	(2) Baseline	(3) Baseline on selected N	(4) Baseline on selected N	(5)	(6)
Variables						
Spring	0.0140***	0.0173***	0.0198***	0.0214***	-0.1474***	-0.0696
	(0.0011)	(0.0013)	(0.0030)	(0.0042)	(0.0503)	(0.0574)
Availability	-0.0172*	-0.0446***	0.1993***	0.2772***	-0.3250	-0.3005
	(0.0095)	(0.0129)	(0.0204)	(0.0290)	(0.3055)	(0.4145)
Month birth	-0.0326***	-0.0336***	-0.0332***	-0.0336***	-0.0333***	-0.0336***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Spring × Availability	0.0136***	0.0143***	-0.0107	-0.0080	0.2144	0.0174
	(0.0048)	(0.0053)	(0.0119)	(0.0172)	(0.1715)	(0.2042)
Opening hours					-0.0420***	-0.0575***
					(0.0093)	(0.0120)
Financial occupancy					-0.0040***	-0.0057***
					(0.0015)	(0.0020)
Paid hours/day					0.0400***	0.0586***
					(0.0143)	(0.0186)
Median family price					0.1526***	0.2180***
					(0.0223)	(0.0318)
Spring × Opening hours					0.0172***	0.0104**
					(0.0044)	(0.0051)
Availability × Opening hours					0.0448*	0.0535*
					(0.0230)	(0.0308)
Spring × Financial occupancy					0.0023***	0.0016**
					(0.0007)	(0.0008)
Availability × Financial occupancy					0.0067	0.0079
					(0.0042)	(0.0057)
Spring × Paid hours/day					-0.0207***	-0.0135*
					(0.0063)	(0.0073)
Availability × Paid hours/day					-0.0420	-0.0514
					(0.0405)	(0.0546)
Spring × Median family price					-0.0216***	-0.0253***
					(0.0059)	(0.0071)
Availability × Median family price					-0.0928	-0.1400
					(0.0635)	(0.0878)
Spring × Availability × Opening hours					-0.0188	-0.0009
					(0.0148)	(0.0184)
Spring × Availability × Financial occupancy					-0.0030	-0.0007
					(0.0022)	(0.0028)
Spring × Availability × Paid hours/day					0.0304	0.0133
					(0.0216)	(0.0278)
Spring × Availability × Median family price					-0.0121	-0.0219
					(0.0142)	(0.0180)
Fixed-effects						
Department	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	3,524,383	3,535,553	1,596,066	1,599,733	1,596,066	1,599,733
Dependent variable mean	0.00724	0.00429	-0.01441	-0.07934	-0.01441	-0.07934

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

Clustered (municipality level) standard-errors in parentheses

Table 7.26: 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

7.6.7 Quantile regressions

Table 7.27: 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, Duflo, and Mullainathan (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 7.29: Reduced form regression: quantile regression using the binary definition of availability (Equation 7) 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 7.30: Reduced form regression: quantile regression using the binary definition of availability (Equation 7) 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 7.31: 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 7.14: First stage regression: dividing the sample between those who move in the last 6 months and those who do not in the FL sample, 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 7.28: Reduced form regression: quantile regression using the continuous definition of availability (Equation 2).

Dependent Variables:	French	French	French	Maths	Maths	Maths
Model:	(1) 25th p.	(2) 50th p.	(3) 75th p.	(4) 25th p.	(5) 50th p.	(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)
av_year_kids_abs	-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 × av_year_kids_abs	0.02277**	0.02116*	0.01264**	0.02277**	0.02116**	0.01264**
	(0.00288)	(0.00196)	(0.00148)	(0.00288)	(0.00196)	(0.00148)