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

Violetta van Veen*
Advisors: Thomas Breda and Delphine Roy

Abstract

I estimate 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, I 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. I use two-sample 2SLS using a large, nationally representative survey to rescale the reduced-form results, finding a positive impact of daycare attendance on compliers of 0.12-0.24 SD. Quantile regressions reveal that the daycare impact is significantly higher for the bottom end of the skills distribution than for the top one: in line with the 'compensatory' model, daycare has a potential equalizing effect.

JEL codes: J13, H52, I28

*Paris School of Economics. violettavanveen@gmail.com. I thank my supervisors Thomas Breda and Delphine Roy for their guidance and for allowing me to use the FL data. I thank Arthur Heim, Pierre Pora and Anne Solaz for their comments and for helping me with finding CAF data.

1 Introduction

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.

A priori, why would an early education intervention benefit the child's cognitive development? Neurological literature[1] has reached a consensus on the fact that responsive caregiving (Gunderson et al., 2013) and language-rich interactions (Cartmill et al., 2013; Hart & Risley, 1995, 2003; Rowe & Goldin-Meadow, 2009) are 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 interactions with trained staff that provide explicit opportunities for skill development, and socialization with other children.

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, I combine administrative data on standardized tests the universe of French children, fine-grained local administrative data on daycare supply, and two different large, nationally representative surveys. I rely on an individual-level instrument that interacts local daycare availability and plausibly exogenous variation in the period 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[2]. I 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. I find a significant and positive effect of daycare attendance on numeracy and literacy skills, in a range of 0.12-0.24 SD, for the compliers with the instrument. The small reduced-form coefficients of around 0.01 SD are rescaled by a first-stage of 7 percentage points, which is relevant and strong considering that the actual percentage of children attending daycare is

[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.

[2]The use of two different and larger datasets than Berger et al. (2021) allows me to have enough power to show the relevance of the interacted instrument and to detect small but significant effects on cognitive development.

around 12%. Heterogeneity by observables does not yield significant results, likely because I can only measure observable characteristics in the two samples at the municipality level, so the ratio between intragroup variation and intergroup variation is larger than using individual characteristics. However, quantile regressions uncover significant heterogeneity of the impact of daycare along the skills distribution, providing 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, I attempt to understand the impact of daycare with respect to counterfactual formal and informal childcare arrangements: the main instrument I 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, as the potential cognitive benefit of daycare vs. home care may be stronger than the one of daycare vs. other formal childcare. I also use use a fixed-effect model on the average local cognitive achievement, to show the effect of changes in the daycare availability, in particular, instrumented by daycare openings.

This paper relates to various strands of literature. First, I 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. Recent and well-identified papers focusing on the impact of 0-2 daycare attendance on cognitive outcomes are summarized in Table 1.1. My results are coherent with the main takeaway message: the effect of daycare attendance is overall positive, stronger for literacy, and depends on the counterfactual type of care.

Focusing on France, most of the literature on childcare arrangements for children aged 0-2 focuses on attending kindergarten (*école maternelle*) at 2 years old - i.e. before the usual beginning at 3 (Filatriau, Fougère, & Tô, 2013; Goux & Maurin, 2010; Heim, 2018). Among those, the most relevant for this thesis is Filatriau et al. (2013), in which the authors use local availability as an IV but find non-significant effects at 6 years old, differently from my results. Berger et al. (2021) is the closest paper to this thesis: using the wave of the Elfe survey and the number of daycare spots every 1000 children as instruments, they find a positive effect of daycare attendance, but they focus on short-term outcomes (at 2 years old). The main innovation of my thesis with respect to Berger et al. (2021) strategy is to use a more plausible exogenous instrument (the interaction between local daycare availability and being born in Spring), and to use another dataset for the first stage, that is 4x larger, observes children born over all the year (while the one they use only observe children born in 4 months in the year, which may be important when the identification builds on the month of birth) and suffers less from attrition. My results are robust to using their same dataset (Table 7.13). While the research question of Pora (2020) focuses on the consequences of opening daycare spots on mother labor market outcomes, the results are extremely relevant for this thesis: mothers do not work more when a daycare center opens, but rather there is a crowding-out of individualized and more costly childcare solutions (childminders and nannies).

This paper also relates to the strain of literature on the cognitive long-term benefits of childcare attendance using regional variation in availability, such as the fact of being born in a municipality where access to daycare centers is guaranteed (Gupta & Simonsen, 2016), or difference-in-differences (DiD) using the staggered expansion of childcare reforms (Cascio, 2009; 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 I 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.

In particular, my quantile heterogeneity analysis builds on Havnes and Mogstad (2015), who extend the DiD approach on local availability to quantile DiD and change-in-change (Athey & Imbens, 2006), Kottelenberg and Lehrer (2017), who recovers individual change-in-change effects of daycare attendance, and Bitler, Hoynes, and Domina (2014), who computes quantile treatment effects using IV-QTE and the randomized allocation of Head Start slots as instrument. The main differences are that my outcome is long-term cognitive skills and not earnings nor short-term cognitive tests and that I 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), I 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)

In terms of methods, this paper contributes to the body of research on childcare decisions using two-sample 2SLS (TS2SLS): Aparicio-Fenoll and Vidal-Fernandez (2015) and Pinto (2022) both use TS2SLS to estimate the effects of informal childcare given by grandmothers on mothers' labor force participation, exploiting retirement age reforms as an IV for grandmothers' retirement decision. Monnet (2019) instead uses TS2SLS to study the effect of participation in kindergarten on children's subsequent development of psychological disorders, but relies on a simple preschool availability IV. Although with a different research question, my results are in line with hers: childcare is more beneficial to disadvantaged children. Differently from these papers, I use administrative data as the "second-stage dataset" of the TS2SLS.

Finally, openings and closings of new schools are commonly used in the literature as proxies or instruments for school availability. For example, both Humlum and Smith (2015) and Kuziemko (2006) use school openings as instruments for class size to study its effect on students' long-run and short-run achievement, while Monarrez, Kisida, and Chingos (2022), Imberman (2011) and Ridley and Terrier (2023) use opening of charter schools as an instrument for their supply relative to public schools to study the role these schools play in their respective district and their relationship with public school students' achievement. The innovation of this paper is to use them in the context of daycare centers, and to link this literature with the 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), finding results in line with it: 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. For example, in the US, Infant Health and Development Program (0-2) (Duncan & Sojourner, 2013) and state-funded preschools (Cascio, 2023) has a much larger positive effect on low-income families, while in Spain home care by mothers was of lower quality than high-quality kindergarten so that positive cognitive outcomes at 15 are driven by children born in low-income families (Felfe et al., 2015). The negative effects on children's well-being found in one of the first studies on the introduction of universal childcare (Baker et al., 2008) and the long-term effects of the same reform (Haeck et al., 2018) are explained by the crowding out of parental care in higher income families (Elango, García, Heckman, & Hojman, 2015), since disadvantaged children had access to subsidized daycare before the reform. The effect of substitution between different formal childcare arrangements depends on the quality of the alternatives: for example, in Colombia, both cognitive and socio-emotional development are hindered by offering places in daycare with a lower quality than home-based nurseries (Bernal, Attanasio, Peña, & Vera-Hernández, 2019).

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

Table 1.1: Literature review on papers focusing on daycare at age 0-2 and the impact on medium- or long-run cognitive skills.

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

2 Context

This thesis 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 up to 45 months of age[3].

Virtually all children enrol in a center-based pre-school in the year they turn 3 (INSEE, 2019): in the 2012-2016 period, there is little variation in this figure, that is always above 97%[4]. Thus, similarly to the Danish context studied by Gupta and Simonsen (2016), the results of this thesis 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, differently from Nordic countries (Rostgaard, 2014). In France, instead, 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).

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*). They can also take care of children of multiple families.
- Licensed childminders (*assistant.e.s maternel.le.s*).
- Daycare (*crèche*), with different options in terms of management and regularity in reception.
- For children aged 2, the possibility to attend kindergarten one year in advance.

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 types of daycare exist:

[3]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).

[4]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 my sample. Including year fixed effect in both my main specifications does not change the results (column 3 and 4 in table 7.20 for the cross-sectional analysis, column 1 and 2 in table 7.53).

- Collective daycare (*crèches collectives*), that takes care of toddlers for up to 8-12 hours per day
  - 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*), that take in children on an occasional basis and often for fewer hours during the day.
- *Multi-accueil*, that can combine occasional and regular care[5].
- *Jardins d'enfants* or *jardins d'eveil*, that take in older children (from 18 months) and are more focused on facilitating the passage to pre-school.

Different daycare options can be managed by different actors. The greatest majority are managed by local governments - usually the municipality or a body of inter-communal cooperation, the EPCI (*Établissement public de coopération intercommunale*), more rarely by the department. The municipality can manage the daycare center directly or the responsibility may fall on the municipality social action center (*centre communal d'action sociale*, CCAS), a public institution chaired by the mayor of the commune. A great number is also managed by non-profit associations, often founded by parents themselves as associations - in this case, the daycare is called *crèche parentale*, and 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, those are often the companies for which the parents work - in this case, these are called *crèches d'entreprises*. 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. Figure 7.1 summarizes the type and management of daycare structures that receive the PSU benefit (*prestation de service unique*). The number of microcrèche and *crèches d'entreprises* is underestimated: the first may be financed through the CMG given to families and not the PSU, the second may be financed by a parent's employer, and only receives the PSU if also children whose parents do not work for the enterprise can attend it.

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

[5]Progressively, *halte garderies* are transforming into *multi-accueil* (Virot, 2017).

Table 2.1: Structural quality indicators of different subsidized childcare arrangements.

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

pedagogics, the quality of interactions may be higher, mimicking better a high educated home environment[6], 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. Each daycare center also needs to present a reception project, that specifies the duration and frequency of care, and a pedagogical project, specifying the "reception, care, development, well-being and stimulation of children" (CAF, 2023).

However, two critiques are moved to the claim that childcare quality is high and uniform across the country. First, the enforcement of controls from the local branches of Social Security is recently deemed insufficient by the General Inspectorate for social affairs (Bohic, Frossard, Itier, & Leconte, 2023). Secondly, standards are usually more related to building safety than day-

[6]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.

care workers' effectiveness in fostering psycho-motor development and socialization of children (De Bodman, De Chaisemartin, Dugravier, & Gurgand, 2017). In this thesis, I am only able to noisily measure the structural quality, using the opening hours, the financial occupancy rate (the number of hours paid by the family divided by the number of theoretical procedures), the average number of hours paid each day the daycare center is open and the median hourly price paid by the family.

2.1.2 Time spent in childcare

Daycare centers can choose their opening hours. From CAF data, it is clear that the great majority are open for 11 hours every day, and most range between 8 and 12 hours[7] (see Figure 7.2). This does not mean that children, especially the youngest ones, attend daycare for the whole day. It is in fact recommended to only gradually increase the time children spend in daycare (WHO, 2020). Focusing on 5 selected departments, Bérardier and Clément (2017) find that the great majority of kids attend daycare between 2 and 8 hours per day, with an average of 5 hours and important differences based on whether the parents work and on the degree of urbanisation of the municipality. For example, in Paris, 36% of children spend more than 8 hours in daycare, compared with 21% in the rest of the selected area.

From figure 7.3, we see that the number of operating days has not evolved much in the considered period, except for an increase in the bottom 10% of the distribution, i.e. with fewer daycare centers open for few days in the year. The average is always just below 230 days per year. There are about 250 working day per year in France, and employees are entitled to 25 days of vacation, so children can potentially go to daycare about every day parents work.

From the Elfe sample (reweighted to be representative of the French population), it appears that most children who attend non-parental childcare do so for 4 or 5 days a week. Childminders more often than daycare centers take care of the child only 4 days a week. Time spent in care is relatively high, with a mode of 40 hours per week (Figure 7.8).

2.1.3 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

[7] The daycare centers open for longer hours are usually those provided by hospitals for their employees.

period I am 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 7.13). However, it may marginally affect the quality of teacher/students interactions[8]. I 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 7.4). On average, families pay around 20% of the total cost (ONAPE, 2016), which is less than 2€ per hour (Figure 7.5). This represents on average 4% of the total income of the family, as estimated with the survey on childcare arrangements conducted by Drees (Villaume, 2015).

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

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

A further way the State finances childcare is through a monthly tax credit and the deduction of contributions, which amounts to 2€ per hour of childcare arrangement. This does not vary with the family income and amounts to 96€ per month in the case of daycare or licensed childminders (ONAPE, 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[9]. Moreover, at least one member of the family needs to work at least one hour or

[8] 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.

[9] Childminders cannot earn more than an amount per day and child cared for (55.35€ in 2023, CAF), mi-

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 7.4. An overview of how many families receive CMG and for which childcare arrangement is reported in Figure 7.10 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).

2.1.3.1 Allocation of daycare slots

Different levels of public institutions are involved in funding childcare. 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, I 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.

2.1.4 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.

crocrèche cannot cost more than 10€ per hour/child.

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[10]. 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 7.11, 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 7.13 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 7.9), 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. In particular, while this preference for collective childcare was predominant in middle and upper classes (Geay, 2014), it is widespread in working-class families too (Collet et al., 2016).

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 7.14), and that the time to find a spot in daycare is usually longer than for other options (Figure 7.12).

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

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

Source	Parents	Grandparents and family	Childminder	Daycare	Nanny	Kindergarten	Other
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.

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. 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. Often, parents declare as the principal childcare arrangement the formal childcare that the child is attending, even though the child spends more time with the parent. For example, if a child attends a daycare center from 9 a.m. to 2 p.m. (5 hours), and the rest of the working hours (7 hours) are spent with a parent, in the Mode de garde survey this child's main childcare is coded as "parents", while when asked, the parent is likely to say that the principal arrangement is daycare.

Indeed, a non-negligible share of children attends multiple childcare arrangements (26%, according to the Elfe survey). The fact of having a complementary childcare arrangement is relatively evenly distributed among the various principal childcare arrangements (Figure 7.15). 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 7.15 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, I am 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 my analysis, I 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.

I use the test administered in September of the first grade for my 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 my main specification, since each item has a different evaluation scale, I standardize the scores for each item, and I 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[11] of each student instead of the score (Table 7.64 for the cross-sectional analysis, table 7.52 for the longitudinal one). To compute the rank, I first compute the rank of each item and then I take the unweighted average rank for all items for each student in maths and French. In my main specification I 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 et al. 2013; Gupta and Simonsen 2016; Heim 2018 among the others).

From the total number of students in the administrative DEPP dataset, I delete those that did not take any test (2.81%), while if some single items are missing, I take the average of the ones that are present. There is no apparent pattern of missingness in the data (Figure 7.17). When the values for the birthday and the gender are missing, I 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, I 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, I average the different scores (this occurs in less than 0.01% of the cases). Finally, I

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

only include children that attend primary school in metropolitan France (mainland France and Corse) and that attend first grade when they are 6 years old. The share of children that are 7 or 5 in first grade is negligible (Figure 7.18), 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 7.63). The final dataset has 3,525,219 individual observations for maths, 3,536,394 for French. Descriptive statistics for the DEPP data are reported in Table 7.3.

I 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, I use administrative data on the number of places provided by each daycare center, from the French Social Security system (CAF)[12]. For each year, from 2007 to 2016, I 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).

I 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[13]. The unit of observation is the municipality × year: for Paris, Marseille and Lyon I observe the births at the municipality and not at the *arrondissement* level[14].

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

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

I also use data on the total theoretical capacity of formal childcare for children under 3 years of age, computed by CAF[15]. This data sums the places available in daycare centers, in kindergartens for children aged 2 years and the actual childcare provision by childminders,

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

[13] The statistics are drawn up on the basis of civil status bulletins issued by mayors, at the time and in the commune where the births took place, and transcripts of birth declarations issued by the courts.

[14] 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).

[15] Available on the Cafdata website. A detailed methodology of this measures is available in Debras and Pélamourgues (2019).

microcrèches and nannies. Thus, while it measures the supply for daycare centers and kindergartens, it measures the intersection between supply and demand for childminders, microcrèches and nannies. In fact, the supply of childcare coverage by childminders and nannies may be somewhat more informal than publicly funded daycare centers[16]. I define the parental care as one minus this total formal coverage rate, at the municipality and at the EPCI level.

3.2.1 Data limitations

One of the biggest limitations of this analysis is that I do not observe the municipality of birth nor the municipality where children live in the DEPP dataset. I 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 I control for the share of children coming from outside the municipality in the school, results are unchanged (Table 7.62).

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 2.1.3, 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, I 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 7.9 for the first stage, column 3 and 4 of table 7.61 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 7.9 for the first stage, column 5 and 6 of table 7.61 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 7.10 for the first stage, column 1 and 2 of table 7.61 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 I don't have data on individual daycare attendance, I 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)

[16]For example, since often childminders also care for their own children or grandchildren, they can decide to practice as a childminders if they find potential clients, otherwise they simply care for their own offspring.

because of a type of measurement error - the division bias. Following Pora (2020), I add the sum of the births as a separate regressor in the analysis, and the results are robust (column 2 of 7.10 for the first stage, column 1 and 2 of table 7.62 for the reduced form).

Another measurement error is due to the fact that I observe newborns in municipalities, but I 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 I 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 I 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, I am 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.

3.3 Data on childcare attendance

In the ideal experiment, I would have data on childcare attendance for each child in France, that can be linked to the scores in primary school. Unfortunately, administrative, universal data on childcare attendance does not exist.

To overcome this, I 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. I 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.

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

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

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[17], 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 municipality level and at the individual level, by multiplying the sampling weights by the inverse of the individual probability of response[18].

Table 7.1 reports descriptive statistics of the FL sample based on the type of childcare arrangement, table 7.2 based on whether or no the child is born in spring.

4 Empirical strategy

4.1 Cross-sectional analysis

In trying to understand whether childcare attendance has an impact on cognitive skills, the main source of endogeneity is the fact that parents choose childcare arrangements. More educated

[17] The clusters are drawn randomly in the municipality, regardless of their size, as it is done in the census (for example, the weight is 3/2 if two clusters are drawn from three in the municipality). This is because the sizes of the clusters are relatively homogeneous.

[18] A logit regression of individual characteristics (gender, age, type of cohabitation, educational qualifications, employment status, immigrant status indicator, region, size of urban unit) on the probability of response is used to predict the individual probability of response.

parents have a higher opportunity cost from working less to take care of the child and are thus more likely to choose formal childcare. At the same time, more educated parents can invest more in other inputs for the children's human capital (e.g. reading more to them).

To address that, I instrument daycare attendance with the interaction between being born in Spring and the local daycare availability. The first-stage regression is:

$$\begin{aligned}\mathbb{1}(Daycare)_{im} =& \beta_1 Spring_i \times Availability_m + \\ & \beta_2 Availability_m + \beta_3 Spring_i + \beta_4 \text{Month of birth}_i + \\ & \mathbf{X}_{im} + \alpha_d + \eta_{im}\end{aligned} \tag{2}$$

And the reduced form regression is:

$$\begin{aligned}\text{Test score}_{im} =& \gamma_1 Spring_i \times Availability_m + \\ & \gamma_2 Availability_m + \gamma_3 Spring_i + \gamma_4 \text{Month of birth}_i + \\ & \mathbf{X}_{im} + \alpha_d + \epsilon_{im}\end{aligned} \tag{3}$$

In both regressions, m indexes the municipality, i indexes the individual children, and d the department. In this cross sectional approach, I only observe each child once and I 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 rationale for including department-level fixed effects (α_d) is that there is a wide regional variation in childcare availability, that may hint at different cultures around childcare. Figure 7.6 shows that for example, childminders are much more common in Brittany, Normandy and Pays de la Loire, daycare availability is much higher in Provence-Alpes-Côte d'Azur and Ile-de-France. Department fixed effects control for this unobserved time-invariant differences, so that the coefficients of the instruments are not driven by it[19]. The covariates that I have in both samples are the child's gender and municipality covariates. I add a linear control for the month of birth[20], so that the $Spring_i$ regressor does not capture the absolute effect of being born in Spring, but only the relative distance of kids born in Spring from the linear month trend (Figure 4.3). The coefficient of interest is γ_1. I use the linear probability model for the first stage regression, but the results are robust to a probit specification (Table 7.13).

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

[19] Since the department 75 and the city of Paris corresponds and I measure the availability at the municipality level, adding the a department fixed effect for the department 75 is equivalent to adding a municipality fixed effect for Paris. This would mean that for Paris, the coefficient on the local daycare availability would only capture the changes in availability from one year to another. To avoid this, I count as a unique department the departments in the inner suburbs (*Petite Couronne*) of Paris, namely 75, 92, 93 and 94. The level of daycare supply is in fact similar (Figure 7.6).

[20] In practice, I code each month of birth with a number (1 for January, 2 for February ecc.) and I include this individual-level variable in the linear regression. The coefficient should be interpreted as the association between the dependent variable and the fact of being born one month later.

when older children leave for kindergarten (see Graph 7.7 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, parents who have a child in spring often have the opportunity to extend their leave until the autumn by combining maternity, parental, and annual leave, thereby increasing their chances of securing a crèche place (Berger et al., 2021).

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[21]. 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, 2010, 2016).

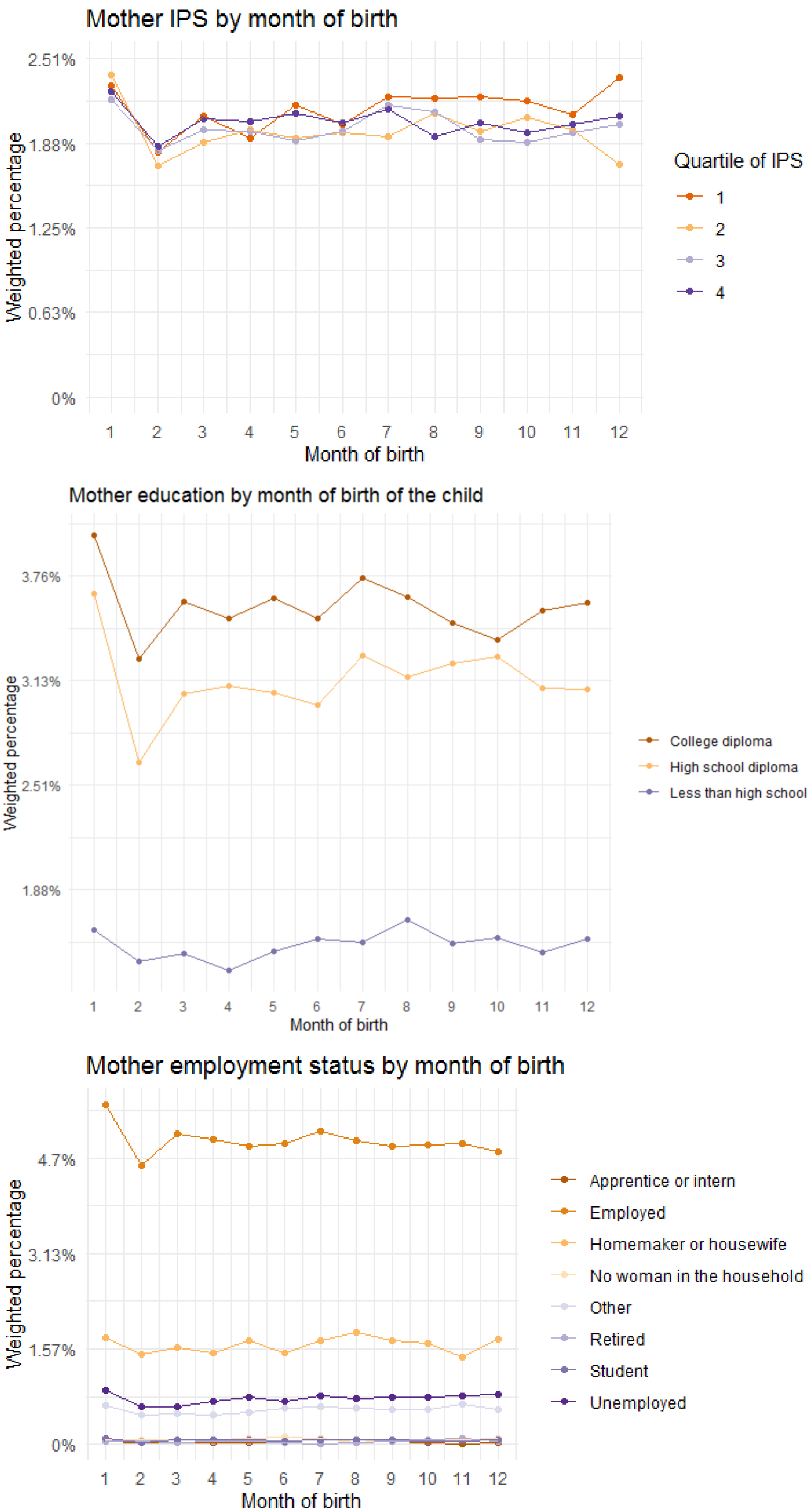
The crucial identifying assumption of the instrumental variable model is the exclusion restriction. For the exclusion restriction to hold, the effect of being born in spring in a municipality with a certain daycare availability on cognitive skills must be only mediated by the daycare attendance. A potential 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.

Being born in Spring is arguably orthogonal 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 older women are when they decide to have a child, the more timing the birth is costly, as waiting for one year increases potential fertility problems, and the average age at birth in France in the 2012-2016 period is relatively high, at 30.5 years (Human Fertility Database, 2021). 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

[21] More often, it is used when there is a staggered introduction of a childcare reform, 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.

by birth timing by this category (column 1 in Table 7.7). 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 (Figure 4.1). 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.



If I were not to include the linear trend, the coefficient of $Spring_i$ would be biased. In fact, all children are tested on the same day, and there is a consensus in the literature that older kids perform better than younger ones[22], so being born in spring affects the likelihood of being assigned a daycare spot, but also a direct effect on the test scores, through a "maturity" effect and the different age at the beginning of the first grade. 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 4.2). For this reason, I add a linear control for the month of birth, so that the $Spring_i$ regressor only captures the relative distance of kids born in spring from the linear month trend (Figure 4.3). However, reassuringly, the coefficient of the instrument is not affected by the inclusion or exclusion of the linear month control (Table 7.8). 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 for the first stage and 5.2 for the reduced form).

As robustness checks, I 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 first stage (Table 7.4) or in the reduced form (Table 7.6). I also show that the definition of spring (which I 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 7.7 for the first stage, table 7.8 for the reduced form).

Using the interaction of local daycare availability and quarter of birth does not require the non-interacted local availability not to have a direct effect on the test scores, as long as the interaction does not have it. However, I run a robustness check controlling for other 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 (Tables 7.16 and 7.17). The results are also robust to the inclusion of municipality covariates, in particular 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 (Tables 7.16 and 7.17).

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

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

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 Bac success, does not correlate strongly with the definition of local daycare availability (Figure 7.16). 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 characteristics (urbanization included) are included in the main specification.

Unfortunately, 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, I can only noisily control for the housing sorting decision of families: using the FL dataset, I split the sample between families that moved in the last 6 months and those who did not, using the Elfe dataset, I 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 7.11), but clearly the decision on where to live may happen before the decision to have a child. Moreover, along with other municipality-level controls, I 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.

If I divide the Elfe sample between those who expressed a preference for daycare or not in the 2-month wave, the instrument only have a significant positive impact on those who did *not* stated that daycare was their ideal childcare arrangement (columns 5 and 6 in Table 7.11). While this result can be hindered by the small sample size (respectively 1,971 families stated daycare as their ideal option, 11,303 reported another option), it is nonetheless a sign that selection bias should not be too big of a problem for the instrument.

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 7.12).

The other assumptions for the instrumental variable framework are the relevance and monotonicity assumption, that is needed to interpret the results under a LATE framework (Imbens & Angrist, 1994). The relevance can be checked in the first stage results (Table 5.1). Considering that the weighted average daycare attendance is 12.46%, the instrument is large and robust. In the main first-stage specification, I cluster errors at the municipality level, to account for unobserved correlation between children living in the same city. However, the sampling strategy of FL entails that around 2% of the children are the only child observed in a municipality ("singleton clusters")[23]. The clustered standard errors simply reduce to the heteroskedasticity-robust one in the special case that there is only one observation in each cluster (Cameron & Miller, 2015). When I cluster the standard errors, the F-test of the main first-stage regression is 9.42,

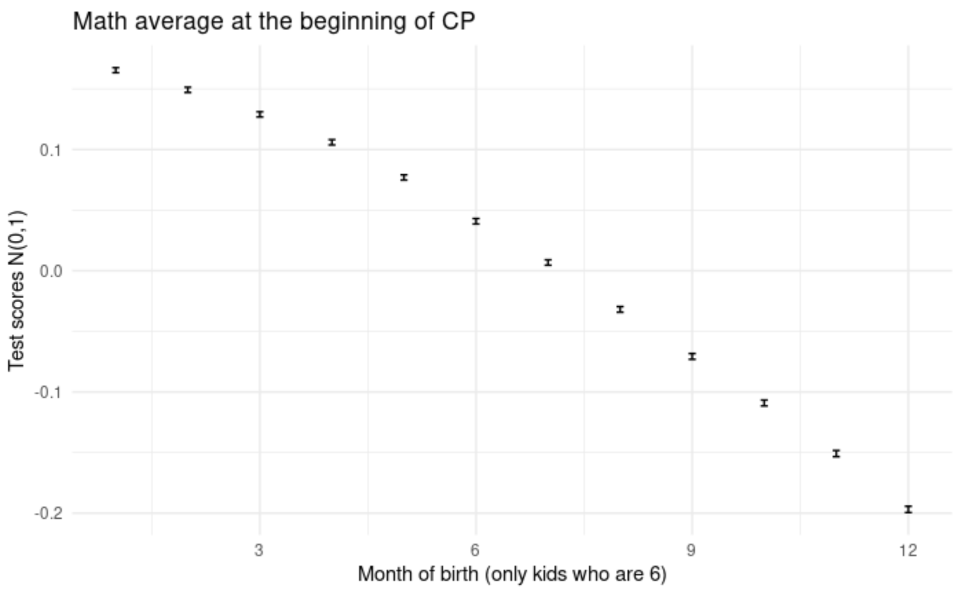
[23]The percentage is even higher in the Elfe survey, 34.4%.

but when I use heteroskedasticity robust standard errors, it is 312.9. The relatively low F-stat is only due to the different number of degrees of freedom of the F distribution when clustering the standard error, that is the number of variables k and $N - k - 1$ without clusterization, k and $N_{clusters} - k - 1$ with clusterization.

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[24] 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 is never significantly negative in all subsamples and under all robustness checks.

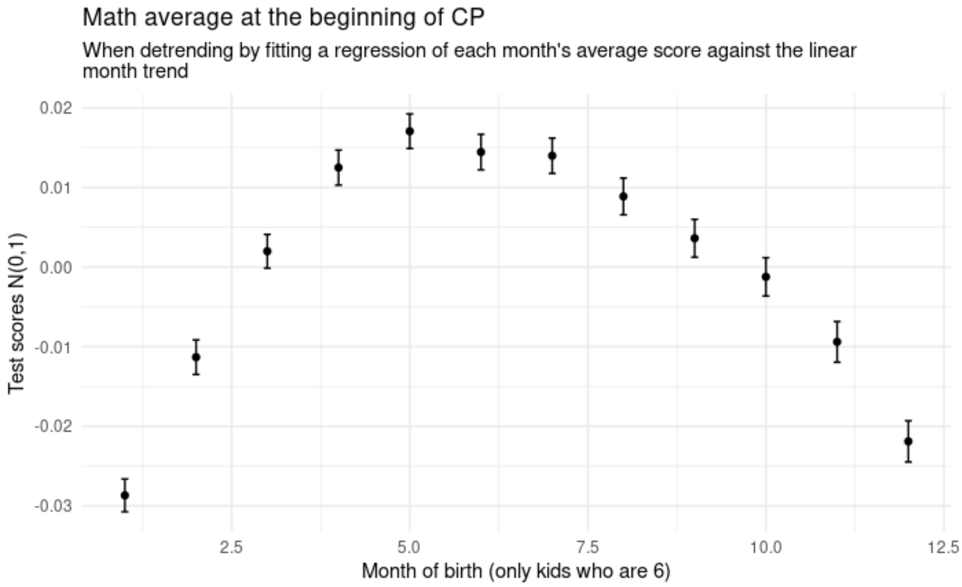
A shortcoming of this empirical strategy is that the instrument has an impact on the probability of attending daycare by affecting the likelihood of being offered a daycare spot, but has no impact on how much time children spend in daycare. Thus, I cannot estimate a dose-response relationship, even if the impact of daycare attendance on cognitive skills is likely to be different for children who attend daycare part-time or full-time, as found in a descriptive way for language skills at 2 in France (Berger et al., 2021).

Figure 4.2: Unconditional maths test scores by month of birth. Source: DEPP.



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

Figure 4.3: Maths test scores by month of birth, detrended from the month of birth, i.e. residuals after fitting an OLS regression with a linear month variable. Source: DEPP.



4.1.1 Two-sample 2SLS

To bridge the results from the first-stage and reduced-form regressions, I use the two-sample two-stage least square estimator (TS2SLS).

TS2SLS dates back to Klevmarken (1982), but has been more widely introduced by Angrist (1990), in a seminal paper where they observe the instruments (being drafted for fighting in Vietnam) and the endogenous regressor (actually going to Vietnam) in one sample, the instruments and the dependent variable (lifetime earnings) in another sample. I am in particular using the TS2SLS estimator proposed by Inoue and Solon (2010), who showed how the TS2SLS estimator is more efficient than the TSIV estimator initially used by Angrist (1990) and Angrist and Krueger (1995).

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 7.17). 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[25], I can safely assume that the two datasets measure the same underlying population.

[25] 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:

$$\begin{aligned} &\text{DEPP data} = \{(Y_{DEPP,i}, \mathbf{z}_{DEPP,i}, \mathbf{x}_{DEPP,i})\}_{i=1}^{N_{DEPP}} \\ &\text{FL data} = \{(Daycare_{FL,j}, \mathbf{z}_{FL,j}, , \mathbf{x}_{FL,j})\}_{i=1}^{N_{FL}} \end{aligned} \tag{4}$$

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.

$$\text{Observed first stage in FL: } Daycare_{FL,j} = \mathbf{z}_{FL,j}\Pi_{FL} + v_{FL,j} \tag{5}$$

$$\text{Observed reduced form in DEPP: } Y_{DEPP} = \mathbf{z}_{DEPPi}\Pi\beta + X_{DEPP}\gamma_{DEPP} + u_i \tag{6}$$

$$\text{Second stage with TS2SLS: } Y_{DEPP} = \mathbf{z}_{FL,i}\Pi\beta + \beta v_{FL,i} + X_{DEPP}\gamma_{DEPP} + \epsilon_i \tag{7}$$

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, I 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 I do not observe the daycare attendance in the DEPP data, but results robust to using different data sources for the first stage (Table 7.13) 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 $E(\mathbf{z}_{FL,j}v_{FL,j}) = 0$. I 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):

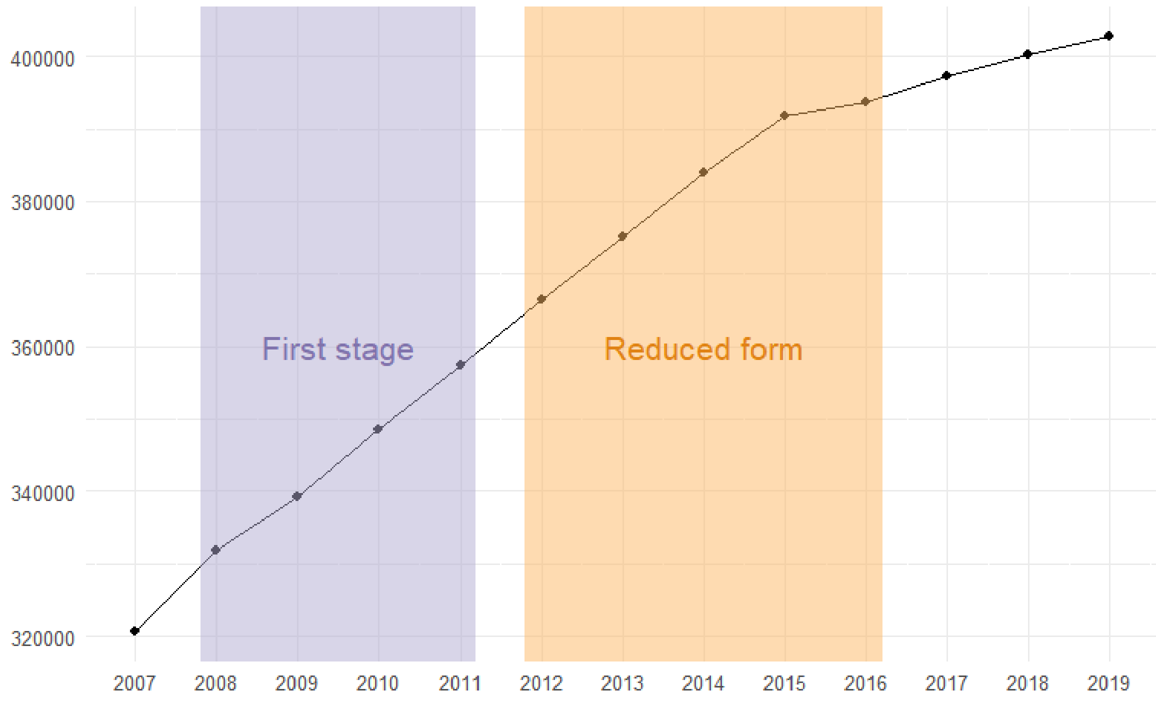
1. generating an estimate of the first stage parameter Π using the FL sample to compute $\hat{\Pi}_{FL}$, the coefficients of the instrument and of individual- and municipality-level covariates.

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.

A potential threat to the first and the second assumptions is that the reduced-form dataset (DEPP) measures outcomes for children born in 2012-2016, the first-stage one (FL) measures daycare attendance for children born in 2008-2011[26]. 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 accomodate 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 7.21 and 7.22). 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 7.11 and section 2.1.4), which interviews families of children born in 2011-2013. The data limitation also entails that the first and second samples do not overlap. If they included children born in the same year, in fact, all children in the first stage sample would be in the second stage sample too, since the DEPP database includes the whole population. While still possible to estimate it, the overlap of the two samples leads the estimator to become a linear combination between the TS2SLS and the simple 2SLS.

Figure 4.4: Change in number of daycare spots in France between 2007 and 2019.



Standard errors of the TS2SLS are bootstrapped, as usual asymptotic errors would fail to take into account that the daycare attendance is a generated regressor[27]. In particular, I estimate

[26]Apart from the MDG survey, that has a small sample size, to the best of my knowledge, other datasets measuring childcare arrangements for children born in 2012-2016 are not available.

[27]However, the asymptotic distribution of TS2SLS has been derived by Ridder and Moffitt (2007), and so is the heteroskedasticity-robust variance covariance matrix (Pacini & Windmeijer, 2016).

the first stage on the FL sample 100 times, every time sampling with replacement the data. I compute the bootstrap standard error of the first sample calculating the standard error of the distribution of the 100 coefficients for each regressor. I export these 100 first-stage models and, to compute the second stage bootstrapped standard errors, I use one different first-stage model and a sample with replacement of the DEPP data every time to compute a different generated $\widehat{Daycare}$ for every bootstrap repetition. For every sample, I then compute the second-stage estimates. The bootstrapped standard errors are the standard error of the distribution of second-stage coefficients.

As for the single-sample 2SLS, I include the endogenous covariates (gender, month of birth, municipality characteristics) in both the first and the second stage. The fact that I use the covariates both to calculate the generated daycare attendance both as regressors in the second-stage sample may pose problems of collinearity. First, as long as it is not perfect, this would simply inflate the standard errors, leading to under-rejecting the null. Second, I calculate the variance inflation factor (VIF) for the predictor variables in the second-stage regression. Results are reported in Table 7.23 and all regressors are well below the rule of thumb of 5, showing that there is no perfect multicollinearity.

4.1.2 Heterogeneity on observables

Research questions on childcare are particularly interesting because often the mean impact hides a wide heterogeneity. For this reason, I proceed by dividing the both the FL (first-stage data) and the DEPP (reduced-form data) datasets according to the covariates I have in both samples. At the individual level, I estimate heterogenous effect by gender. I also split the FL sample into children whose mother has an IPS above and below the median, and the DEPP sample into children whose school's IPS is above or below the median. Other characteristics I use to understand heterogenous effects of daycare attendance are the degree of urbanization, an indicator variable for whether the municipality has a percentage of secondary sector workers above or below the median, a percentage of stable tertiary jobs above or below the median, a percentage of temporary jobs above or below the median, the female labor force participation above or below the median. Finally, there are some variables that I can measure at the municipality level in the FL dataset, at the school level in the DEPP dataset: the percentage of managers, the percentage of manual workers and the median income. For each, in both samples, I create an indicator variable equal to 1 if the school (in the DEPP data) or the municipality (in the FL data) is above the median, and I split the samples based on it.

Splitting the sample is analogous to running a regression with an interaction term for all independent variables (Wooldridge, 2010). Compared to simply interacting the instrument, it allows all the independent variables to have a different coefficient: for example, the coefficient of the non-interacted $Availability_m$ may be different in rural or urban cities. I report results both for the regressions on each half of the sample and for the regressions on the full sample with an interaction between the instrument and the indicator variable (for example, $Spring_i \times Availability_m \times Gender_i$) in Subsection 7.3.9. Results are virtually unchanged. I do not add department fixed effects in these regressions: for example, if I run the baseline regression on only municipalities below the national median of female labor force participation, it may happen that only one municipality in the department is included in the sample. Thus, including a department fixed effect would absorb the variation on $Availability_m$, that only varies at the municipality level.

4.1.3 Heterogeneity on dependent variable

To better investigate the differential impact of childcare attendance, I disaggregate the maths and French scores in more granular skills. 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.

Moreover, for every item, the Ministry sets *a priori* a sufficient threshold. The great majority of students have no insufficient items (Figure 7.19), and I 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, I can see the impact of daycare attendance on the likelihood of reducing developmental issues.

Finally, I want to study the effect of childcare attendance along the distribution of cognitive skills through a quantile regression. The rationale is that, following Bitler et al. (2014), I 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). Most of the literature on universal childcare for children aged 0-2 (for example, all papers summarized in Table 1.1) 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).

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 my setting, I have few covariates, and the results are virtually unchanged when I include those (column 3 of Table 5.2). 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 my 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), I do not interpret the coefficients as individual childcare effects, but rather I 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.

I first run a quantile regression of my baseline specification without department fixed effects.

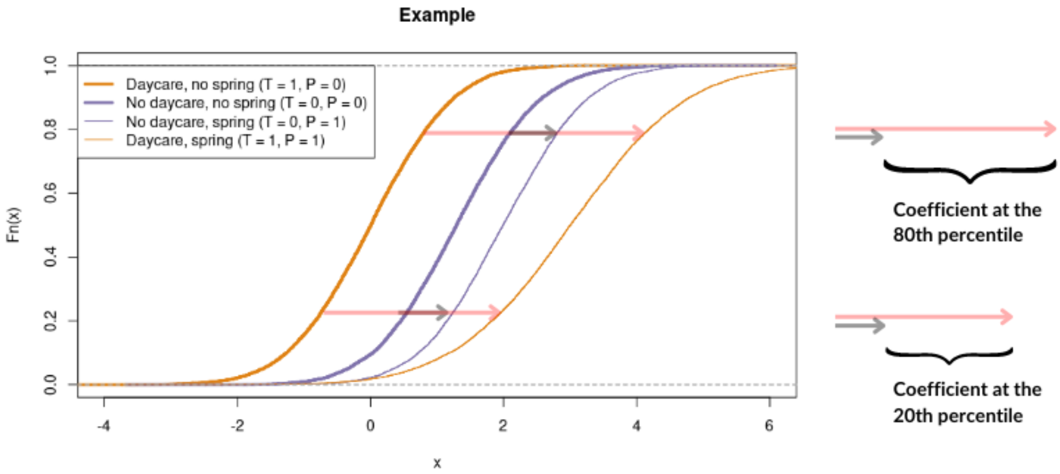
Then, I discretize the availability measure into municipalities that have no daycare facilities in the year when the child is born (74.4% of municipalities, 28.5% of children) and those that have at least 1 daycare spot (25.6% of municipalities, 71.5% of children). The main reason why I decide to define the daycare supply as a binary variable is that this allows to divide the population in 4 groups (born in Spring or not, in a municipality with or without at least one daycare center) and thus plot the cumulative distribution function and understand what is going on beneath the surface of the quantile regression estimator. This also allows for a less computationally heavy estimation.

$$\begin{aligned} &\text{Test scores}_{im} = \delta_1 Spring_i \times \mathbf{1}\{Availability_m > 0\} + \\ &\delta_2 \mathbf{1}\{Availability_m > 0\} + \delta_3 Spring_i + \epsilon_{im} \end{aligned} \tag{8}$$

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.

This coefficient has the same estimation as a difference-in-differences estimator, however, my context lacks credibility in the assumptions needed to identify this estimator as an ATT, for reasons that I detail in Appendix 7.1. 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 column 4 in Table 7.10, results for the reduced form in Table 7.25. In this specification I am no longer controlling linearly for the month of birth effect. I test the robustness of results with the availability defined linearly in columns 2, 4, 6 and 8 of table 7.25. The coefficient of the interaction is virtually unchanged.

Figure 4.5: Example of the binary quantile regression.



However, I am primarily interested in estimating equation 8 for each quantile of the distribution. Figure 4.5 uses randomly generated data to illustrate it: the coefficient δ_1 of the binary instrument at quantile τ is:

$$\begin{aligned}\delta_1(\tau) = &F^{-1}(Score_\tau|Spring_i = 1, Av = 1) - F^{-1}(Score_\tau|Spring_i = 0, Av = 1) - \\ &[F^{-1}(Score_\tau|Spring_i = 1, Av = 0) - F^{-1}(Score_\tau|Spring_i = 0, Av = 0)]\end{aligned} \tag{9}$$

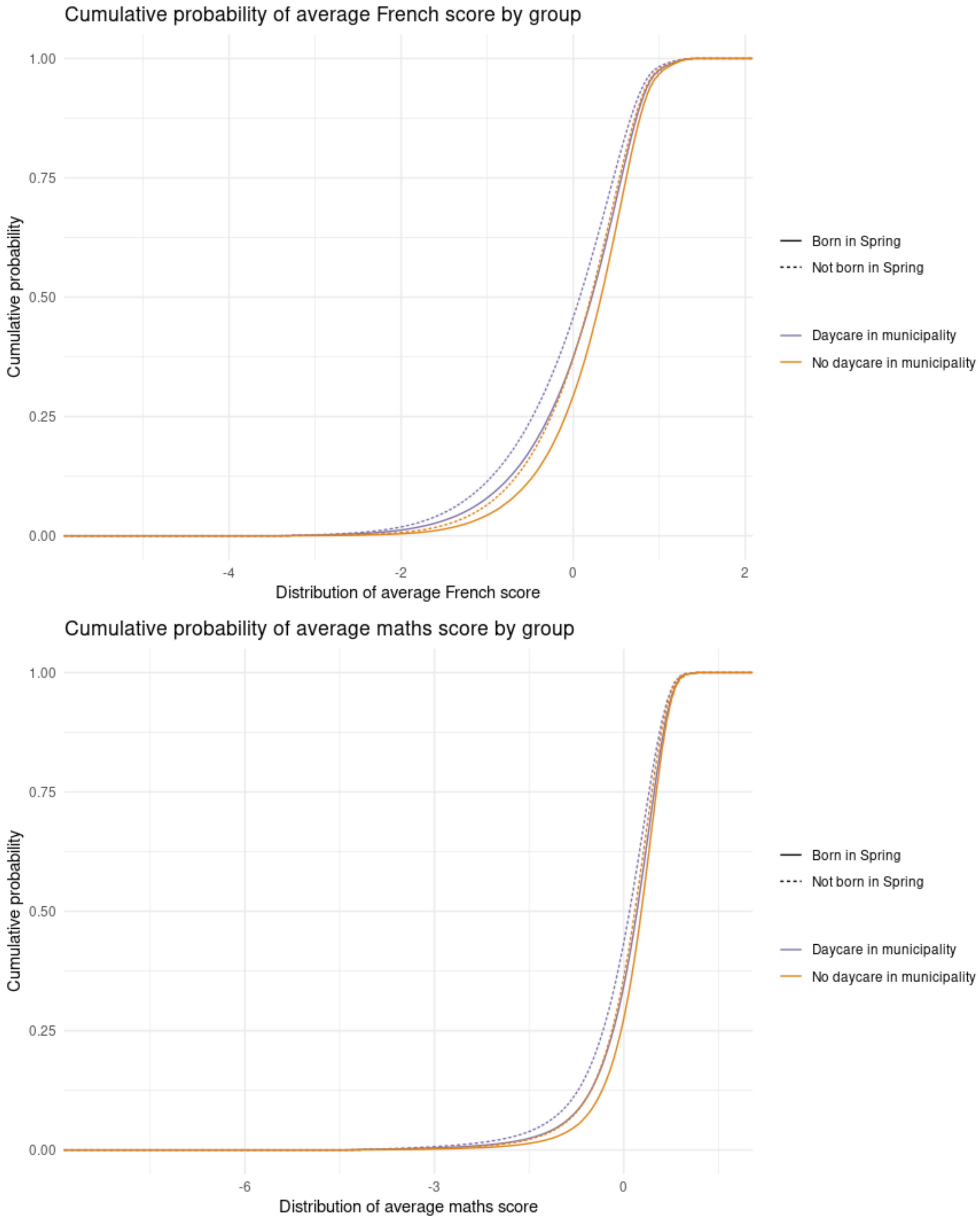
I use bootstrapped standard errors with K = 100[28].

In particular, the first difference is represented in Figure 4.5 by the red arrow, the second one by the black arrow. As shown in the graph, the coefficient of interest $\delta_1(\tau)$ may differ for different quantiles. In the example in the graph, the reduced-form coefficient on the test scores is larger at the top of the distribution, thus increasing the inequality of the distribution. Difference along the distribution may be driven by at least two mechanisms: daycare workers being more effective for low-skills children (for example, devoting more time to them), or different counterfactual types of care of children at different points in the distribution of cognitive skills.

Figure 4.6 plots the actual empirical cumulative distribution function for the test scores in French and mathematics.

[28]Using a higher number of repetitions is an easily implementable further robustness check.

Figure 4.6: Actual empirical cumulative distribution function for the test scores in French and mathematics.



4.2 Longitudinal analysis and counterfactual type of care

One of the main challenges in the childcare literature is that it is difficult to understand what would be the counterfactual type of care in case the child did not attend daycare. So far, I only studied the effects of daycare attendance compared to all other potential counterfactuals.

Estimating the impact of daycare with respect to other counterfactuals has in particular been studied in the context of the US Head Start program, using probability matching (Zhai et al., 2014), Bayesian principal stratification framework, a generalization of IV (Feller et al., 2016), an extension of the LATE framework with compliers drawn from specific counterfactual alternatives (Kline & Walters, 2016). Without randomization in the offer of places, as in the HSIS study, but only relying on an instrumental variable that changes the participation at the margin, applying such methods does not yield credible results. Moreover, the HSIS dataset includes an indication of the type of care for both children who have been offered a Head Start spot and not, while I do not even observe if the child has attended daycare, much less other types of childcare - that often have higher degrees of informality, and thus are more difficult to measure[29].

However, I have access to a measure of how many parents care for their children themselves. This variable is clearly highly endogenous: mothers who stop working to care for their children are more likely to be poorer and with a lower level of education that those who do not.

The idea of regressing both the daycare availability and the parental care is to compare the association between those two types of the care and cognitive skills with a third, omitted, possibility: childcare provided by childminders, nannies or kindergartens[30].

To partially account for this endogeneity, I aggregate the test scores data at the municipality level and I run the following regression, where each observation is either municipality $\times$ year or EPCI $\times$ year.

$$\text{Mean test scores}_{mt} = \alpha_1 \text{Availability}_{mt} + \alpha_2 \text{Parental}_{mt} + \delta_m + \varepsilon_{mt} \tag{10}$$

Where m indexes the municipality or the EPCI, t is the year and there are municipality or EPCI fixed effects δ_m. In this way, the observable and unobservable municipality characteristics that do not change over time are captured by the municipality fixed effect. The only variation captured by the coefficient of interest α_1 is driven by the changes in daycare availability in the municipality or EPCI.

The condition for consistency of the fixed-effect estimator α_1 is that unobserved factors that have an impact on the average test scores are not correlated with the daycare availability measured each year: $E(\varepsilon_{mt}|\text{Availability}_{m,2012}, ..., \text{Availability}_{m,2016})$ (Wooldridge, 2010). However, daycare availability may have an impact on the unobserved kindergarten quality, and this may in turn have an effect on the average test scores at the municipality level, so this assumption is unlikely to be verified in general. We thus need a plausibly exogenous source of variation in daycare availability.

[29] For example, data on the total coverage of formal childcare in France does not rely on the supply of childminders and nannies spots, but directly on the observed number of children they care for (i.e. the intersection between supply and demand).

[30] Ideally, I would like to further make a distinction between kindergarten and single childcare providers such as childminders and nannies. These are likely to both have different impacts on children's cognitive skills and be chosen by different families (kindergarten is in fact free). Municipality-level or EPCI-level data on the number of kindergarten spots for 2-year old children are collected by Depp, so an easily implementable pathway for future investigation is to include them.

The great majority of municipalities (74.3%) never change their daycare availability: they have 0 daycare centers for all the 5 years covered by the panel data (see municipality-level changes in the maps in Figure 7.21 and 7.22). The other changes are driven by three mechanisms: first, the number of daycare spots may remain the same, but the number of children born in the municipality may change. Secondly, the number of daycare centers may remain the same, but the number of daycare spots may increase, for example because the daycare hired more personnel. Thirdly, a new daycare center may open in the municipality.

The variation caused by a daycare center opening or closing is likely to be the more exogenous type of variation. For example, the number of children born in a municipality can be correlated to municipality $\times$ year shocks (e.g. a local economic crisis caused by a single industry in the municipality) that I am unable to capture. For this reason, I instrument the daycare availability with the changes in availability caused by a daycare center opening or closing. The relevance of the instrument is tested in columns 5 and 6 of Table 5.5. Exogeneity is plausible: the process to open a daycare takes several years, between finding or building a premise that meets the CAF requirements, applying for the approval of the department PMI (Children and Mother Protection), finding the personnel despite the shortages, so it is unlikely to be correlated with municipality $\times$ year shocks to the cognitive skills. Even though municipalities that open and do not open a daycare center are likely to be different (e.g. different budgets), this difference is likely to be time-invariant in a 5-year panel, and thus absorbed by the municipality fixed effect. Likely, the only way through which a daycare opening benefits the cognitive skills of children born in that year is through an increased daycare attendance[31].

Moreover, while parents may decide to sort themselves into living in a municipality, it is less likely that they can predict where new daycare centers are opened - especially if they are opened in time for their child to attend them. For these reasons, the changes at the municipal level, often due to a reform, are used to define treatment and control groups in the childcare literature (Cascio, 2009; Felfe & Lalive, 2018; Felfe et al., 2015; Havnes & Mogstad, 2011, 2015; Pora, 2020).

Aggregating test scores at the municipality $\times$ year level entails comparing skills of different children, increasing the noise in the measurement of the average skills at the municipality level. Some schools only have a few students that take the test (1.2% of the municipalities only have one child), leading to a more volatile average test scores. However, this classical measurement error should only bias towards zero the coefficients.

[31] To test this hypothesis, the ideal data is a panel where the unit of observation are children, and they are sampled multiple times before they turn 3. The sample size and the geographical dispersion of these children need to be large enough to capture the effects of the few and sparse daycare openings. I can then test whether a daycare opening increases daycare attendance. However, FL is a cross-sectional survey and Elfe has too few, selected observations and samples only less than 3000 municipalities (less than 10% of the municipalities in France).

5 Results

5.1 Cross-sectional analysis

I substitute the definition of $Availability_m$ (equation 1) in the first stage regression (equation 2) to interpret the coefficient of interest:

$$\begin{aligned}\mathbb{1}(Daycare)_{im} =& \beta_1 Spring_i \times \frac{\text{Places in daycare centers}_{m,t}}{\text{Births}_{m,t-2} + \text{Births}_{m,t-1} + \text{Births}_{m,t}} + \\ & \beta_2 \frac{\text{Places in daycare centers}_{m,t}}{\text{Births}_{m,t-2} + \text{Births}_{m,t-1} + \text{Births}_{m,t}} + \beta_3 Spring_i + \\ & \beta_4 \text{Month of birth}_i + \mathbf{X}_{im} + \alpha_d + \eta_{im}\end{aligned} \tag{11}$$

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

$$\frac{\partial \mathbb{1}(Daycare)_{im}}{\partial \text{Places}_m} = \beta_1 Spring_i \times \frac{1}{\text{Births}_m} + \beta_2 \frac{1}{\text{Births}_m} \tag{12}$$

Thus, the coefficient of interest β_1 capture by how much one marginal place in daycare increases the daycare attendance 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[32]. 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.

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. An additional daycare place in the municipality, keeping the number of births fixed, increases the probability of attending childcare by 29 p.p. if the child is not born in spring, by 36.5 p.p. if she is. 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 7.13): in the Elfe survey, an additional daycare place in the municipality, keeping the number of births fixed, increases the probability of attending childcare by 34 p.p. if the child is not born in spring and is 1 year old, by 49 p.p. if he is. If the child is 2 years old, the magnitude is of 43 p.p. if she is not born in Spring, of 59 p.p. if she is.

[32] Let's say that the births depend on the places in daycare: $\mathbb{1}(Daycare)_{im} = (\beta_1 Spring_i \times \beta_2)\frac{\text{Places}_m}{\text{Births}_m(\text{Places}_m)} + \beta_3 Spring_i + \beta_4 \text{Month of birth}_i + \mathbf{X}_{im} + \alpha_d + \eta_{im}$. Then, the true marginal effect of an additional place in daycare is: $\frac{\partial \mathbb{1}(Daycare)_{im}}{\partial \text{Places}_m} = (\beta_1 Spring_i + \beta_2)\frac{\text{Births}_m - Places_m \frac{\partial \text{Births}_m}{\partial \text{Places}_m}}{\text{Births}_m^2}$. 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.

Table 5.1: Baseline first-stage regression, errors clustered at the municipality level

Dependent Variable:			Daycare		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
(Intercept)	0.1004***				
	(0.0088)				
Spring	0.0136**	0.0128**	0.0130**		
	(0.0059)	(0.0057)	(0.0057)		
Availability	0.2874***	0.1870***	0.1254***	0.1863***	
	(0.0526)	(0.0374)	(0.0277)	(0.0375)	
Month of birth	-0.0034***	-0.0035***	-0.0035***		
	(0.0007)	(0.0007)	(0.0007)		
Spring × Availability	0.0750**	0.0763**	0.0769**	0.0768**	0.1137**
	(0.0377)	(0.0362)	(0.0358)	(0.0360)	(0.0451)
Municipality covariates		Yes			
Fixed-effects					
Department		Yes	Yes	Yes	
Month of birth				Yes	Yes
Municipality × Year					Yes
Fit statistics					
Observations	45,480	45,480	44,429	45,480	45,480
DV mean	0.12016	0.12016	0.12188	0.12016	0.12016
F-test	9.4274	0.62927	0.51306	0.58641	30.569

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). The first column is the baseline specification. The second column includes department fixed effect. The third column includes municipality-level controls (degree of urbanization, labor force participation for men and women aged 25-54 in the 2013 census, percentage of occupational categories (self-employed, manual workers, managers, middle managers) in the 2013 census, percentage of employed in different industries every year and the percentage of homeowners and vacant houses in the 2013 census, mean income in the municipality in 2013, number of libraries and child-parent drop-in center). The fourth column includes month fixed effects instead of the linear month control. The fifth column, along with the month fixed effect, included municipality × year fixed effects. Standard errors are heteroskedasticity robust and clustered at the municipality level are reported in parentheses.

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

Table 5.2: 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)		
Month of birth	-0.0327***	-0.0336***	-0.0326***	-0.0336***	-0.0328***	-0.0338***				
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)				
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. 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). 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 5.2). The interpretation of the magnitude is akin to the interpretation of the first stage: 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.

Both the reduced-form and second-stage results are robust to the inclusion of department fixed effects (column 2 of table 5.1, columns 3 and 4 of table 5.2) and of municipality-level covariates (column 3 of table 5.1, columns 5 and 6 of table 5.2). I also add month of birth fixed effects instead of a linear control for the month of birth and an indicator variable for being born in Spring and results are virtually unchanged (column 5 of table 5.1, columns 7 and 8 of table 5.2), which is not surprising since the association between the month of birth and the test scores is strongly linear (see Figure 4.3). Finally, I include month fixed effects and Municipality × Year fixed effects. 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. The first-stage coefficient is even larger, while the reduced-form coefficient is still positive and significant, and the magnitude is similar (column 5 of table 5.1, columns 9 and 10 of table 5.2). Finally, I add School × Year fixed effects, to account for the self-selection of more advantaged students attending the same schools (column 1 and 2 of 7.20), and results are robust.

Apart from all the robustness checks that I already described in other sections (to the definition of $Spring_i$ and $Availability_m$, to the decision to move from one municipality to another, to the level where the daycare availability is measured), a further problem may be that the daycare availability distribution is extremely right-skewed, thus single outliers may be driving the relationship between availability and test scores. However, this may be more of a problem when I do not interact the availability (see a more thorough discussion in subsection 5.2) and transforming the availability with a natural logarithm or a inverse hyperbolic sine does not change the results. The same is true for using heteroskedasticity-robust standard errors instead of errors clustered at the municipality level (Table 7.67) or adding school-level characteristics to the reduced form regression (Table 7.18 for maths and 7.19 for French). Finally, a potential problem is that I 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 7.20).

The magnitudes of the reduced form coefficients are statistically different for French and maths at the 5% threshold[33]. The impact on literacy skills is larger than the one on numeracy ones, coherently with Drange and Havnes (2019), that using the offer of a daycare place as an instrument, find a reduced-form impact of 0.05 SD in literacy and 0.03 in numeracy at age 7 in the Norwegian context. Similarly, Ludwig and Phillips (2007) find insignificant reduced-form results on a pre-mathematics test (Woodcock-Johnson applied problems) but positive reduced-form impact on spelling, letter identification, vocabulary letter naming administered at age 4, with coefficients ranging from 0.05 to 0.24 SD. While larger than my results, these are also driven by a more relevant and clear-cut instrument, the offer of a place in a daycare (HSIS study in the US). Finally, results are coherent with evidence from Denmark (Gupta & Simonsen, 2016): the reduced-form results of guaranteeing daycare is 0.08 SD and significant for literature GPA at 14 and 0.01 and insignificant for maths GPA. The reasons are likely to be common in the different countries: the day-to-day activities in daycare are more focused on socialization and language development than on numeracy skills.

It is interesting to see if daycare centers of different quality have a different impact on the early accumulation of cognitive skills. Ideally, one would want to observe and measure the process quality - the quality of the interaction between children and daycare workers. Collecting such data is however extremely costly. I can rely on process quality measures, that are collected and published by CAF[34], aggregated at the municipality and EPCI level. The teachers/students ratio is mandated at the national level, so the measures include the number of hours the daycare center is open, the financial occupancy rate, i.e. the number of hours paid by the family divided by the number of theoretical procedures, the average number of hours paid each day the daycare

[33] This holds true in all the main specifications, except the one without fixed effects (column 1 and 2 of Table 5.2), where they are different at the 10% level (p-value = 0.058).

[34] Data is available on CAF website.

center is open and the median hourly price paid by the family.

However, the availability of data is not optimal, since the quality indicators are only available for a subset of municipalities, and only from 2014 on. Since I have data on daycare attendance from 2007 to 2011, for the first stage I regress the indicator for the earlier year available, 2014, but the childcare quality may change rapidly. To account for the sample selection, I first run the main specification on the observations for whom the quality indicators are not missing. At the municipality level, deleting these observations does not change substantially the coefficient of the instrument, but it loses its significance. Including quality indicators do not change the coefficients of interest (Table 7.21 for the first stage, table 7.22 for the reduced form). Interacting the instrument with these quality indicators, coefficients are insignificant.

5.1.1 Two-sample 2SLS

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 notation from equation 2 and 3 and the estimation from the baseline regressions with department fixed effects:

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

$$\frac{0.0136}{0.0763} = 0.1782 \tag{13}$$

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

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

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 5.1). Since I use LPM to predict the probability[35], some results are outside of the 0-1 interval, but I 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, I 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

[35] An easily implementable robustness check is to see if the results are robust to removing the assumption of linearity in parameters.

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.

Figure 5.1: Distribution of the generated $\widehat{Daycare}$.

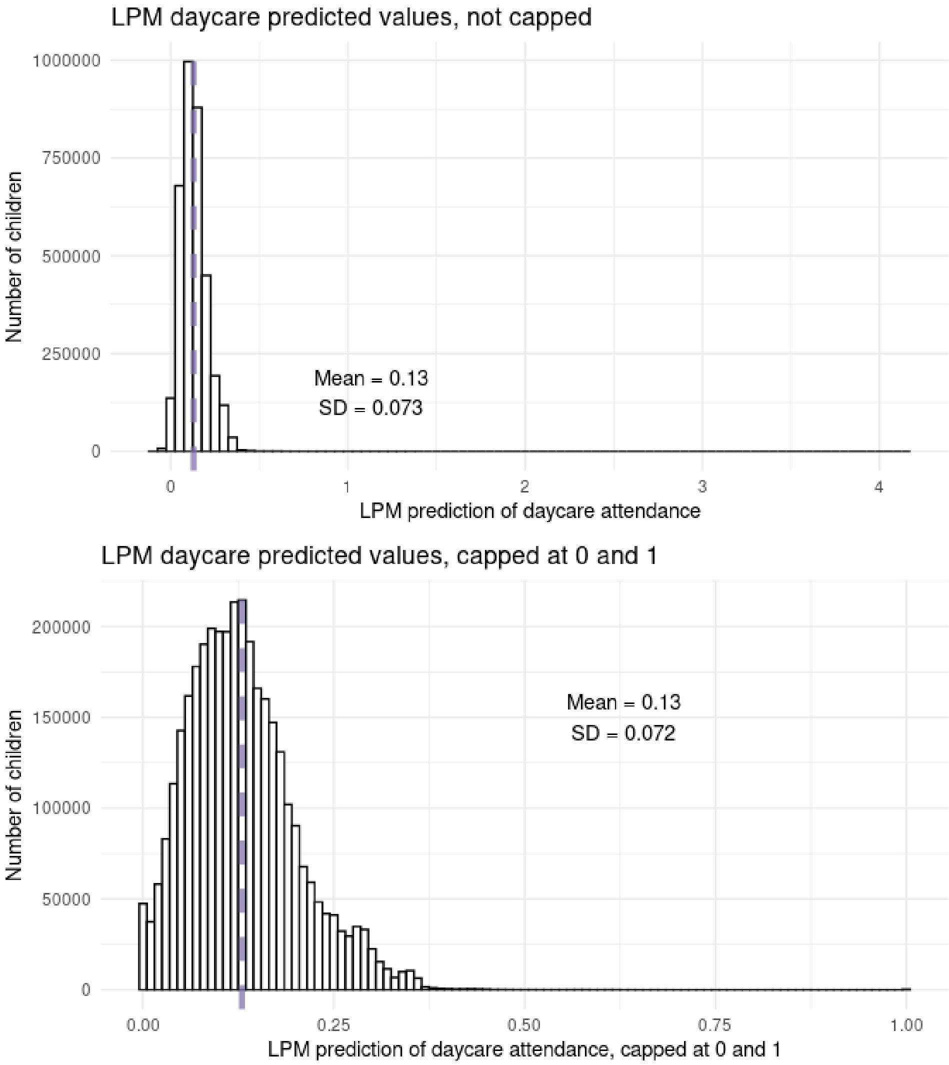


Table 5.3: Results for the two-sample 2SLS, without coefficients of the covariates (results with the covariates coefficients are in Table 7.24 in the Appendix).

	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

Results for the first stage are the same as column 3 in Table 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 13). It is however somewhat surprising, considering the rest of the results, that the coefficient on numeracy skills is larger than the one on literacy skills: further checks are needed to test if such difference is robust.

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

5.1.2 Heterogeneity on observables

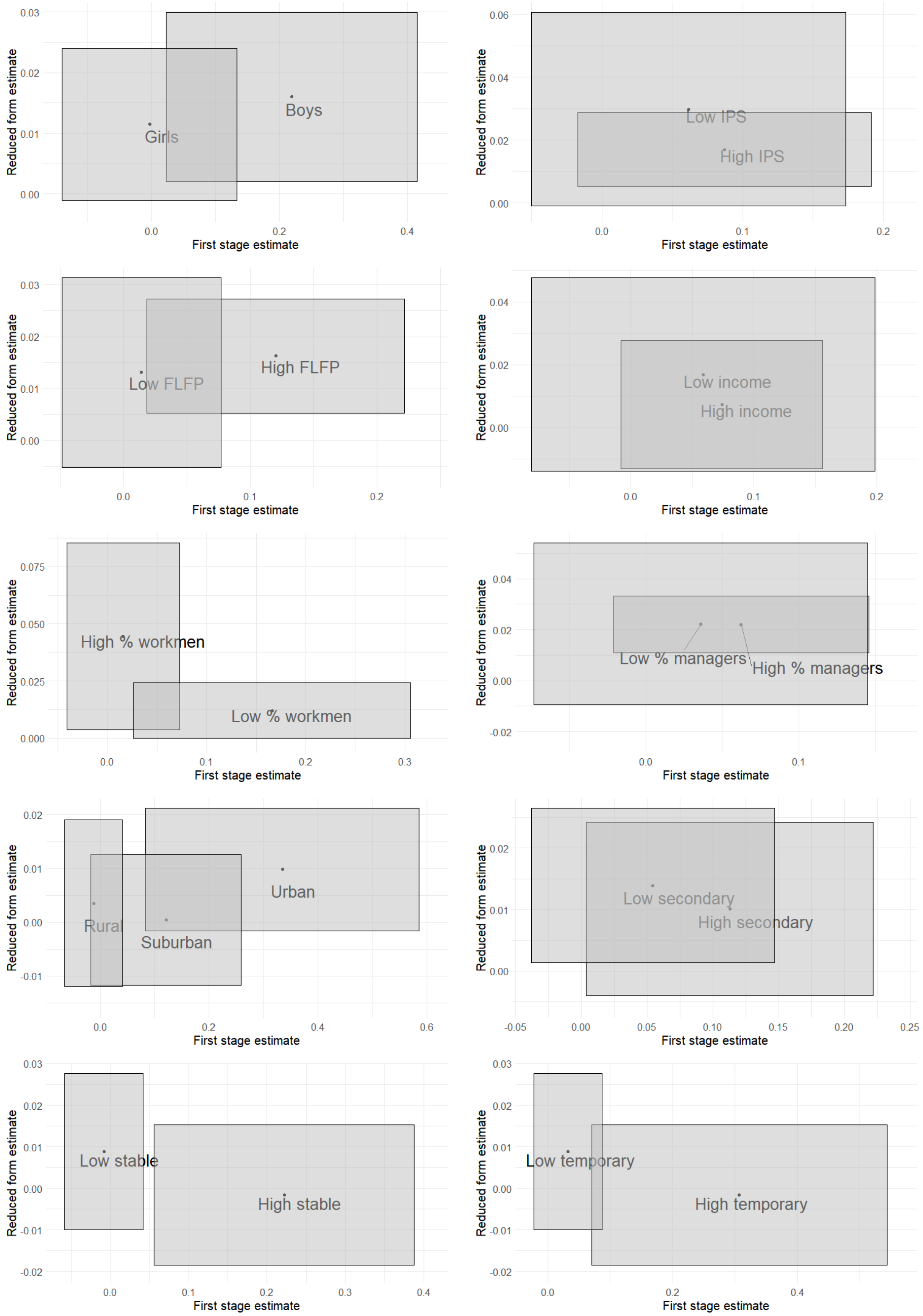
For ease of comparison, I report the heterogeneity results in the graphs in Figure 5.2, where the first stage estimate is on the x-axis, and the confidence interval of it are the vertical lines of the rectangle around each point. The reduced-form estimate is on the y-axis, and the horizontal borders of the rectangle are the confidence interval of the reduced-form estimate. Thus, if the rectangles overlap, the difference in the two groups is not significant. I also report all coefficients of the regressions in section 7.3.9. While the first stage is significantly different in some cases, in particular for children born in urban vs. rural municipalities, the reduced form coefficients are never statistically different.

Estimating sub-group mean impacts may yield imprecise results, if the intra-group variation in effects is relatively large compared to the inter-group variation (Bitler, Gelbach, & Hoynes, 2006). This may be further worsened by the fact that I currently do not observe individual characteristics of children in the DEPP data (except for the gender), so I rely on municipality and school characteristics as a proxy. This is even more problematic as I use the school municipality as a proxy for the children municipality of residence[36]. 92% of children attend an elementary school in the same municipality where they live, and even when there is not a school, dispersed intercommunal pedagogical grouping (*regroupements pédagogique intercommunal dispersé*)

In comparison, differential impacts by subgroups have mostly been found by looking at individual characteristics, such as parents' education (Gupta & Simonsen, 2010; Havnes & Mogstad, 2011), parents' earnings (Havnes & Mogstad, 2015; Rege, Solli, Størksen, & Votruba, 2018), language spoken at home (Bitler et al., 2014; Hindman & Wasik, 2015), ethnicity (Bitler et al., 2014; Cascio, 2009; Garces, Thomas, & Currie, 2002), single- or double-parent families (Kottelenberg & Lehrer, 2017; Stahl, Schober, & Spiess, 2018). I use different proxies to identify more and less advantaged children (IPS, job stability, labor force participation, social categories), but unfortunately, always at the municipality or school level: if families with different characteristics have a different counterfactual type of care in absence of daycare, and thus differential effects of being offered a place in daycare, the variation at the municipality level is not enough to see it.

[36]The main expansion to this paper would be to have access to DEPP data on middle school outcomes, that also contain the IPS of the mother and father of each child, and each child's municipality of residence.

Figure 5.2: Heterogeneity on observables results. On the x-axis, the coefficient and confidence interval of the first stage estimate is reported, on the y-axis, the coefficient and confidence interval of the reduced form estimate.



I also find no significant difference for gender in the first-stage nor in the reduced-form results. Research on universal childcare systems often find no differential effects for gender (Gupta and Simonsen 2010, Havnes and Mogstad 2015, see Magnuson et al. 2016 for a meta-analysis), although with exceptions (Felfe et al., 2015; Fort, Ichino, & Zanella, 2020).

5.1.3 Heterogeneity on dependent variable

Results for the reduced form analysis disaggregating more granularly the test scores reveal that the coefficient of interest has a similar magnitude across different skills for both maths (Table 7.65) and French (Table 7.66). For French, the coefficient of the instrument on oral comprehension is only larger than the coefficient on letter recognition at the 10% significance level. Among numeracy skills, the coefficient of the instrument on geometry is not significant, while the coefficient on number recognition is significantly larger than the overall math coefficient. In interpreting these results, it is important to keep in mind that those children went to kindergarten before the test, and that there are dynamic complementarities (Cunha & Heckman, 2007) and substitutabilities between skills acquired in daycare and kindergarten. For example, kindergarten teachers may invest more attention in children that have lower cognitive skills as a result of their childcare arrangement.

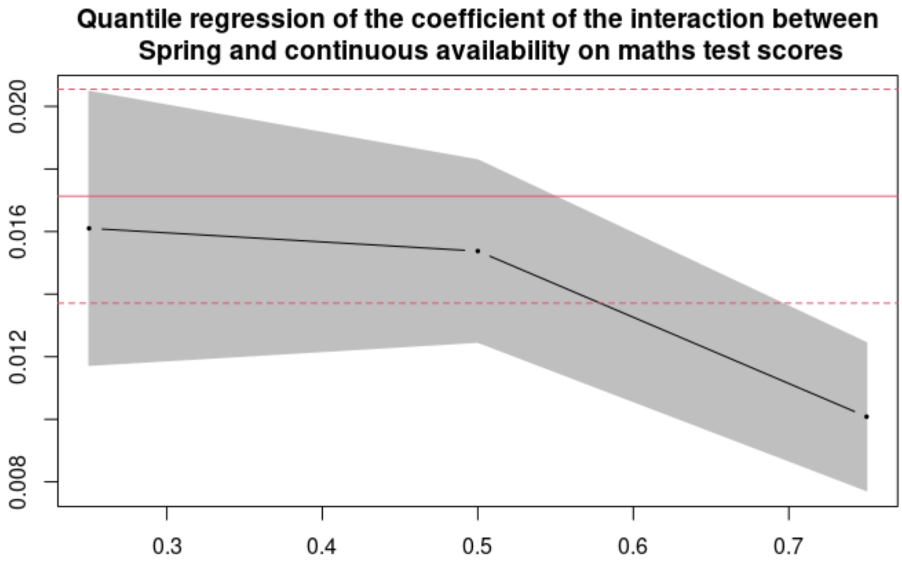
Results using ranks instead of standardized test scores are in line with the baseline ones: keeping the number of children in the municipality fixed, a marginal daycare spot increase the rank position of a child born in Spring by 0.23 positions in maths and 0.35 positions in French, on a scale of ranks from 0 to 100 (Table 7.64).

I also use 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 by 0.6 p.p., while the effect is not significant in maths: this is further evidence that daycare may have a differential impact on different types of skills.

Finally, results for the quantile regressions using the main specification are reported in Figure 5.3 (the tables with the coefficients and standard errors are in Table 7.26). Due to computational constraints, I report the ITT coefficient of the interaction only at the 25th, 50th and 75th percentile. Coherently with the compensatory hypothesis (Cunha et al., 2010), I find larger effects of childcare attendance at the bottom of the skills distribution, but the coefficient is statistically different from 0 in all three quantiles. Only the effect at the 75th percentile for French is statistically different from the coefficient estimated with OLS on the total sample of children. While these effects should not be interpreted as an individual ITT[37], since the rank invariance assumption is not likely to hold, the distributional effect of childcare is to decrease the inequality in the skills distribution.

[37] I do not refer to children at the x quantile, but only to the x quantile itself.

Figure 5.3: Results of the quantile regression using the main specification (Equation 3) for French and maths test scores. The red line is the OLS coefficient for the whole sample.



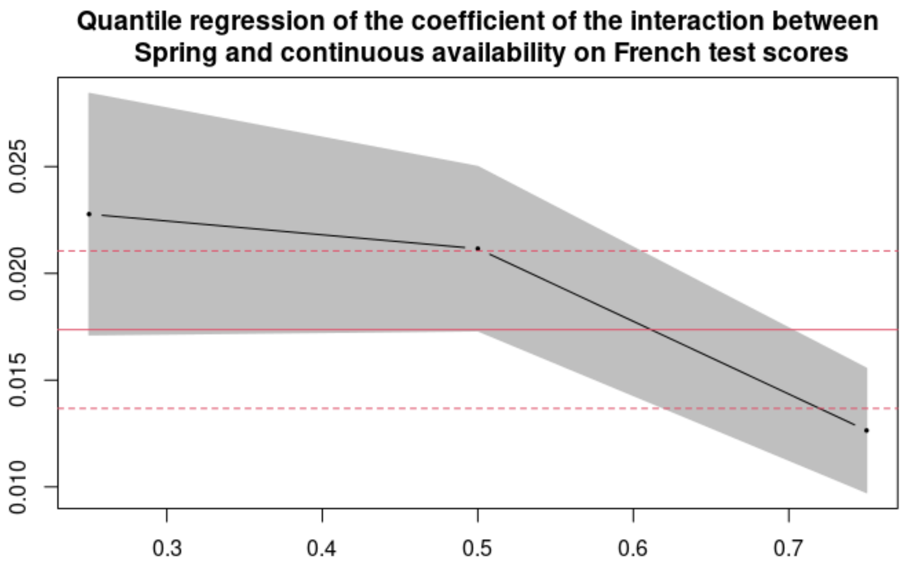
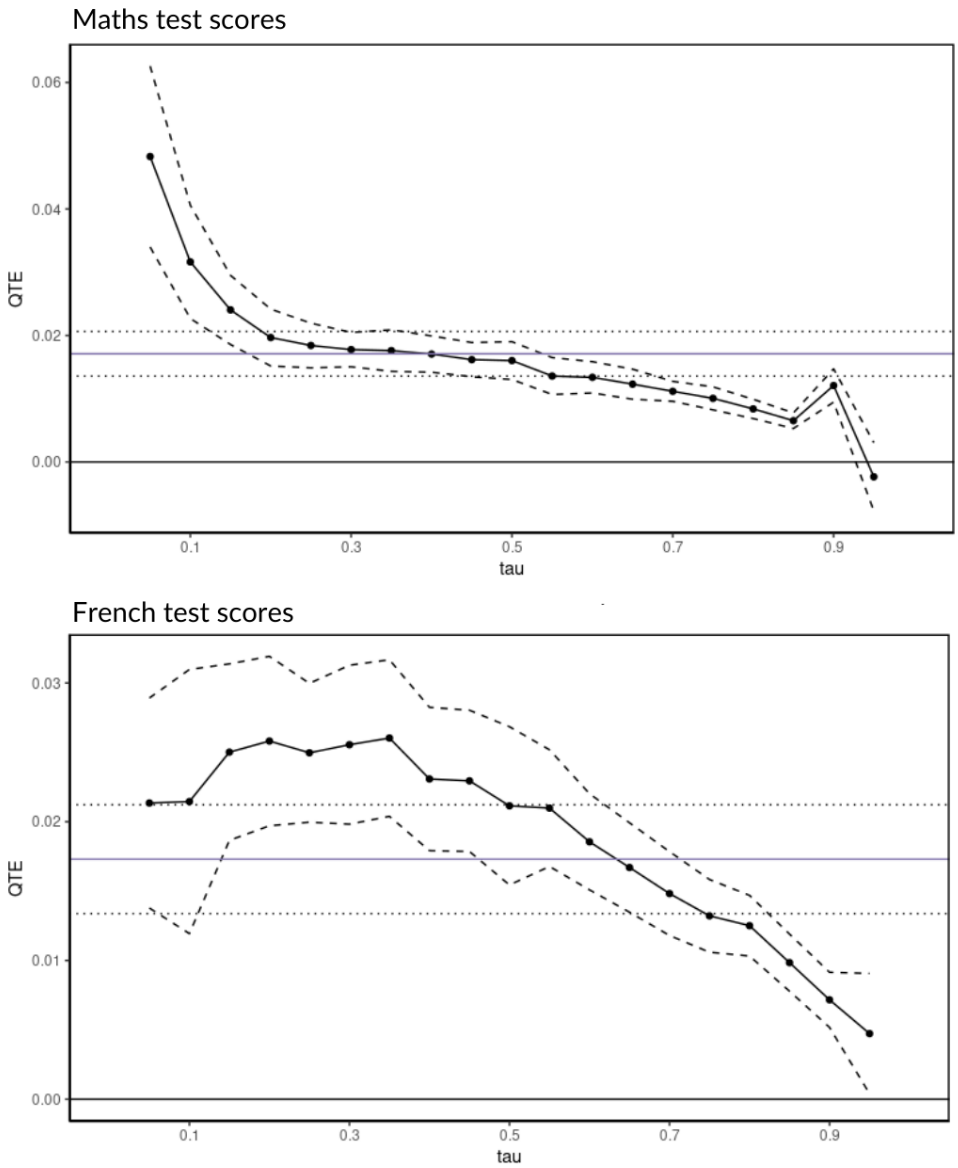


Figure 5.4: Results of the quantile regression defining the daycare availability as a binary variable (Equation 8) for French and maths test scores. The solid purple line is the OLS coefficient for the whole sample, dotted lines are the confidence interval bounds.



Results for the specification with the binary availability (equation 8) are reported in Figure 5.4, 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 7.25) are also reported. Coherently with the specification with the continuous availability, 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 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 7.20).

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 et al., 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 mine, 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.

5.2 Longitudinal analysis and counterfactual type of care

Descriptive evidence on the substitution patterns and the margins of adjustment of daycare availability is provided in Table 7.49. In this table, I am simply regressing the municipality daycare availability on an indicator variable for whether the childcare arrangement of the child is a daycare center, a childminder, parental care or grandparents (Panel A). In line with Pora's (2020) findings, the association between the local daycare availability and childminders care is much more negative than the association between local daycare availability and parental care. Far from any causal evidence, this hints at a stronger substitution effect between childminders and daycare, rather than between parental care and daycare. In Panel B, I regress my main cross-sectional first-stage specification (equation 2) 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 This intuition may provide an insight for future research and would also explain why in the cross-sectional reduced-form results the coefficient of the interaction is robustly positive: while the impact on cognitive skills of switching from a childminder to daycare may be small, the impact of switching to daycare from parental care are expected to be larger and significant.

Figure 5.5: Distribution of the daycare availability at the municipality level.

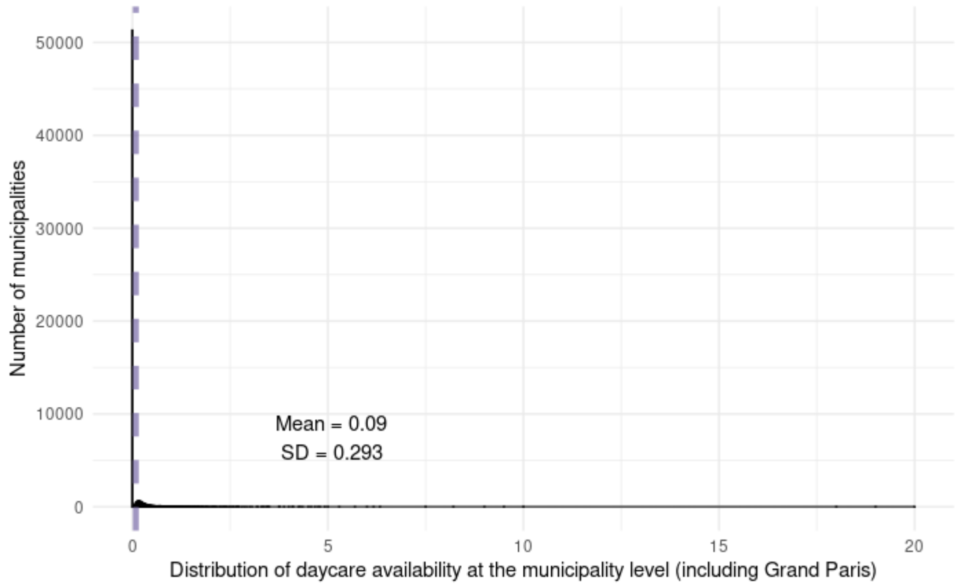


Figure 5.6: Distribution of the daycare availability at the EPCI level, without excluding the Metropole du Grand Paris EPCI.

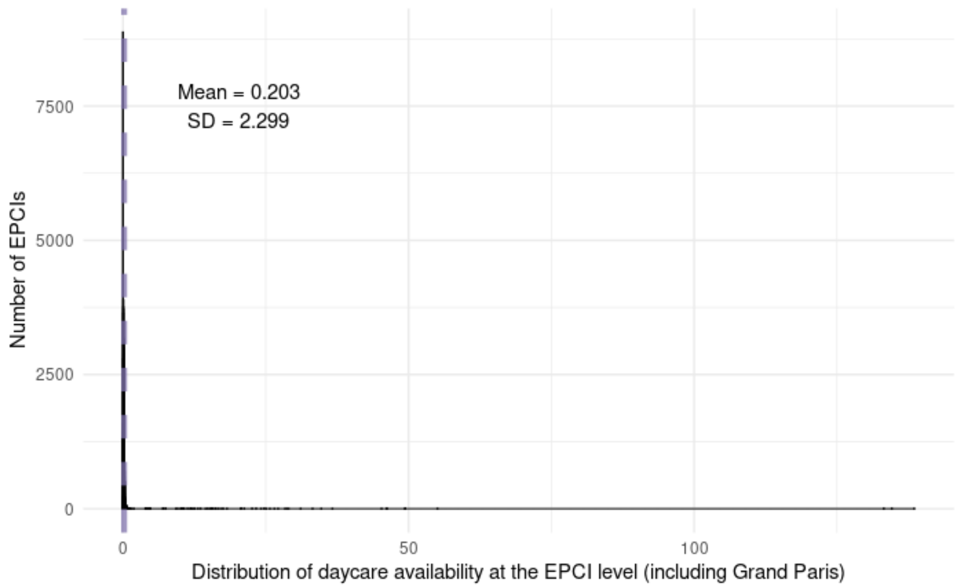
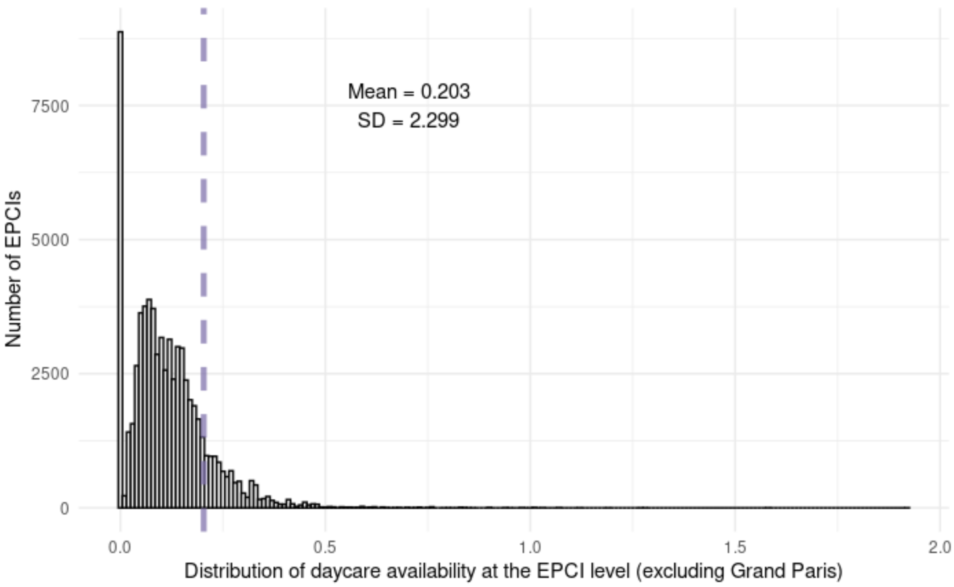


Figure 5.7: Distribution of the daycare availability at the EPCI level, excluding the Metropole du Grand Paris EPCI.



Before describing the fixed-effect model results, since in the fixed-effect specification the variation is driven by those municipalities and EPCIs whose daycare availability did change over time (25.7% of municipalities and 86.6% of EPCIs), robustness of results to outliers is of particular importance. The distribution of daycare availability is extremely right-skewed both at the municipality level (Figure 5.5)[38] and at the EPCI level (Figures 5.6). In the specification using the availability at the EPCI level, I exclude the municipalities that are part of the Metropole du Grand Paris EPCI, because when different EPCIs merge into the Metropole du Grand Paris, the daycare availability of these municipalities changes abruptedly: while the number of available places remains around the same, the denominator of $Availability_m$ increases, since it includes all children born in the Metropole du Grand Paris. The EPCI is so large (123 municipalities, 3 departments) that it is unlikely that families living in one part of it send their children to the opposite part. Moreover, since the mobility trajectories around the Paris area are different from those in the rest of France, I exclude those municipalities from the main specification and the distribution is much less right-skewed (see Figure 5.7).

Results are robust to including municipalities in the Grand Paris Metropole, but accounting for the right-skewness of the daycare availability taking the natural logarithm of ($Availability_m$ + 1) or the inverse hyperbolic sine of it (Tables 7.57 and 7.56). While the interpretation of the magnitude of the $\ln(Availability_m + 1)$ is not straightforward, the sign can still be interpreted. The asinh transformation (defined as $ln(y + \sqrt{y^2 + 1}))$) is usually preferred to the logarithmic

[38] One may wonder how it is possible that some municipalities have an availability as large as 18 places per child. This outlier is the municipality of Labathude (46), with 187 inhabitants and a daycare with 18 places: the availability is 18 in 2015, as no children were born in 2015 and 2013, and only 1 child was born in 2014. Another example is Salles (47): with 322 inhabitants and a daycare of 10 spots: in 2015 the availability is 10 places for 1 child, then when 3 more child are born in 2014, it decreases to 2. I test the robustness to exclusion to outliers and to transformations to put less weight on the outliers in Table 7.56 for the availability defined at the municipality level, and I use the availability defined at the EPCI level for rural municipalities, at the municipality level for urban ones.

transformation (Bellemare & Wichman, 2020), but results are similar in both cases, as they are when trimming the distribution of the daycare availability by excluding the top and bottom 0.001% and 0.01% of observations: the coefficient on the daycare availability is either positive but small or a well-estimated 0.

Moreover, when I include the parental care, I need to discard one year of my 5-year panel, since the total formal coverage that I use to measure the parental care is only available from 2013. I test the robustness of the specification without the parental care on the 2013-2016 interval in Table 7.50.

Table 5.4: Baseline municipality fixed effect specification, measuring childcare at the municipality and EPCI level (excluding Metropole du Grand Paris EPCI)

Dependent Variables:	Maths mean		French mean		Maths mean		French mean	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Daycare avail.	0.0080	0.0056	0.0158**	0.0148*				
	(0.0063)	(0.0073)	(0.0065)	(0.0078)				
Parental		-0.0142*		-0.0358***				
		(0.0078)		(0.0088)				
Daycare avail. (EPCI)					0.0527*	0.0372	0.2064***	0.1564***
					(0.0309)	(0.0299)	(0.0609)	(0.0543)
Parental (EPCI)						-0.1190***		-0.3361***
						(0.0219)		(0.0314)
Fixed-effects								
Municipality	Yes	Yes	Yes	Yes				
EPCI					Yes	Yes	Yes	Yes
Fit statistics								
Observations	69,579	66,876	69,580	66,877	69,043	68,357	69,043	68,357
DV mean	0.09046	0.09048	0.06380	0.06399	0.04519	0.04509	0.00256	0.00236

Clustered (municipality level) standard-errors in parentheses

Table 5.5: Municipality fixed effects specifications: 2SLS using daycare openings and closings

	Second stage				**First stage**	
	Maths mean		French mean		Daycare avail.	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Coefficient Names						
Daycare avail.	-0.0944	-0.0898	-0.1430	-0.1503		
Parental		-0.0144*		-0.0361***		-0.0022
Δ daycare avail. for openings or closing					0.3580***	0.3458***
Fixed-effects						
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	69,579	66,876	69,580	66,877	69,579	66,876
DV mean	0.09046	0.09048	0.06380	0.06399	0.08966	0.08848
F-test					1,628.5	1,636.4

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

Clustered (municipality level) standard-errors in parentheses

Results from the main specification (5.4) show that one more daycare place, keeping the number of children in the municipality constant, has no effect on Mathematics average test scores, but a positive, significant and small effect for French. The magnitude of around 1.5% of SD are in line with the reduced form evidence from the cross-sectional analysis. At the EPCI level, the effects are stronger (15%-20% of a standard deviation) for French, and, coherently, not significant for maths. The larger effect is likely due to the fact that the variation of the childcare availability is smaller the larger is the geographical unit. An increase in the level of parental care is negatively associated with the average level of test scores both at the municipality and EPCI level. While this association is simply correlational, controlling for the level of parental care does not change the coefficients of the daycare availability. Compared to the omitted category of formal childcare provided by childminders, nannies and kindergartens, the daycare availability seems to have a small but significant positive effect on the language skills, while parental care have a negative coefficient. No effect is found on the average mathematics test scores in the municipality, somewhat coherently with the lower coefficient in maths in the cross sectional analysis, and with smaller or non-significant impacts from universal childcare in Norway (Drange & Havnes, 2019), Denmark (Gupta & Simonsen, 2016) and the US (Ludwig & Phillips, 2007). Since neither childminders nor daycare workers place particular attention in their curriculum to pre-maths activities, it is likely that the maths skills are not affected[39].

Instrumenting the daycare availability with the openings, the coefficient on the daycare availability is no longer different from 0. The coefficient on the parental care has a magnitude similar to the OLS main specification. It would be interesting to run this 2SLS specification on availability measured at the EPCI level, given the larger and more robust results of the OLS specification. However, the instrument of school openings is not relevant enough when measured at the EPCI level.

Even if the negative coefficient of parental care is biased by selection, the results are coherent with the findings of Zhai et al. (2014), Feller et al. (2016) and Kline and Walters (2016): Head Start yields significant short-term benefits for the academic performance of children who would otherwise receive home care, while its impact on children attending alternative preschools is negligible. Note that in the French case, childminders, nannies and kindergartens do not provide the exact same service, simply funded by another source, as in the case of kindergartens not funded by Head Start. It is also interesting to note that such relationship holds for childcare for children aged 0-2, while Head Start provide kindergarten care for children aged 3 to 5.

Results are robust to definition of cognitive skills using ranks instead of standardized test scores: while the sign of the coefficient of the daycare availability at the EPCI level on the average French rank at the municipality level is negative, the magnitude is so small that it is closer to a well-estimated 0 than to a negative coefficient (Table 7.52).

Results are also robust to including year fixed effects and to the exclusion of children that were tested in September 2020 (Table 7.53 for the availability defined at the municipality level, Table 7.54 at the EPCI level). The rationale for the exclusion of 2020 is that while the school closure policies were enforced at the national level, the adaptation to online schooling may have been different for different municipalities or EPCIs, in particular because of different level of technology readiness and home overcrowding. Results are also robust to using standard errors that account for serial correlation and heteroskedasticity (Newey & West, 1986) (Table 7.53 and 7.54).

I take the average test scores for children born in a municipality in Spring or not, since this gives them an edge in the probability of actually attending daycare: even if fuzzy, this may isolate better those who actually attended the daycare from those who did not. At the EPCI level, the coefficient on the daycare availability is larger for children born in Spring, further confirming that they are more likely to actually attend and benefit from daycare (Table 7.55). At the municipality level, however, the small positive coefficient seems to be driven by children who are not born in Spring (Table 7.55).

Dividing the sample between urban, rural and suburban municipalities, the positive coefficient of daycare availability on language skills seems to be driven by urban municipalities (Table 7.58). On the one hand, this is coherent with a higher point estimate of the reduced form for children in a urban municipality in the cross-sectional results. On the other hand, however,

[39] Virtually all French children attend preschool, where they do pre-maths activities. There is no evidence that daycare attendance gives children an edge in pre-maths or maths skills that are measured when the child is 6.

these are also the municipalities where the changes in daycare availability are more pronounced, while the greatest majority of rural municipalities have 0 crèches for the whole period (thus, the coefficient on daycare availability is only estimated with a smaller variation). A similar reasoning applies to dividing the sample between those municipalities that have a population below and above the median: comparing the magnitude of the coefficients, children born in municipalities with a population above the median seem to benefit more from daycare provision (Table 7.60), but the significance is likely to be driven by a higher variation in the daycare provision. The coefficient on daycare provision is not significantly different in municipalities where the women labor force participation is above or below the national average (Table 7.59).

6 Conclusion

In this paper I 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 main strategy relies on a TS2SLS estimation: in particular, the first stage is estimated on the FL survey and shows that the interaction between being born in Spring and the local availability increases the probability of attending daycare by 7 p.p. 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. The TS2SLS estimation finds sizable results for the compliers with the instrument, in the order of magnitude of 0.12-0.24 SD. With the exception of gender, observable characteristics are measured at the municipality level, that is likely too aggregated a level to detect any significant heterogeneity based on observables. However, 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. This is particularly not straightforward without having individual data on daycare attendance, much less on the alternative types of childcare. I use a fixed-effect model to account for changes in the supply of different childcare alternatives, but the 2SLS strategy based on school openings yields insignificant results.

Among the directions for future research, the first and foremost is to evaluate the characteristics of compliers, nevertakers and always takers of the instrument (Abadie, 2002, 2003; Angrist & Pischke, 2009), using the availability defined as a binary variable: how are those who are born in spring in a municipality with at least one daycare center different from the rest of the population? A first attempt to answer this question is the balance table of the FL sample based on being born in spring or not (Table 7.2).

Secondly, 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 I 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 I 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.

References

Abadie, A. (2002). Bootstrap tests for distributional treatment effects in instrumental variable models. *Journal of the American statistical Association*, *97*(457), 284–292.

Abadie, A. (2003). Semiparametric instrumental variable estimation of treatment response models. *Journal of econometrics*, *113*(2), 231–263.

Andresen, M. E. (2019). *Child care for all? treatment effects on test scores under essential heterogeneity* (Tech. Rep.). Working Paper, Statistics Norway.

Angrist, J. D. (1990). Lifetime earnings and the vietnam era draft lottery: evidence from social security administrative records. *The american economic review*, 313–336.

Angrist, J. D., & Krueger, A. B. (1995). Split-sample instrumental variables estimates of the return to schooling. *Journal of Business & Economic Statistics*, *13*(2), 225–235.

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion.* Princeton university press.

Aparicio-Fenoll, A., & Vidal-Fernandez, M. (2015). Working women and fertility: the role of grandmothers' labor force participation. *CESifo Economic Studies*, *61*(1), 123–147.

Athey, S., & Imbens, G. W. (2006). Identification and inference in nonlinear difference-in-differences models. *Econometrica*, *74*(2), 431–497.

Auzet, L., Bigot, K., & Dajoux, S. (2014). Les assistant(e)s maternel(le)s: près de chez soi, le mode d'accueil toujours majoritaire dans les côtes-d'armor. *Octant Analyse*(58).

Baker, M., Gruber, J., & Milligan, K. (2008). Universal child care, maternal labor supply, and family well-being. *Journal of political Economy*, *116*(4), 709–745.

Baker, M., Gruber, J., & Milligan, K. (2015). *Non-cognitive deficits and young adult outcomes: The long-run impacts of a universal child care program* (Tech. Rep.). National Bureau of Economic Research.

Bayer, P., Ferreira, F., & McMillan, R. (2007). A unified framework for measuring preferences for schools and neighborhoods. *Journal of political economy*, *115*(4), 588–638.

Bedard, K., & Dhuey, E. (2006). The persistence of early childhood maturity: International evidence of long-run age effects. *The Quarterly Journal of Economics*, *121*(4), 1437–1472.

Bellemare, M. F., & Wichman, C. J. (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, *82*(1), 50–61.

Berger, L. M., Panico, L., & Solaz, A. (2021). The impact of center-based childcare attendance on early child development: Evidence from the french elfe cohort. *Demography*, *58*(2), 419–450.

Bernal, R., Attanasio, O., Peña, X., & Vera-Hernández, M. (2019). The effects of the transition from home-based childcare to childcare centers on children's health and development in colombia. *Early childhood research quarterly*, *47*, 418–431.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly journal of economics*, *119*(1), 249–275.

Bitler, M. P., Gelbach, J. B., & Hoynes, H. W. (2006). What mean impacts miss: Distributional effects of welfare reform experiments. *American Economic Review*, *96*(4), 988–1012.

Bitler, M. P., Hoynes, H. W., & Domina, T. (2014). *Experimental evidence on distributional effects of head start* (Tech. Rep.). National Bureau of Economic Research.

Blau, D., & Currie, J. (2006). Pre-school, day care, and after-school care: who's minding the kids? *Handbook of the Economics of Education*, *2*, 1163–1278.

Bohic, D. N., Frossard, J.-B., Itier, C., & Leconte, T. (2023, Mars). *Qualité de l'accueil et prévention de la maltraitance dans les crèches: Tome 1 : Rapport* (Tech. Rep. No. 2022-062R). Membres de l'Inspection générale des affaires sociales.

Borderies, F. (2013). L'offre d'accueil collectif des enfants de moins de trois ans en 2011. *SERIE STATISTIQUES-DOCUMENT DE TRAVAIL-DREES*(184).

Borjas, G. J. (1980). The relationship between wages and weekly hours of work: The role of division bias. *The Journal of Human Resources*, *15*(3), 409–423.

Bérardier, M., & Clément, J. (2017). Les déterminants de la durée d'accueil en Eaje. *l'e-ssentiel*(174). (Publication électronique de la Direction des statistiques, des études et de la recherche)

CAF. (2023). *Le guide psu.* TSA – 20 avenue Jean Jaurès – CS 25000 – 73023 CHAMBERY cedex: Caisse d'allocations familiales de la Savoie.

Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of human resources*, *50*(2), 317–372.

Camilli, G., Vargas, S., Ryan, S., & Barnett, W. S. (2010). Meta-analysis of the effects of early education interventions on cognitive and social development. *Teachers college record*, *112*(3), 579–620.

Card, D., & Krueger, A. (1994). Minimum wages and employment: A case study of the fast-food industry in new jersey and pennsylvania. *The American Economic Review*, *84*(4), 772–793.

Carta, F., & Rizzica, L. (2018). Early kindergarten, maternal labor supply and children's outcomes: evidence from italy. *Journal of Public Economics*, *158*, 79–102.

Cartmill, E. A., Armstrong III, B. F., Gleitman, L. R., Goldin-Meadow, S., Medina, T. N., & Trueswell, J. C. (2013). Quality of early parent input predicts child vocabulary 3 years later. *Proceedings of the National Academy of Sciences*, *110*(28), 11278–11283.

Cascio, E. U. (2009). *Do investments in universal early education pay off? long-term effects of introducing kindergartens into public schools* (Tech. Rep.). National Bureau of Economic Research.

Cascio, E. U. (2023). Does universal preschool hit the target? program access and preschool impacts. *Journal of Human Resources*, *58*(1), 1–42.

Chetty, R., Friedman, J. N., Hilger, N., Saez, E., Schanzenbach, D. W., & Yagan, D. (2011). How does your kindergarten classroom affect your earnings? evidence from project star. *The Quarterly journal of economics*, *126*(4), 1593–1660.

Choi, J., Gu, J., & Shen, S. (2018). Weak-instrument robust inference for two-sample instrumental variables regression. *Journal of Applied Econometrics*, *33*(1), 109–125.

CNAF-DSER. (2016). *IMAJE - INDICATEURS SUR LES ASSISTANT(E)S MATERNEL(LE)S.* Indicateurs de Mesure de l'Accueil des Jeunes Enfants (IMAJE).

Collet, A., Cartier, M., Czerny, E., Gilbert, P., Lechien, M.-H., & Monchatre, S. (2016). *Les arrangements conjugaux autour des modes de garde: arbitrages sous contrainte et effet de socialisation* (Unpublished doctoral dissertation). Ministère des Affaires sociales et de la Santé.

Council, N. R., et al. (2000). From neurons to neighborhoods: The science of early childhood development.

Cour des Comptes. (2013). *L'accueil des enfants de moins de trois ans: une politique ambitieuse, des priorités à mieux cibler.* Paris. http://www. ladocumentationfrancaise. fr/rapportspublics/134000811 ....

Cunha, F., & Heckman, J. (2007). The technology of skill formation. *American economic review*, *97*(2), 31–47.

Cunha, F., Heckman, J. J., & Schennach, S. M. (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, *78*(3), 883–931.

Currie, J., & Thomas, D. (1995). Does head start make a difference? *The American Economic Review*, *85*(3), 341–364. Retrieved 2023-07-11, from http://www.jstor.org/stable/2118178

De Bodman, F., De Chaisemartin, C., Dugravier, R., & Gurgand, M. (2017). Investissons dans la petite enfance. l'égalité des chances se joue avant la maternelle. *Terra Nova*, *31*, 46–49.

Debras, B., & Pélamourgues, B. (2019). DOSSIER D'ÉTUDE Collection des documents de travail de la Cnaf. Taux de couverture territorialisé de l'accueil du jeune enfant. Méthodologie, interprétations et limites. *Cnaf - Dser*(E203). (Collection des documents de travail de la Cnaf)

Deming, D. (2009). Early childhood intervention and life-cycle skill development: Evidence from head start. *American Economic Journal: Applied Economics*, *1*(3), 111–134.

Drange, N., & Havnes, T. (2019). Early childcare and cognitive development: Evidence from an assignment lottery. *Journal of Labor Economics*, *37*(2), 581–620.

Duflo, E. (2001). Schooling and labor market consequences of school construction in indonesia: Evidence from an unusual policy experiment. *American economic review*, *91*(4), 795–813.

Duncan, G. J., Dowsett, C. J., Claessens, A., Magnuson, K., Huston, A. C., Klebanov, P., ... others (2007). School readiness and later achievement. *Developmental psychology*, *43*(6), 1428.

Duncan, G. J., & Magnuson, K. (2013). Investing in preschool programs. *Journal of economic perspectives*, *27*(2), 109–132.

Duncan, G. J., & Sojourner, A. J. (2013). Can intensive early childhood intervention programs eliminate income-based cognitive and achievement gaps? *Journal of human resources*, *48*(4), 945–968.

Elango, S., García, J. L., Heckman, J. J., & Hojman, A. (2015). Early childhood education. In *Economics of means-tested transfer programs in the united states, volume 2* (pp. 235–297). University of Chicago Press.

Fabre, M. (2021). Influence de la ruralité sur les résultats scolaires à l'entrée à l'école primaire. *Éducation & formations*(102), 285–313.

Fack, G., & Grenet, J. (2010). When do better schools raise housing prices? evidence from paris public and private schools. *Journal of public Economics*, *94*(1-2), 59–77.

Fagnani, J. (2014). Equal access to quality care: Lessons from france on providing high-quality and affordable early childhood education and care. In *An equal start?* (pp. 77–100). Policy Press.

Felfe, C., & Lalive, R. (2018). Does early child care affect children's development? *Journal of*

Public Economics, *159*, 33–53.

Felfe, C., Nollenberger, N., & Rodríguez-Planas, N. (2015). Can't buy mommy's love? universal childcare and children's long-term cognitive development. *Journal of population economics*, *28*(2), 393–422.

Feller, A., Grindal, T., Miratrix, L., & Page, L. C. (2016). Compared to what? variation in the impacts of early childhood education by alternative care type.

Filatriau, O., Fougère, D., & Tô, M. (2013). Will sooner be better? the impact of early preschool enrollment on cognitive and noncognitive achievement of children.

Fort, M., Ichino, A., & Zanella, G. (2020). Cognitive and noncognitive costs of day care at age 0–2 for children in advantaged families. *Journal of Political Economy*, *128*(1), 158–205.

Garces, E., Thomas, D., & Currie, J. (2002). Longer-term effects of head start. *American economic review*, *92*(4), 999–1012.

Geay, B. (2014). Les relations entre parents et personnels d'accueil de jeunes enfants. la transmission des normes au prisme des rapports entre classes sociales. *Revue des politiques sociales et familiales*, *118*(1), 35–44.

Gormley Jr, W. T., Gayer, T., Phillips, D., & Dawson, B. (2005). The effects of universal pre-k on cognitive development. *Developmental psychology*, *41*(6), 872.

Goux, D., & Maurin, E. (2010). Public school availability for two-year olds and mothers' labour supply. *Labour Economics*, *17*(6), 951–962.

Grenet, J. (2009). Academic performance, educational trajectories and the persistence of date of birth effects. evidence from france. *Unpublished manuscript*.

Gunderson, E. A., Gripshover, S. J., Romero, C., Dweck, C. S., Goldin-Meadow, S., & Levine, S. C. (2013). Parent praise to 1-to 3-year-olds predicts children's motivational frameworks 5 years later. *Child development*, *84*(5), 1526–1541.

Gupta, N. D., & Simonsen, M. (2010). Non-cognitive child outcomes and universal high quality child care. *Journal of Public Economics*, *94*(1-2), 30–43.

Gupta, N. D., & Simonsen, M. (2016). Academic performance and type of early childhood care. *Economics of Education Review*, *53*, 217–229.

Haeck, C., Lebihan, L., & Merrigan, P. (2018). Universal child care and long-term effects on child well-being: Evidence from canada. *Journal of Human Capital*, *12*(1), 38–98.

Hart, B., & Risley, T. R. (1995). *Meaningful differences in the everyday experience of young american children.* Paul H Brookes Publishing.

Hart, B., & Risley, T. R. (2003). The early catastrophe. *Education review*, *17*(1).

Havnes, T., & Mogstad, M. (2011). No child left behind: Subsidized child care and children's long-run outcomes. *American Economic Journal: Economic Policy*, *3*(2), 97–129.

Havnes, T., & Mogstad, M. (2015). Is universal child care leveling the playing field? *Journal of public economics*, *127*, 100–114.

Heckman, J., Pinto, R., & Savelyev, P. (2013). Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review*, *103*(6), 2052–2086.

Heckman, J. J., Moon, S. H., Pinto, R., Savelyev, P. A., & Yavitz, A. (2010). The rate of return to the highscope perry preschool program. *Journal of public Economics*, *94*(1-2), 114–128.

Heckman, J. J., Smith, J., & Clements, N. (1997). Making the most out of programme evaluations and social experiments: Accounting for heterogeneity in programme impacts. *The Review of Economic Studies*, *64*(4), 487–535.

Heim, A. (2018). Quand la scolarisation à 2 ans n'a pas les effets attendus : leçons des méthodes d'évaluations. *France Strategie*.

Hindman, A. H., & Wasik, B. A. (2015). Building vocabulary in two languages: An examination of spanish-speaking dual language learners in head start. *Early Childhood Research Quarterly*, *31*, 19–33.

Human Fertility Database. (2021). *Human fertility collection.* Available at www.fertilitydata.org.

Humlum, M. K., & Smith, N. (2015). Long-term effects of school size on students' outcomes. *Economics of Education Review*, *45*, 28–43.

Imbens, G., & Angrist, J. (1994). Identification and estimation of local average treatment effects. *Econometrica*, *62*(2), 467–475.

Imberman, S. A. (2011). The effect of charter schools on achievement and behavior of public school students. *Journal of Public Economics*, *95*(7-8), 850–863.

Inoue, A., & Solon, G. (2010). Two-sample instrumental variables estimators. *The Review of Economics and Statistics*, *92*(3), 557–561.

INSEE. (2019). Fiche population: Enfants - population scolaire des 1er et 2nd degrés. *France, portrait social. Édition 2019*. https://www.insee.fr/fr/statistiques/4238377?sommaire=4238781#tableau-figure2.

INSEE. (2020). *Tableaux de l'économie française, Édition 2020. natalité – fécondité.* Institut national de la statistique et des études économiques. Retrieved from https://www.insee.fr/fr/statistiques/4277635?sommaire=4318291

Jessen, J., Schmitz, S., & Waights, S. (2020). Understanding day care enrolment gaps. *Journal of Public Economics*, *190*, 104252.

Karoly, L. A., Greenwood, P. W., Everingham, S. S., Houbé, J., & Kilburn, M. R. (1998). *Investing in our children: What we know and don't know about the costs and benefits of early childhood interventions.* Rand Corporation.

Khawand, C., & Lin, W. (2015). *Finite sample properties and empirical applicability of two-sample two-stage least squares* (Tech. Rep.). Working paper, Dept. Econ., Michigan State Univ.

Klevmarken, A. (1982). *Missing variables and two-stage least-squares estimation from more than one data set* (Tech. Rep.). IUI Working Paper.

Kline, P., & Walters, C. R. (2016). Evaluating public programs with close substitutes: The case of head start. *The Quarterly Journal of Economics*, *131*(4), 1795–1848.

Kottelenberg, M. J., & Lehrer, S. F. (2017). Targeted or universal coverage? assessing heterogeneity in the effects of universal child care. *Journal of Labor Economics*, *35*(3), 609–653.

Kuziemko, I. (2006). Using shocks to school enrollment to estimate the effect of school size on student achievement. *Economics of Education Review*, *25*(1), 63–75.

Laporte, C. (2019). *Attentes, besoins et contraintes des parents en matière de conciliation vie familiale et vie professionnelle: Les premiers enseignements de l'enquête embleme* (No. 208). Cnaf / TMO Régions.

Le Bouteillec, N., Kandil, L., & Solaz, A. (2014). Who are the children enrolled in french daycare centres? *Population Societies*, *514*(8), 1–4.

Ludwig, J., & Phillips, D. (2007). The benefits and costs of head start. social policy report. volume 21, number 3. *Society for Research in Child Development*.

Magnuson, K. A., Kelchen, R., Duncan, G. J., Schindler, H. S., Shager, H., & Yoshikawa, H. (2016). Do the effects of early childhood education programs differ by gender? a meta-analysis. *Early childhood research quarterly*, *36*, 521–536.

Martinot, P., Dehaene, S., Bressoux, P., Huguet, P., Potier-Watkins, C., Sprenger-Charolles, L., & Ziegler, J. (2021, September). *Qu'apprend-on des évaluations de CP-CE1 ? Note du Conseil scientifique de l'éducation nationale (CSEN)* (Note du CSEN No. 2021 - 03). Conseil scientifique de l'éducation nationale (CSEN). Retrieved from https://www.reseau-canope.fr/fileadmin/user_upload/Projets/conseil_scientifique_education_nationale/Note_CSEN_2021_03.pdf

Maurin, É., Roy, D., et al. (2008). *L'effet de l'obtention d'une place en crèche sur le retour à l'emploi des mères et leur perception du développement de leurs enfants* (Tech. Rep.). CEPREMAP.

Micheau, J., Molière, E., Ohnheiser, S., & Chazal, J. (2010). Les modes d'organisations des crèches collectives et les métiers de la petite enfance. *ETUDES ET RESULTATS-DREES*(732).

Ministère de l'Éducation nationale et de la Jeunesse. (2023). *Repères cp 2023: Guide pour le professeur - Évaluations des acquis et besoins des élèves au cp.* France: Ministère de l'Éducation nationale et de la Jeunesse.

Monarrez, T., Kisida, B., & Chingos, M. (2022). The effect of charter schools on school segregation. *American Economic Journal: Economic Policy*, *14*(1), 301–340.

Monnet, J. (2019). The effect of preschool participation on intellectual and behavioral disorder diagnoses: Evidence from surveys on children's health. *Economics of Education Review*, *68*, 136–147.

Moreau, N. (2023). The zero effect of income tax on the timing of birth: some evidence on french data. *International Tax and Public Finance*, *30*(3), 757–783.

Nelson, C. A., & Sheridan, M. A. (2011). Lessons from neuroscience research for understanding causal links between family and neighborhood characteristics and educational outcomes. *Whither opportunity*, 27–46.

Newey, W. K., & West, K. D. (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix.

Noble, K. G., Houston, S. M., Brito, N. H., Bartsch, H., Kan, E., Kuperman, J. M., ... others (2015). Family income, parental education and brain structure in children and adolescents. *Nature neuroscience*, *18*(5), 773–778.

Noboa-Hidalgo, G. E., & Urzua, S. S. (2012). The effects of participation in public child care centers: Evidence from chile. *Journal of Human Capital*, *6*(1), 1–34.

OECD. (2016). *Starting strong iv: Monitoring quality in early childhood education and care country note: France.* Organisation for Economic Co-operation and Development.

OECD. (2021). Oecd family database: Enrolment in childcare and pre-school. https://www.oecd.org/els/soc/PF3_2_Enrolment_childcare_preschool.pdf.

ONAPE. (2016). L'accueil du jeune enfant en 2017 - données statistiques et recherches qualitatives. *OBSERVATOIRE NATIONAL DE LA PETITE ENFANCE*. https://www.caf.fr/sites/default/files/medias/cnaf/Nous_connaitre/Recherche_et_statistiques/Onape/AJE_2018_bd.pdf.

Pacini, D., & Windmeijer, F. (2016). Robust inference for the two-sample 2sls estimator. *Economics letters*, *146*, 50–54.

Pailhé, A., & Solaz, A. (2012). Durée et conditions de retour à l'emploi des mères après une naissance. *Retraite et société*(2), 51–77.

Pinto, M. F. (2022). Stay at home with grandma, mom is going to work: The impact of grandmothers' retirement on mothers' labor decisions. *Economic Development and Cultural Change*.

Pora, P. (2020). *Keep working and spend less?: Collective childcare and parental earnings in france*. INSEE, Institut national de la statistique et des études économiques.

Rege, M., Solli, I. F., Størksen, I., & Votruba, M. (2018). Variation in center quality in a universal publicly subsidized and regulated childcare system. *Labour Economics*, *55*, 230–240.

Régnier-Loilier, A., & Wiles-Portier, E. (2010). Choosing the time of year for births: A barely perceptible phenomenon in france. *Population*, *65*(1), 188–203.

Ridder, G., & Moffitt, R. (2007). The econometrics of data combination. *Handbook of econometrics*, *6*, 5469–5547.

Ridley, M., & Terrier, C. (2023). Fiscal and education spillovers from charter school expansion. *Journal of Human Resources*.

Rocher, T. (2016). Construction d'un indice de position sociale des élèves. *Éducation & formations*(90), 5–27.

Rostgaard, T. (2014). Family policies in scandinavia.

Rowe, M. L. (2008). Child-directed speech: Relation to socioeconomic status, knowledge of child development and child vocabulary skill. *Journal of child language*, *35*(1), 185–205.

Rowe, M. L., & Goldin-Meadow, S. (2009). Differences in early gesture explain ses disparities in child vocabulary size at school entry. *Science*, *323*(5916), 951–953.

Schweinhart, L. J. (2005). *Lifetime effects: the high/scope perry preschool study through age 40* (No. 14). High/Scope Foundation.

Shager, H. M., Schindler, H. S., Magnuson, K. A., Duncan, G. J., Yoshikawa, H., & Hart, C. M. (2013). Can research design explain variation in head start research results? a meta-analysis of cognitive and achievement outcomes. *Educational Evaluation and Policy Analysis*, *35*(1), 76–95.

Sowell, E. R., Peterson, B. S., Thompson, P. M., Welcome, S. E., Henkenius, A. L., & Toga, A. W. (2003). Mapping cortical change across the human life span. *Nature neuroscience*, *6*(3), 309–315.

Stahl, J. F., Schober, P. S., & Spiess, C. K. (2018). Parental socio-economic status and childcare quality: Early inequalities in educational opportunity? *Early childhood research quarterly*, *44*, 304–317.

Tamis-LeMonda, C. S., Bornstein, M. H., & Baumwell, L. (2001). Maternal responsiveness and children's achievement of language milestones. *Child development*, *72*(3), 748–767.

The Council of the European Union. (2019). *Council recommendation of 22 may 2019 on high-quality early childhood education and care systems.* Official Journal of the European Union, C 189/4, 5.6.2019, p. 4–14. (ST/9014/2019/INIT)

Urruticoechea, A., Oliveri, A., Vernazza, E., Giménez-Dasí, M., Martínez-Arias, R., & Martín-Babarro, J. (2021). The relative age effects in educational development: A systematic review. *International journal of environmental research and public health*, *18*(17), 8966.

US Department of Health. (2012). *Head start impact study: Final report. washington, dc.*

van Huizen, T., & Plantenga, J. (2018). Do children benefit from universal early childhood education and care? a meta-analysis of evidence from natural experiments. *Economics of Education Review*, *66*, 206–222.

Villaume, S. (2015). Combien dépensent les familles pour la garde de leurs enfants de moins de 3 ans? *Études et résultats*(930), 8.

Virot, P. (2017). Le choix de la crèche comme mode d'accueil, entre bénéfices pour l'enfant et adaptation aux contraintes. *Études et Résultats, DREES*(1014).

WHO. (2020). *Improving early childhood development: Who guideline.* World Health Organization.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data.* MIT press.

Zhai, F., Brooks-Gunn, J., & Waldfogel, J. (2014). Head start's impact is contingent on alternative type of care in comparison group. *Developmental psychology*, *50*(12), 2572.

7 Appendix

7.1 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 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, I define daycare attendance as the treatment, and the observed outcomes are: Test scores$_i$ = $Daycare_i \times$ Test scores$_i$($Daycare_i$ = 1) + (1 − $Daycare_i$) × Test scores$_i$($Daycare_i$ = 1). In my 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:

$$\begin{aligned}\gamma_{DD} = & E[Y_i(1)|G_i = 1, E_i = 1] - E[Y_i(0)|G_i = 1, E_i = 0] \\ & - (E[Y_i(0)|G_i = 0, E_i = 1] - E[Y_i(0)|G_i = 0, E_i = 0])\end{aligned} \tag{14}$$

This is clearly not my 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:

$$\begin{aligned}\gamma_{DD} = \{ & E[Y_i(1)|T(1) = 1, G_i = 1, E_i = 1] - E[Y_i(0)|T(1) = 1, G_i = 1, E_i = 0] - \\ & (E[Y_i(0)|T(1) = 1, G_i = 0, E_i = 1] - E[Y_i(0)|T(1) = 1, G_i = 0, E_i = 0])\} \\ & \times P[T(1) = 1|G_i = 1, E_i = 1]\end{aligned} \tag{15}$$

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 my case, children aged

0 to 2).

However, at least two further problems hinder the identification of a DD parameter in my 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 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 my case, however, in the absence of a significant reform, daycare attendance is considered the treatment, and not an outcome.

7.2 Graphs

7.2.1 Daycare availability (Main source: CAF)

Figure 7.1: Childcare facilities financed by PSU, disaggregated by type and management. Source: CAF

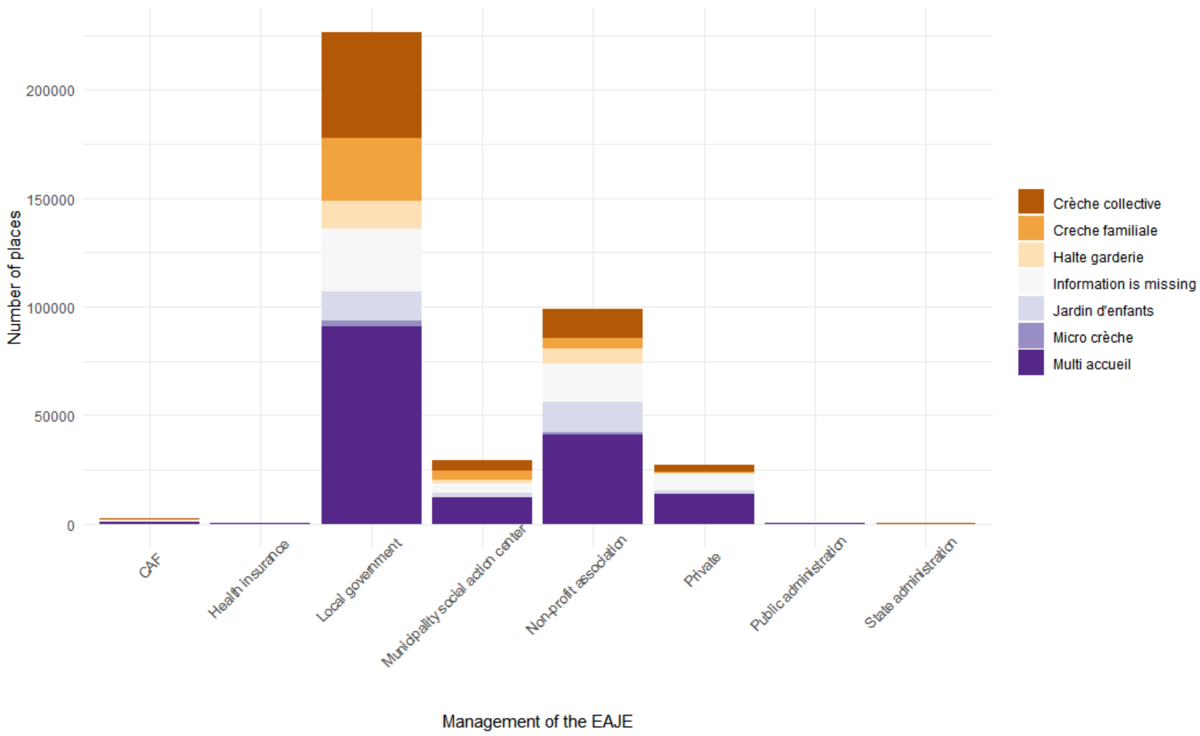


Figure 7.2: Distribution of daycare operating hours. Source: CAF

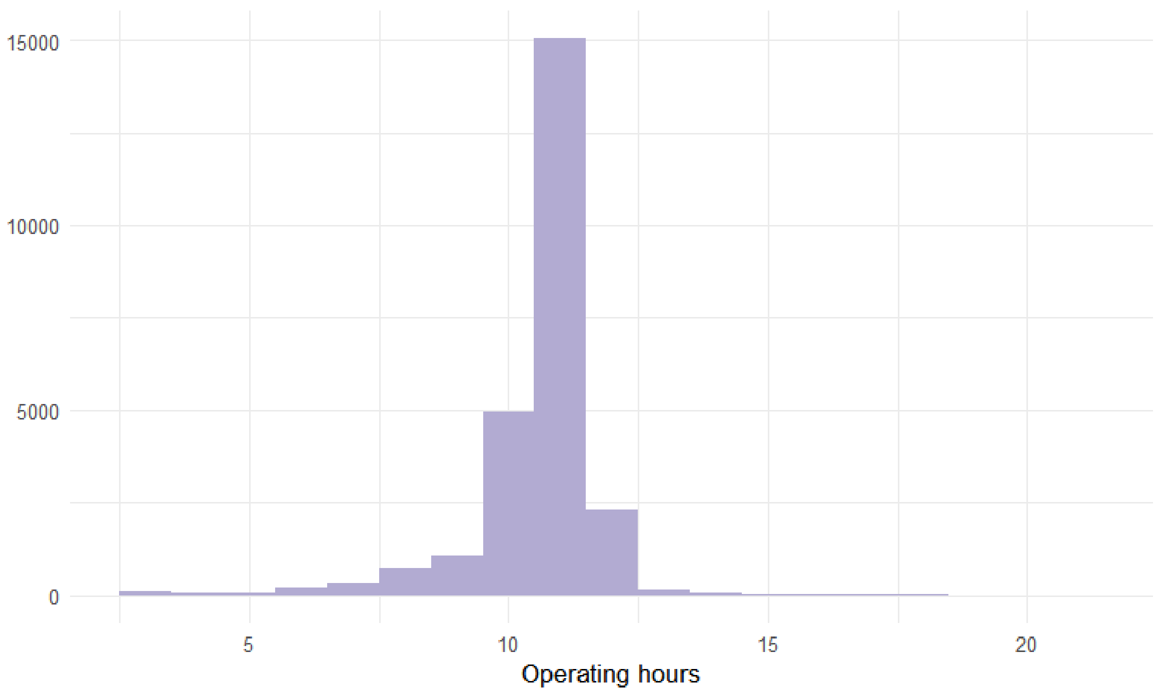


Figure 7.3: Evolution of the distribution of the number of days daycare centers are open in France. Source ONAPE (2016).

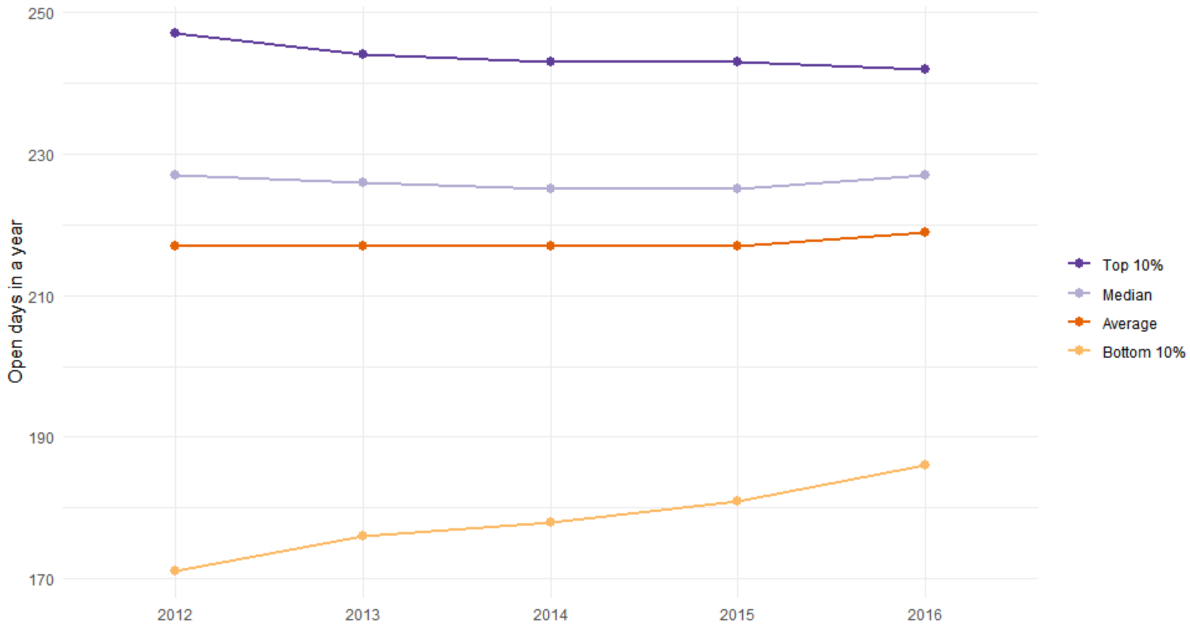


Figure 7.4: Price for families and costs for the public finances. Source: ONAPE (2016).

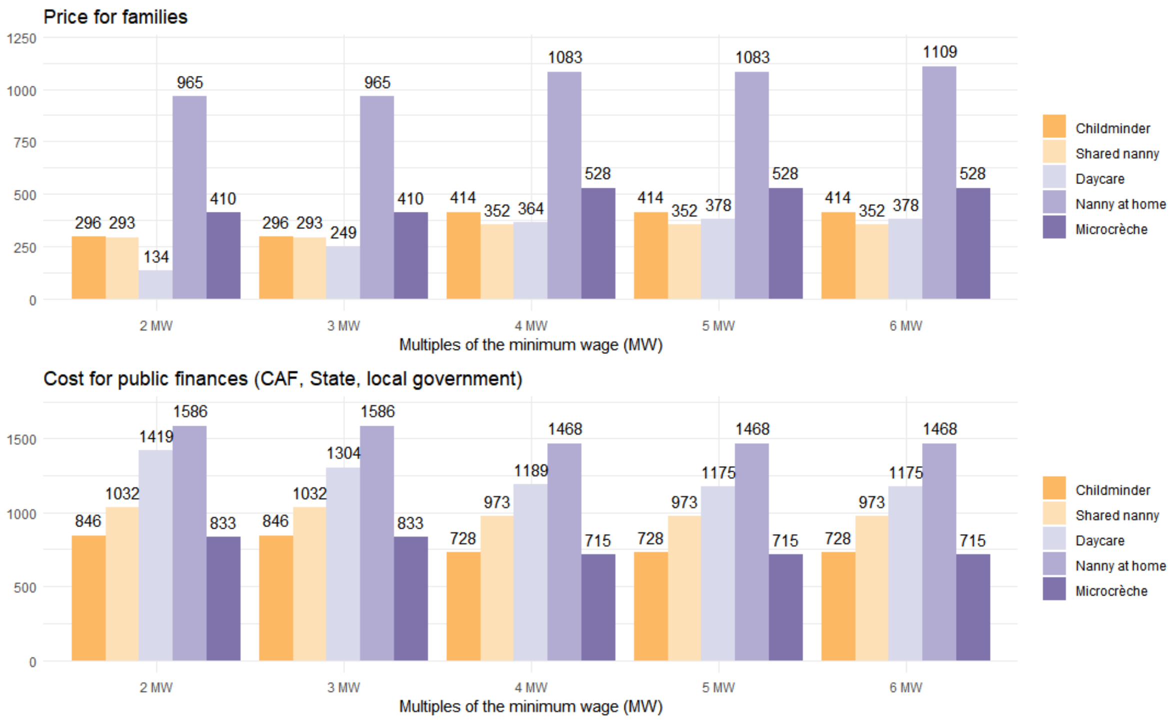


Figure 7.6: Regional variation in daycare and childminders availability in 2012. Source: ONAPE (2016).

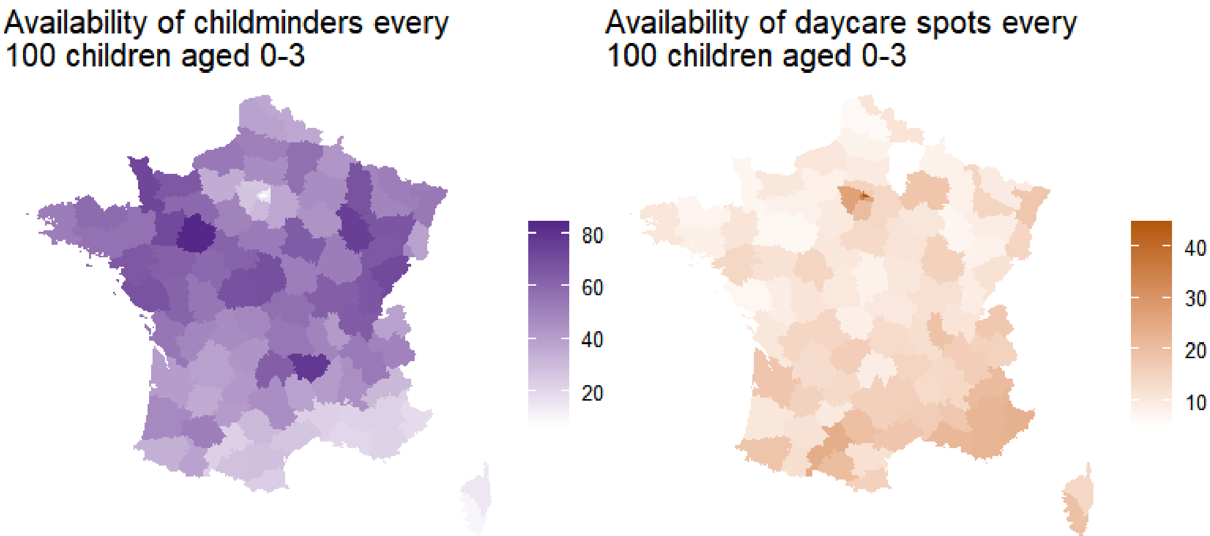


Figure 7.5: Median hourly price for families. Source: CAF.

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

Figure 7.7: Months when the child begins daycare, based on month of birth. Source: Elfe.

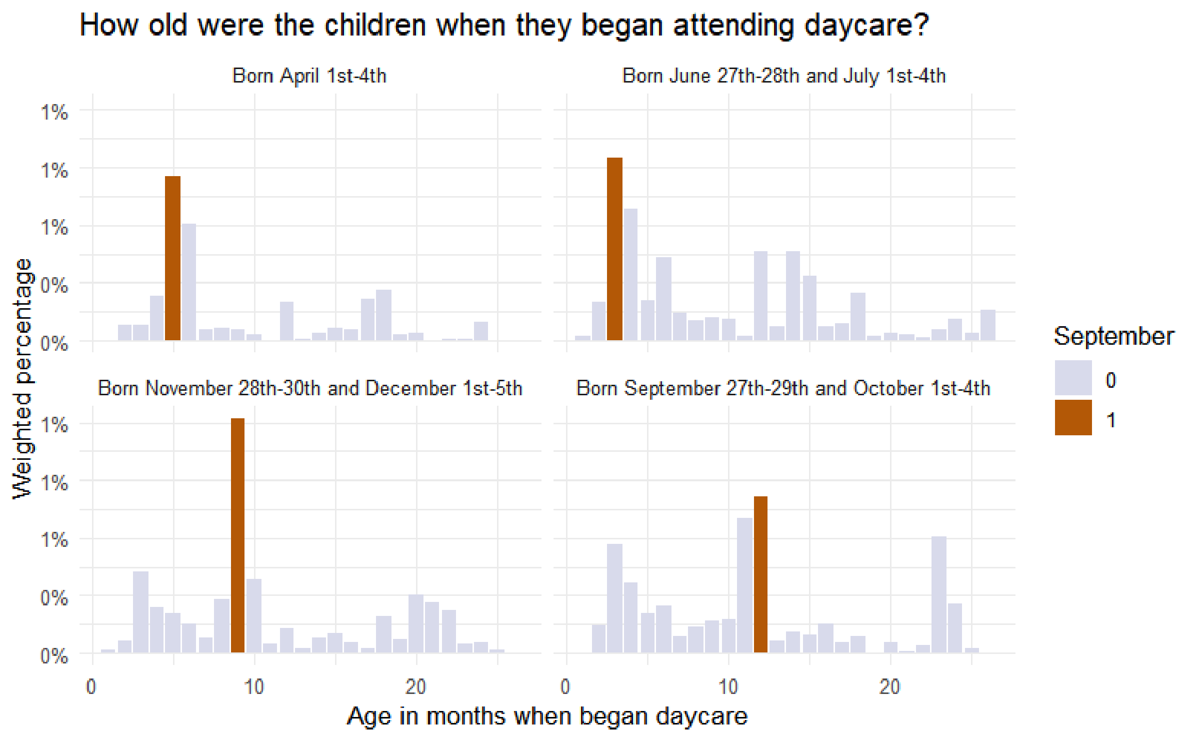


Figure 7.8: Distribution of days and hours spent in childcare by type of childcare arrangement. Source Elfe.

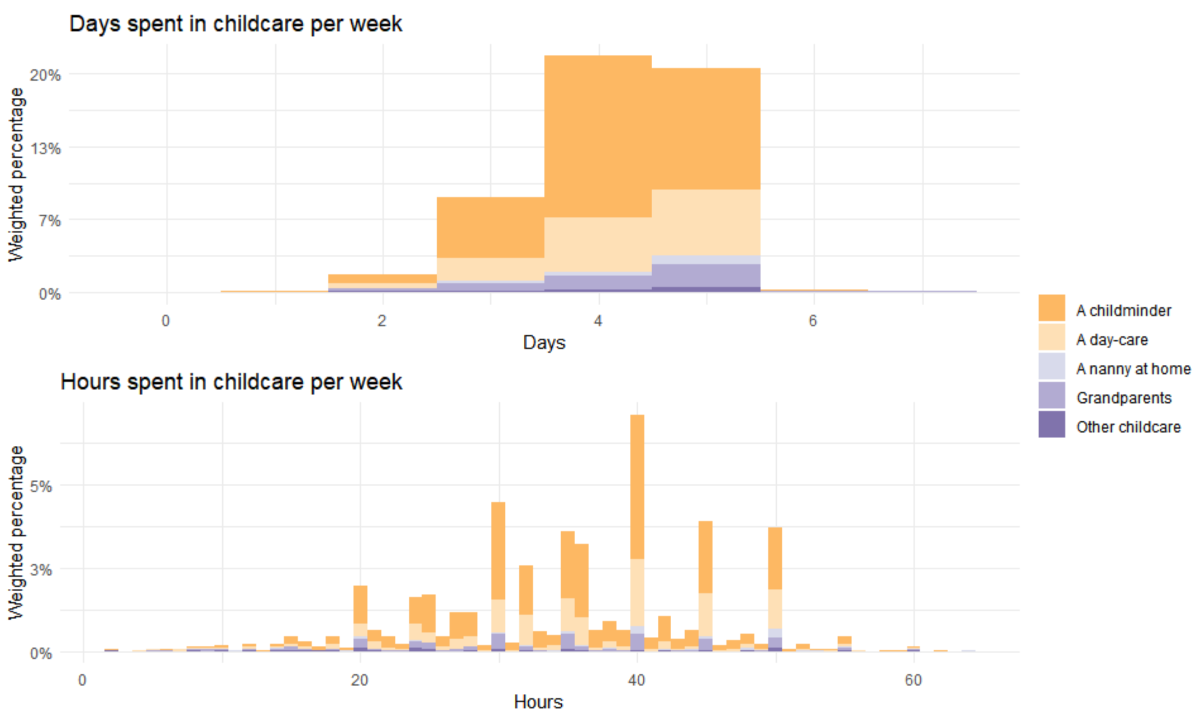


Figure 7.9: Satisfaction with the opening hours by type of childcare arrangement. Source: MDG.

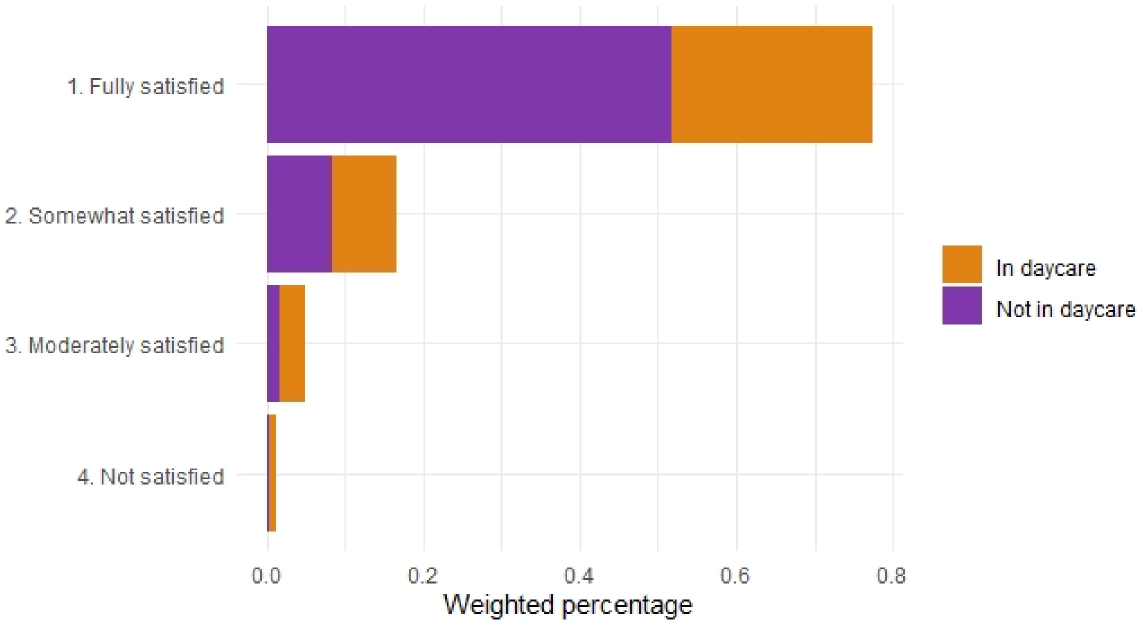
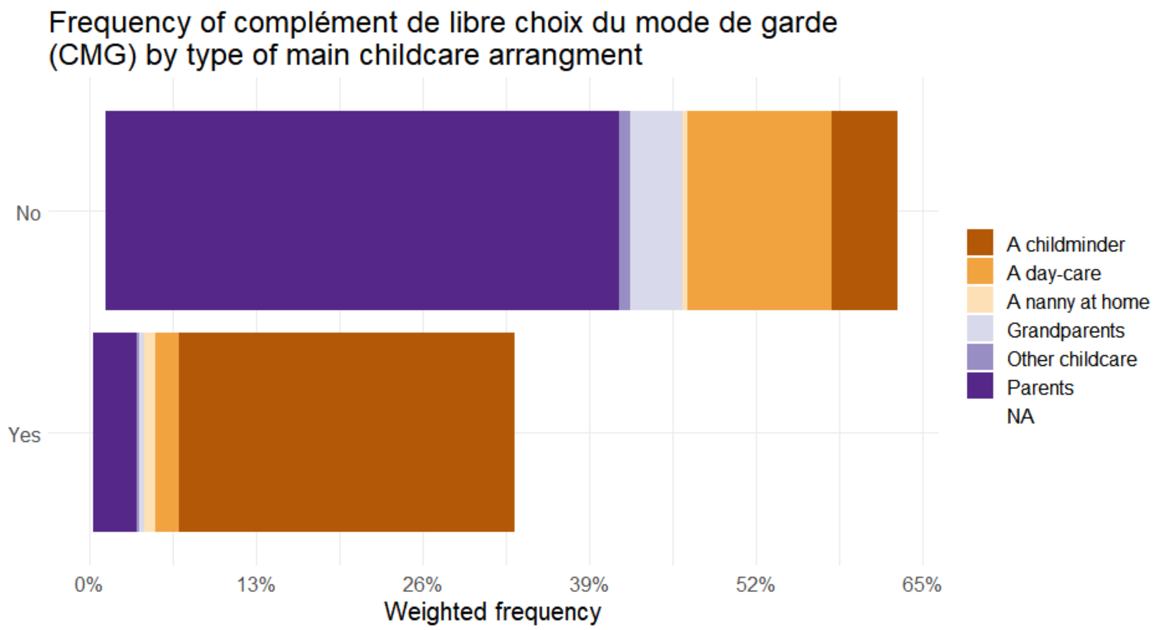


Figure 7.10: CMG when the child is 1 year old. Source: Elfe.



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

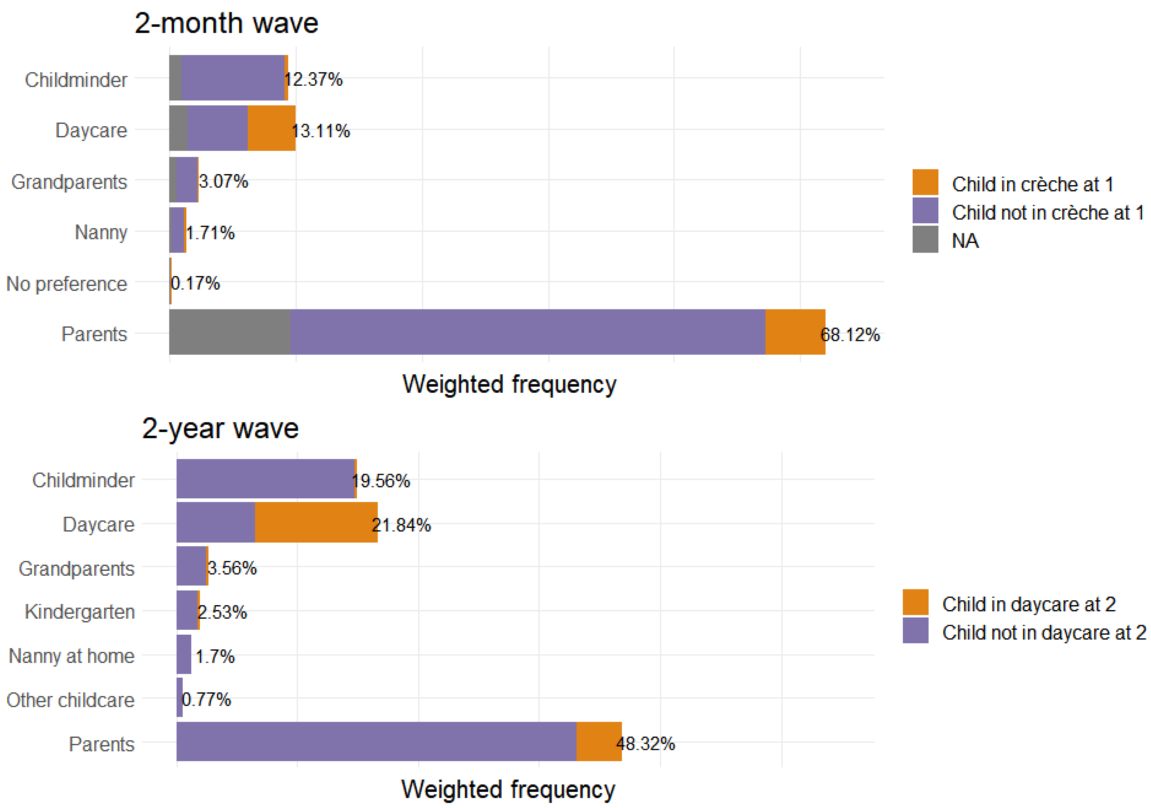


Figure 7.12: Months of research before finding the first paid childcare arrangment. Source: MDG.

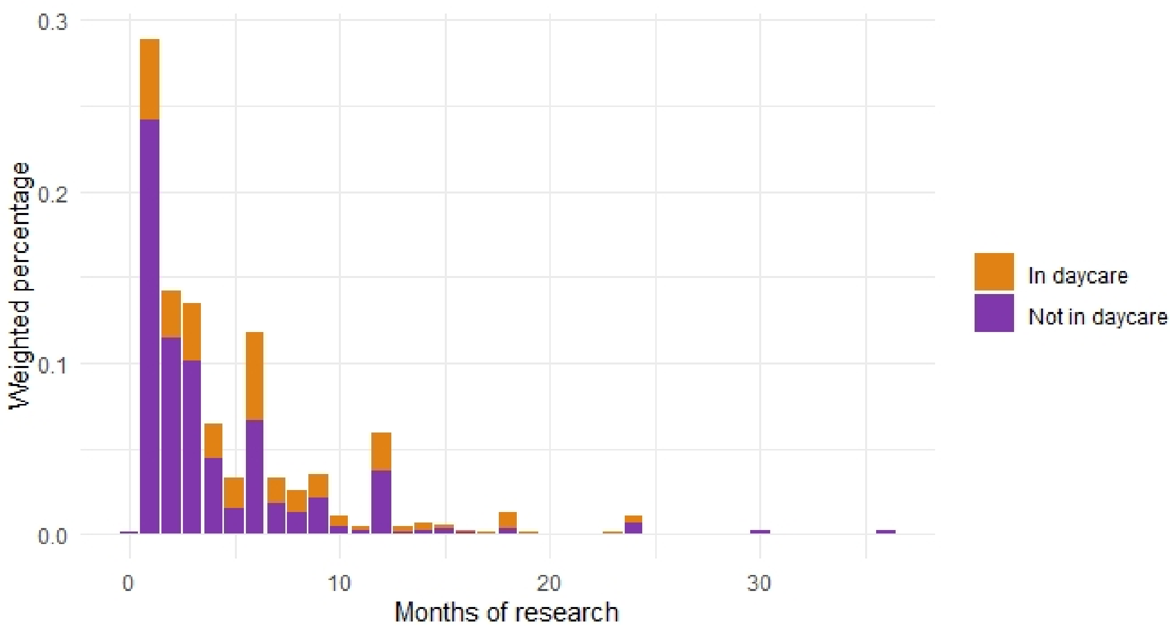


Figure 7.13: Reasons for the choice of daycare or a licensed childminder as preferred childcare arrangement. Source: own elaboration based on Enquête Mode de garde 2013.

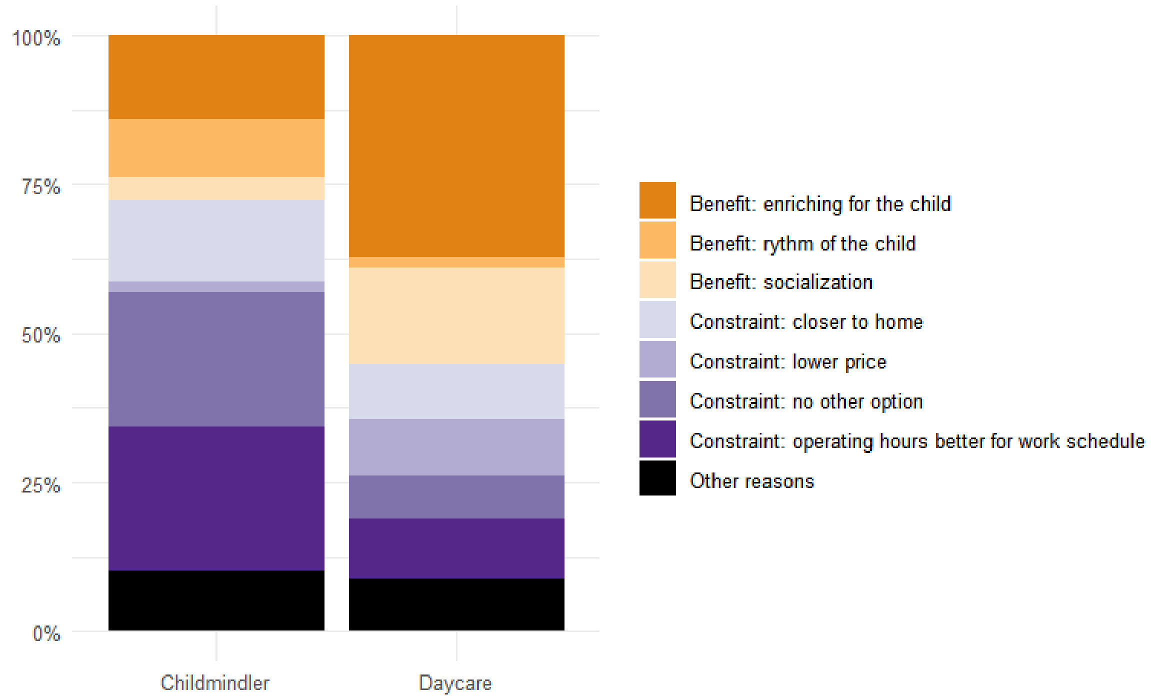


Figure 7.14: Alluvial diagram of the changes in childcare arrangement of children between 1 and 2 years of age. Source: Elfe survey

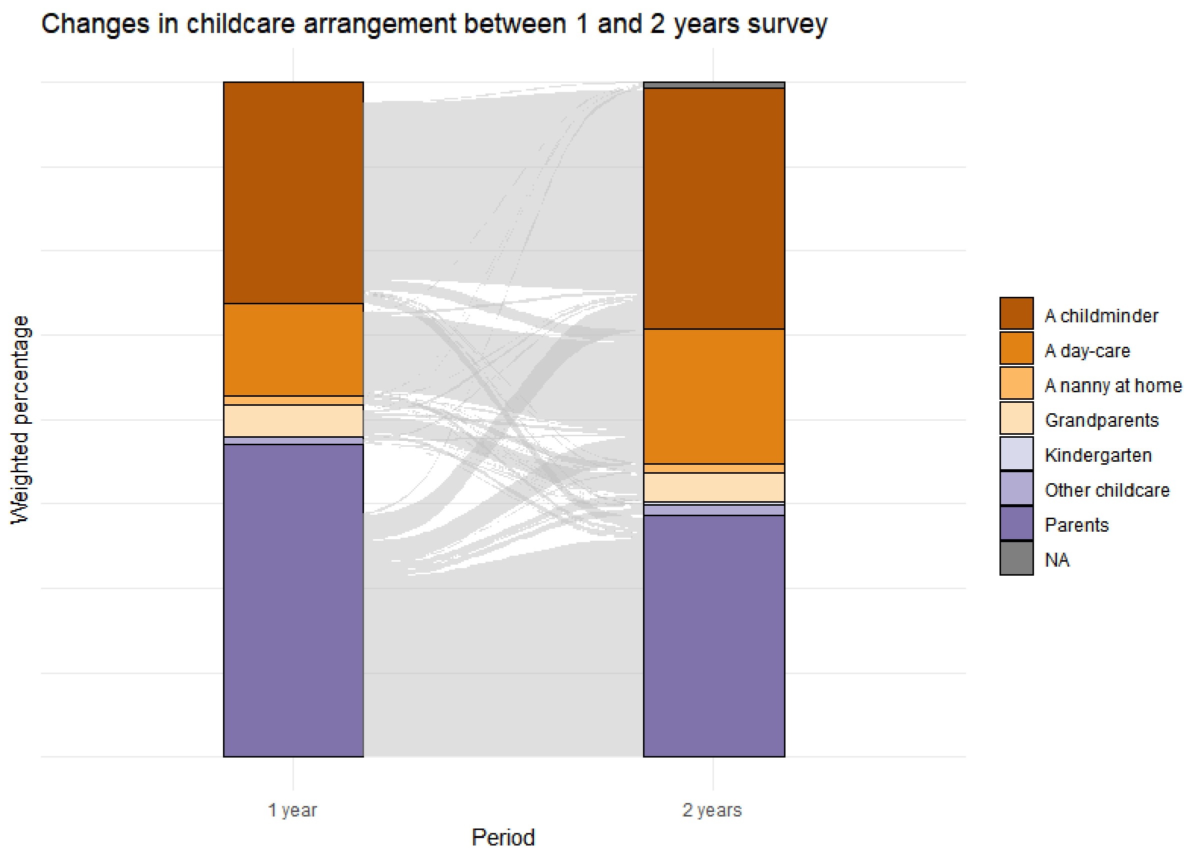
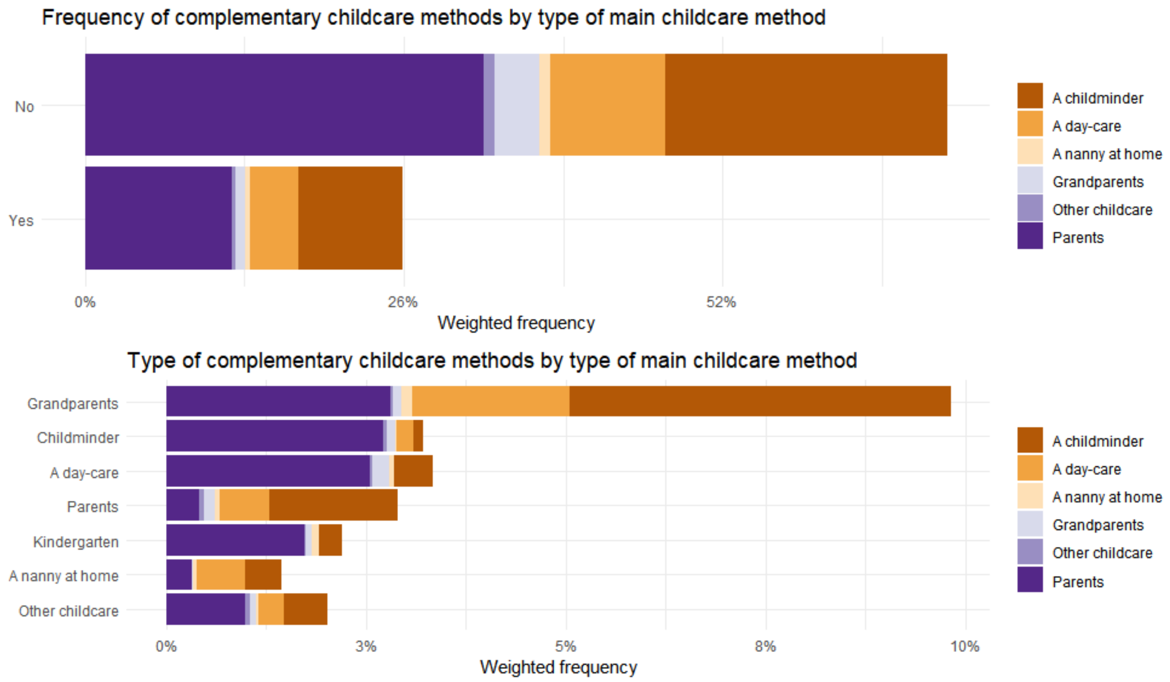
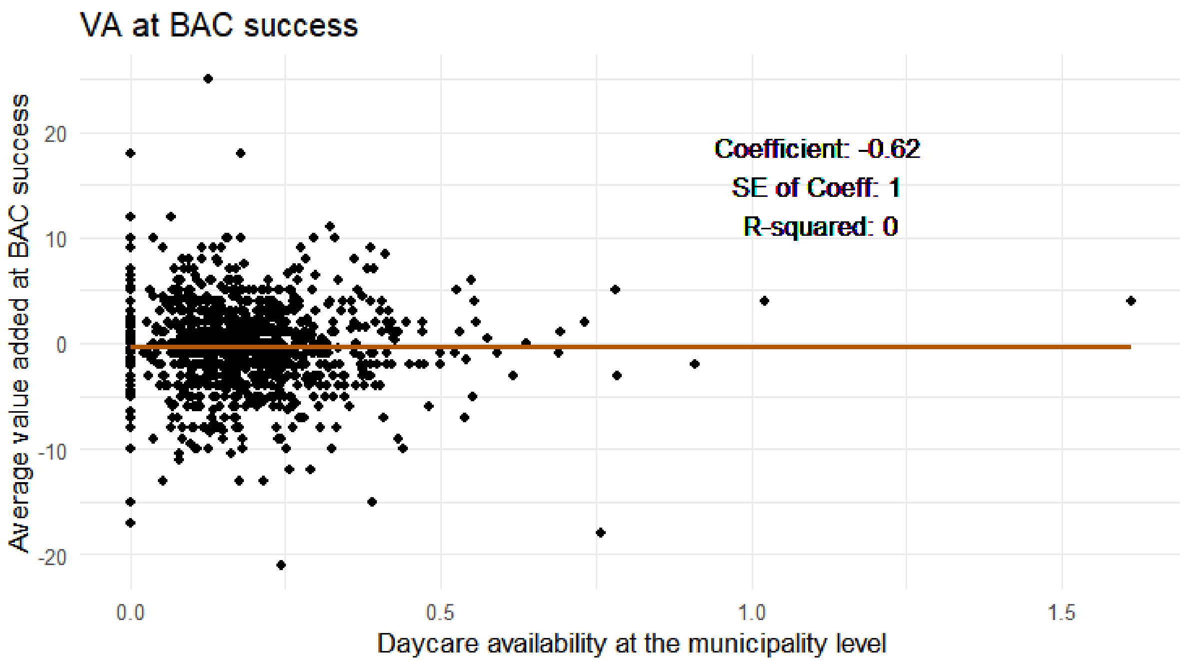


Figure 7.15: Frequency and type of complementary childcare method by type of main childcare method. Source: Elfe survey



7.2.3 Descriptive graphs from DEPP

Figure 7.16: 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).



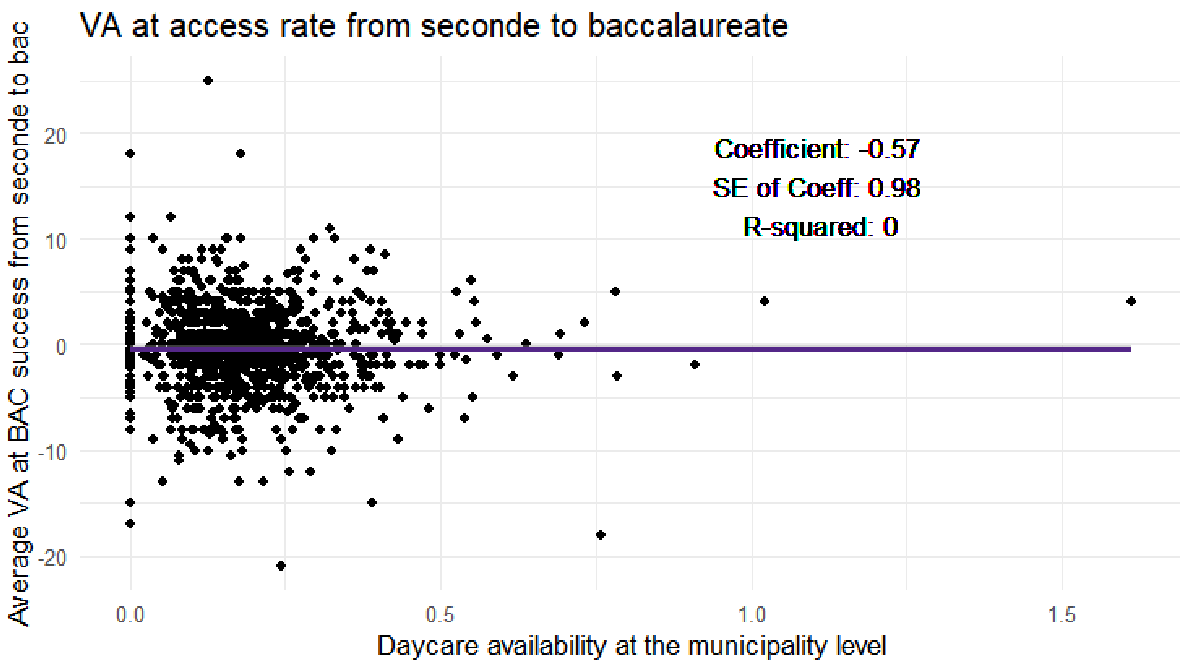


Figure 7.17: Patterns of missingness in DEPP data.

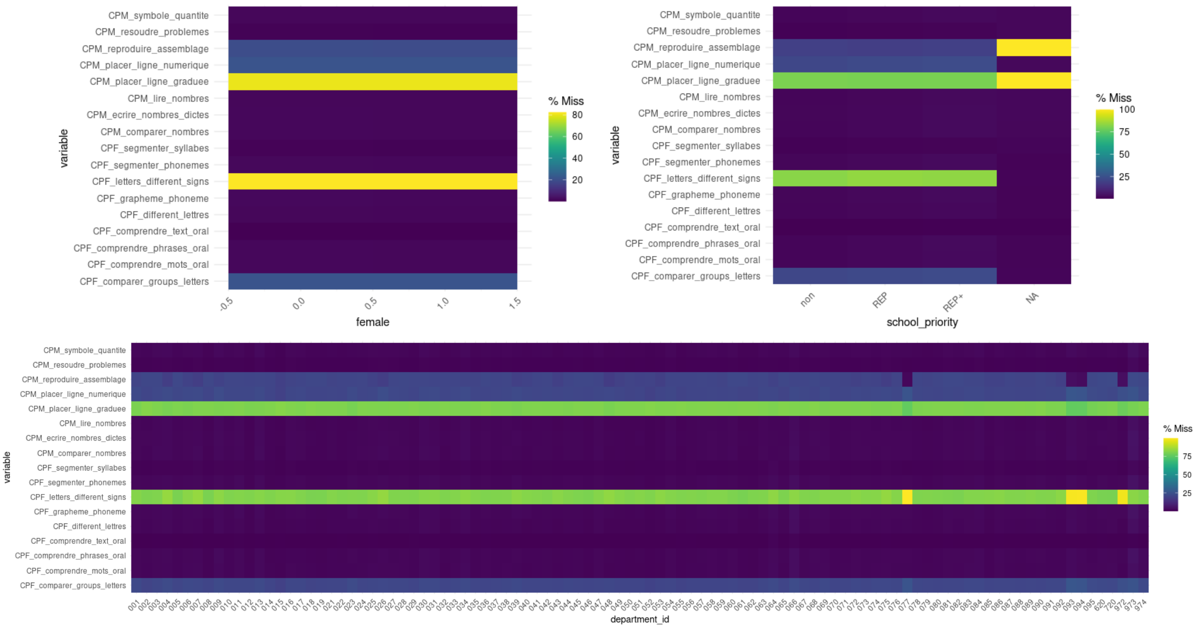


Figure 7.18: Distribution of children that are belated by one year or one year in advance. Source: DEPP.

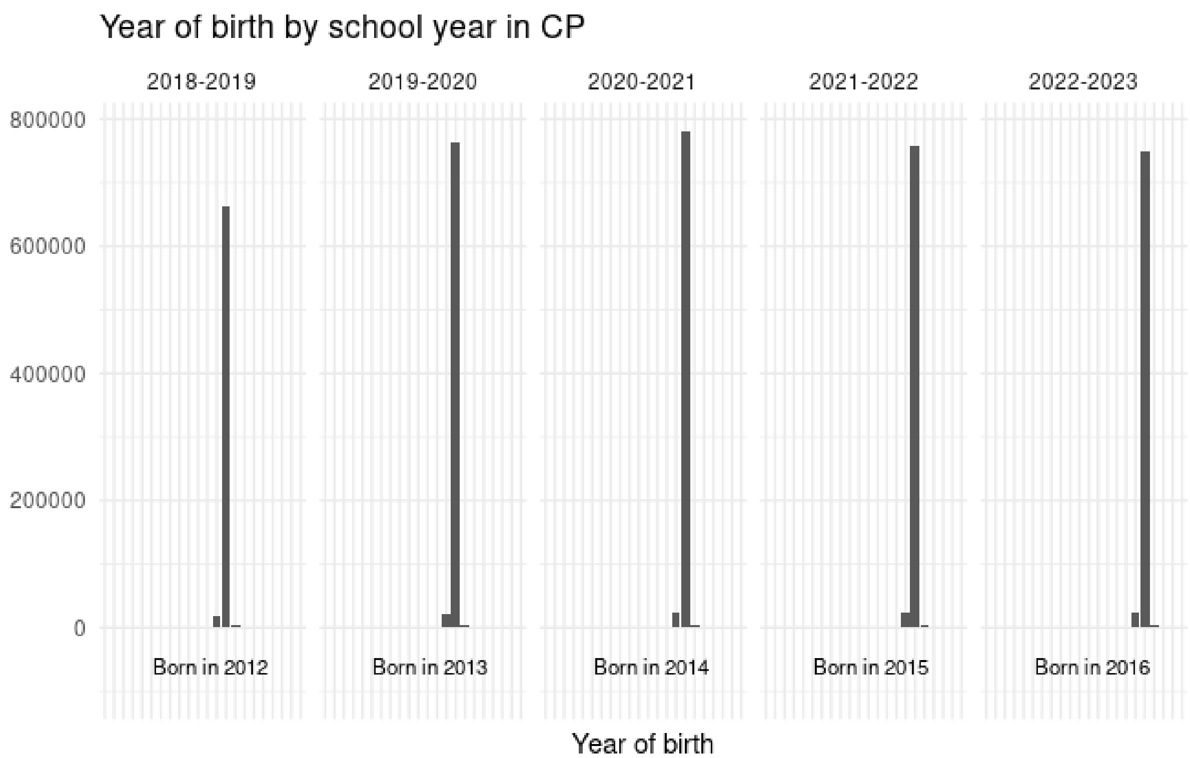


Figure 7.19: Distribution of number of children by number of insufficient items in Maths (left) and French (right). Source: DEPP.

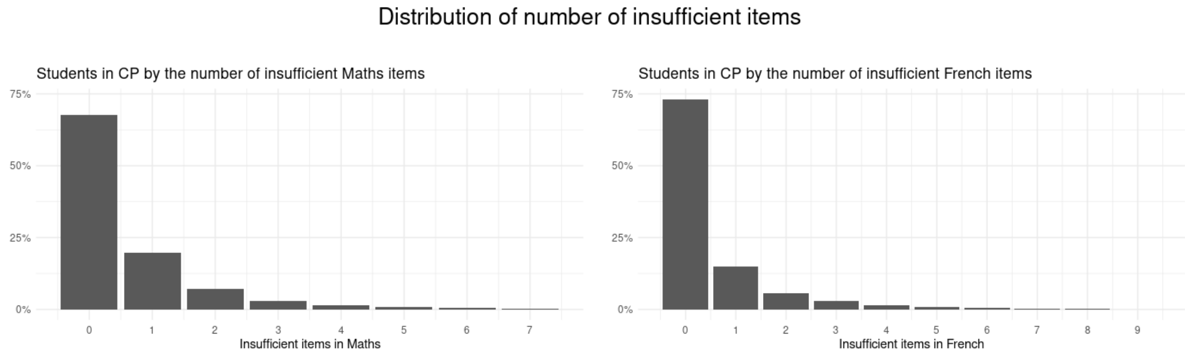
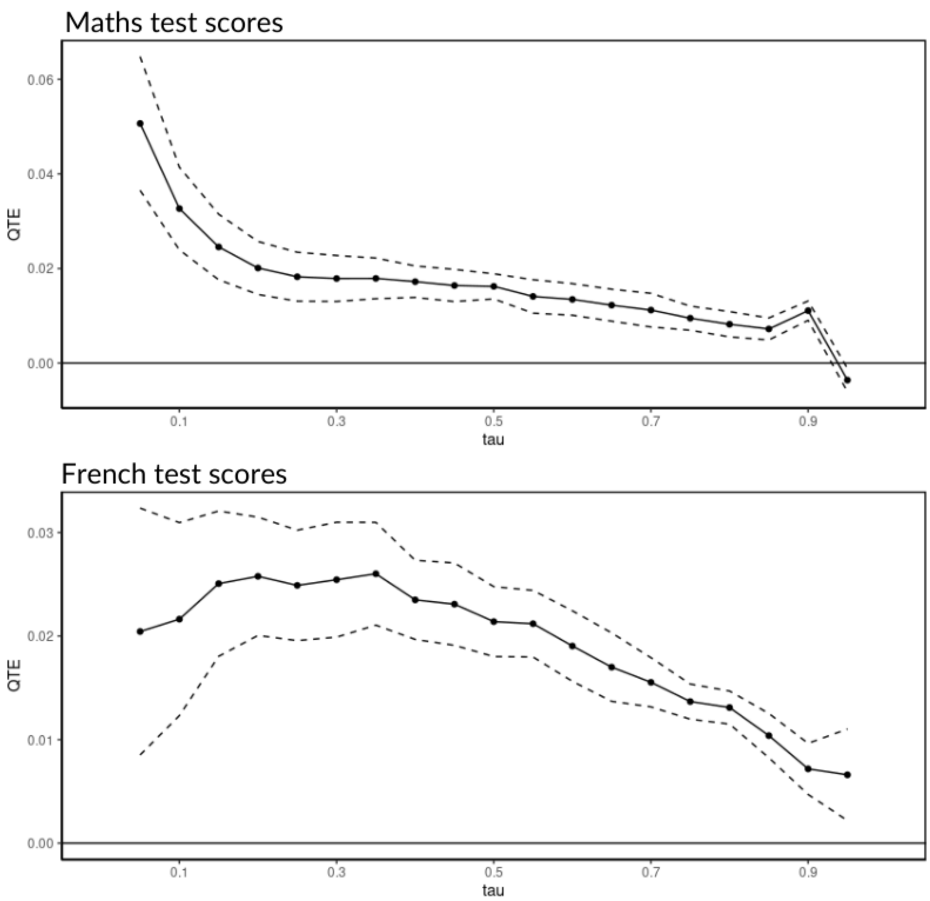


Figure 7.20: Results from the quantile regression with the binary definition of daycare availability, excluding Ile-de-France. Source: DEPP.



7.2.4 Maps

Figure 7.21: Change in daycare availability from 2011 to 2016 per French region. Source: CAF and birth registries (INSEE).

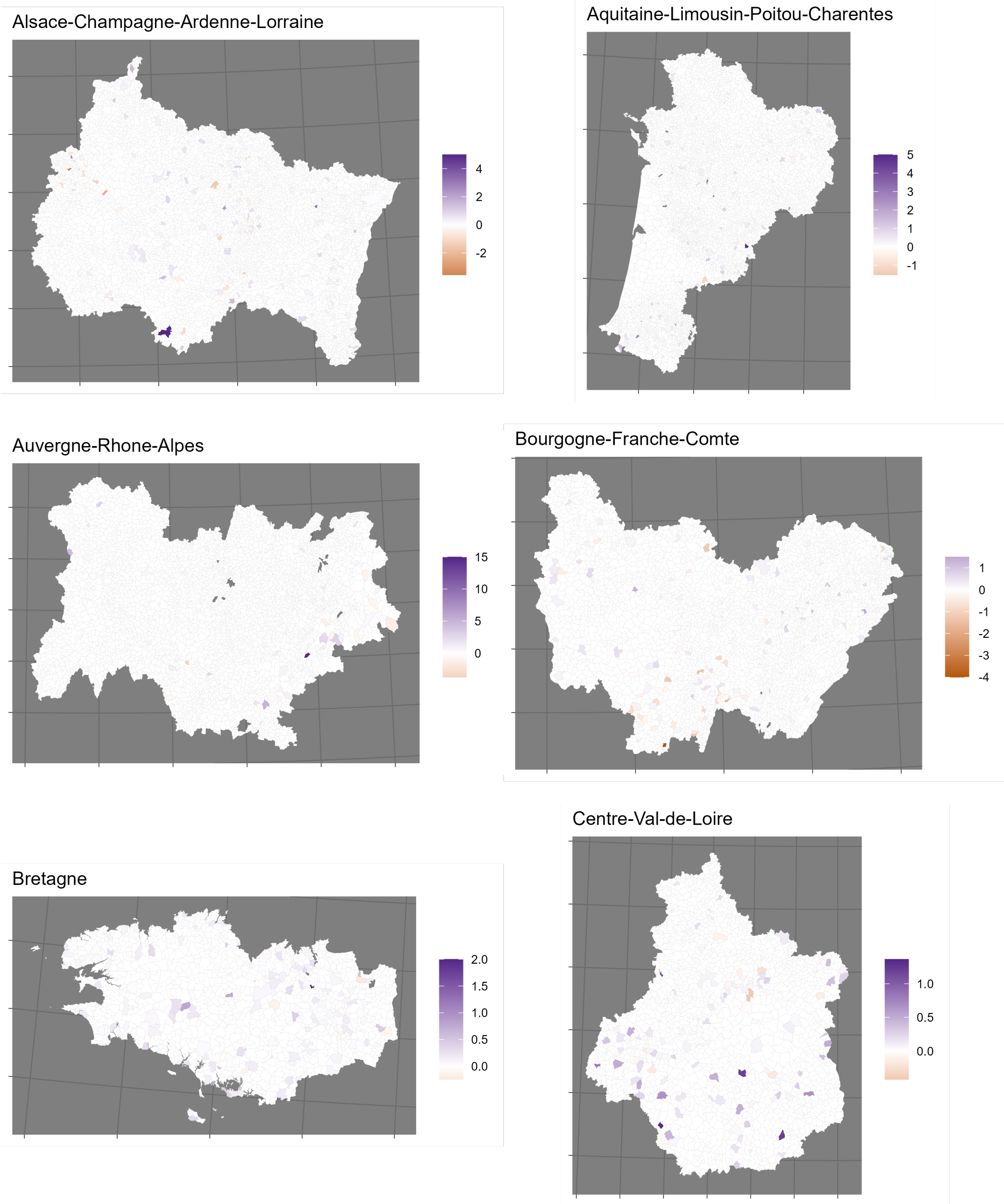
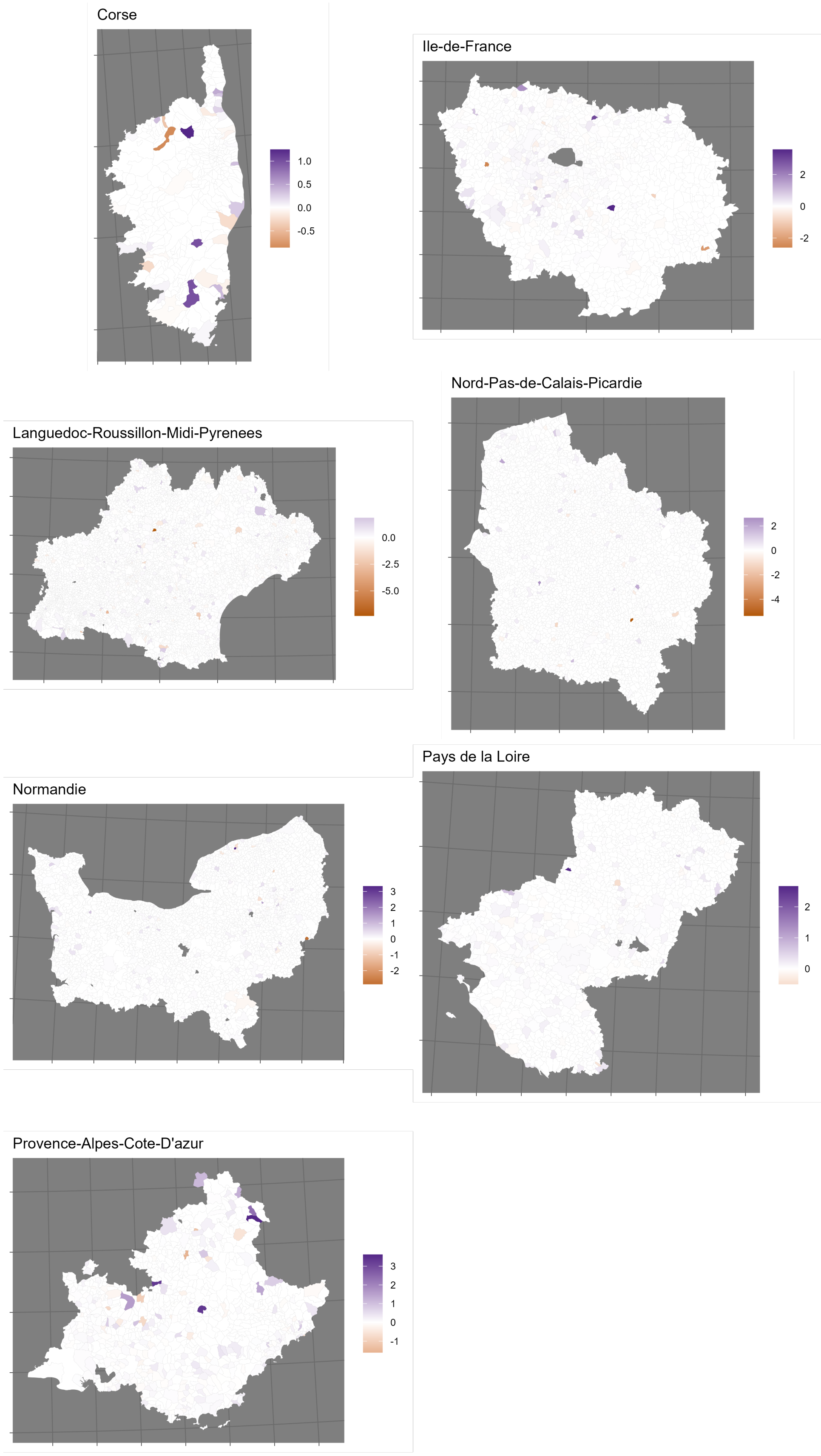


Figure 7.22: Change in daycare availability from 2011 to 2016 per French region. Source: CAF and birth registries (INSEE).



7.3 Tables

7.3.1 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

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

Dependent Variable:	Daycare				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
(Intercept)	0.1004***				
	(0.0073)				
Spring	0.0136	0.0128*	0.0130**		
	(0.0092)	(0.0070)	(0.0061)		
Availability	0.2874***	0.1870***	0.1254***	0.1863***	
	(0.0416)	(0.0307)	(0.0233)	(0.0308)	
Month of birth	-0.0034***	-0.0035***	-0.0035***		
	(0.0006)	(0.0006)	(0.0006)		
Spring × Availability	0.0750	0.0763*	0.0769**	0.0768*	0.1137***
	(0.0610)	(0.0432)	(0.0344)	(0.0432)	(0.0332)
Municipality covariates		Yes			
Fixed-effects					
Department		Yes	Yes	Yes	
Month of birth				Yes	Yes
Municipality × Year					Yes
Fit statistics					
Observations	45,480	45,480	44,429	45,480	45,480
R^2	0.02679	0.04349	0.04858	0.04419	0.21121
Within R^2		0.01218	0.01794	0.00884	0.00050
Mean DV:	0.1201	0.1201	0.1201	0.1201	0.1201

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 7.6: 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 7.7: 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).

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

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

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

Clustered (municipality level) standard-errors in parentheses

7.3.3 Robustness checks to the measure of daycare availability

Table 7.9: 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 7.10: 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 $\times$ 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 $\times$ $\mathbb{1}(Availability > 0)$					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 7.12: 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

7.3.4 Robustness checks using different first stage samples

Table 7.13: 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*

7.3.5 Robustness checks to the choice of the standard errors

Table 7.14: 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

7.3.6 Further robustness checks in the cross-sectional specification

Table 7.15: 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 7.16: 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							2.88×10^{-5}***	1.54×10^{-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 7.17: 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 $\times$ 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 7.18: 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 7.19: 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 7.20: 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 7.21: 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 7.22: 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

7.3.7 Two-sample 2SLS

Table 7.23: Variance inflation factors of the two-sample 2SLS

Variable	GVIF	Degrees of freedom	$\text{GVIF}^{(1/(2\times Df))}$
Creche generated	9.406818	1	3.067054
Month birth	1.492679	1	1.221752
female	1.023504	1	1.011684
Homeowners pct	7.658549	1	2.767408
overcrowded pct	8.356243	1	2.890717
vacant houses	1.796688	1	1.340406
LFP men 25 54	2.313422	1	1.520994
LFP women 25 54	3.592656	1	1.895430
cadres pct	4.752092	1	2.179929
% workmen	2.346207	1	1.531733
selfemployed pct	2.009751	1	1.417657
urbanization 9 cat	4.260806	8	1.094821
employees 2012 GS1 Industrie p	1.427744	1	1.194883
employees 2012 GS2 Construction p	1.451061	1	1.204600
employees 2012 GS3 Commerce p	1.693295	1	1.301267
horeca	1.874236	1	1.369027
marchands	2.402781	1	1.550090
interim	1.529744	1	1.236828
employees 2012 GS7 Services non marchands p	1.639339	1	1.280367
median income	5.401188	1	2.324046
nb libraries p	1.369607	1	1.170 leap 2014 p
1.133819	1	1.064809	
Department codes	190.201902	95	1.028007

Source. Author's calculations based on the FL survey, France, 2011, CAF daycare availability data, France, 2012-2016 and birth registries (INSEE), France, 2012-2016 and DEPP data, 2018-2023.

Table 7.24: 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

7.3.8 Quantile regressions

Table 7.25: 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 7.27: Reduced form regression: quantile regression using the binary definition of availability (Equation 8) 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 7.28: Reduced form regression: quantile regression using the binary definition of availability (Equation 8) 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

7.3.9 Heterogeneity on observables

Table 7.29: First stage regression: heterogeneity based on gender.

Dependent Variable:		Daycare	
Model:	(1) Boys	(2) Girls	(3)
Variables			
(Intercept)	0.1050***	0.0952***	0.1036***
	(0.0122)	(0.0091)	(0.0116)
Spring	-0.0013	0.0196*	-0.0006
	(0.0136)	(0.0115)	(0.0136)
Availability	0.2795***	0.2977***	0.2795***
	(0.0725)	(0.0470)	(0.0725)
Month of birth	-0.0036***	-0.0032***	-0.0034***
	(0.0008)	(0.0010)	(0.0007)
Spring × Availability	0.2188**	-0.0037	0.2188**
	(0.1001)	(0.0699)	(0.1001)
Female			-0.0069
			(0.0102)
Spring × Female			0.0196
			(0.0219)
Availability × Female			0.0182
			(0.0712)
Spring × Availability × Female			-0.2225
			(0.1527)
Fit statistics			
DV mean	0.12340	0.11679	0.12016
F-test	10.317	8.5098	4.8539

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 7.30: Reduced form regression: heterogeneity based on gender.

Dependent Variables:	Maths	French	Maths	French	Maths	French
Model:	(1) Girls	(2) Girls	(3) Boys	(4) Boys	(5)	(6)
Variables						
Spring	0.0141***	0.0183***	0.0140***	0.0168***	0.0159***	0.0188***
	(0.0015)	(0.0016)	(0.0016)	(0.0018)	(0.0015)	(0.0017)
Availability	-0.0253***	-0.0533***	-0.0097	-0.0364***	-0.0074	-0.0345***
	(0.0098)	(0.0132)	(0.0098)	(0.0133)	(0.0096)	(0.0131)
Month of birth	-0.0321***	-0.0330***	-0.0332***	-0.0342***	-0.0326***	-0.0336***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Spring × Availability	0.0116**	0.0115*	0.0155**	0.0160**	0.0155**	0.0161**
	(0.0059)	(0.0064)	(0.0064)	(0.0071)	(0.0063)	(0.0070)
Female					0.0233***	0.1281***
					(0.0011)	(0.0012)
Spring × Female					-0.0038**	-0.0026
					(0.0019)	(0.0021)
Availability × Female					-0.0204***	-0.0208***
					(0.0045)	(0.0056)
Spring × Availability × Female					-0.0039	-0.0046
					(0.0077)	(0.0084)
Fixed-effects						
Department	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,732,555	1,737,919	1,791,828	1,797,634	3,524,383	3,535,553
DV mean	0.01646	0.06678	-0.00168	-0.05612	0.00724	0.00429

Clustered (municipality level) standard-errors in parentheses

Table 7.31: First stage regression: heterogeneity based on school IPS, defining it as "high" is above the median, "low" if below.

Dependent Variable:	Daycare		
Model:	(1) High IPS	(2) Low IPS	(3)
Variables			
(Intercept)	0.1644***	0.0515***	0.0664***
	(0.0154)	(0.0064)	(0.0063)
Spring	0.0145	0.0116	0.0048
	(0.0105)	(0.0081)	(0.0082)
Availability	0.2904***	0.2275***	0.2276***
	(0.0798)	(0.0288)	(0.0287)
Month of birth	-0.0057***	-0.0013*	-0.0034***
	(0.0011)	(0.0007)	(0.0007)
Spring × Availability	0.0870	0.0615	0.0615
	(0.0532)	(0.0570)	(0.0569)
high mother ips			0.0810***
			(0.0126)
Spring × high mother ips			0.0174
			(0.0137)
Availability × high mother ips			0.0631
			(0.0816)
Spring × Availability × high mother ips			0.0254
			(0.0778)
Fit statistics			
DV mean	0.17060	0.07606	0.12091
F-test	10.280	5.7037	8.5237

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

Notes: Median = 96

Table 7.32: Reduced form regression: heterogeneity based on school IPS, defining it as "high" is above the median, "low" if below.

Dependent Variables:	Maths	French	Maths	French	Maths	French
Model:	(1) High	(2) High	(3) Low	(4) Low	(5)	(6)
Variables						
Spring	0.0128***	0.0138***	0.0089***	0.0098***	0.0185***	0.0203***
	(0.0016)	(0.0018)	(0.0023)	(0.0027)	(0.0024)	(0.0029)
Availability	0.0022	0.0037	-0.1681***	-0.2200***	-0.1884***	-0.2441***
	(0.0064)	(0.0078)	(0.0198)	(0.0278)	(0.0207)	(0.0284)
Month of birth	-0.0299***	-0.0301***	-0.0354***	-0.0360***	-0.0326***	-0.0331***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Spring × Availability	0.0136**	0.0170***	0.0342**	0.0298*	0.0344**	0.0295*
	(0.0056)	(0.0063)	(0.0134)	(0.0157)	(0.0146)	(0.0171)
high school ips					0.1902***	0.2657***
					(0.0052)	(0.0070)
Spring × high school ips					-0.0151***	-0.0165***
					(0.0029)	(0.0033)
Availability × high school ips					0.2099***	0.2695***
					(0.0219)	(0.0294)
Spring × Availability × high school ips					-0.0208	-0.0126
					(0.0156)	(0.0186)
Fixed-effects						
Department	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,381,717	1,383,689	1,360,042	1,363,131	2,747,876	2,752,948
DV mean	0.11874	0.10476	-0.10014	-0.20547	0.01023	-0.04907

Clustered (municipality level) standard-errors in parentheses

Table 7.33: First stage regression: heterogeneity based on school % of managers and teachers among parents, defining it as "high" is above the median, "low" if below.

Dependent Variable:	Daycare		
Model:	(1) High % managers	(2) Low % managers	(3)
Variables			
(Intercept)	0.1471***	0.0703***	0.0839***
	(0.0162)	(0.0058)	(0.0060)
Spring	0.0199*	0.0135**	0.0073
	(0.0112)	(0.0059)	(0.0061)
Availability	0.2136***	0.2917***	0.2917***
	(0.0660)	(0.0322)	(0.0322)
Month of birth	-0.0054***	-0.0016**	-0.0035***
	(0.0012)	(0.0007)	(0.0007)
Spring × Availability	0.0623	0.0360	0.0358
	(0.0426)	(0.0556)	(0.0556)
high % managers			0.0491***
			(0.0135)
Spring × high % managers			0.0190
			(0.0118)
Availability × high % managers			-0.0780
			(0.0733)
Spring × Availability × high % managers			0.0263
			(0.0699)
Fit statistics			
DV mean	0.16834	0.08579	0.12155
F-test	1.5829	5.3400	5.2676

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

Notes: Median = 12.8

Table 7.34: Reduced form regression: heterogeneity based on school % of managers and teachers among parents, defining it as "high" is above the median, "low" if below.

Dependent Variables:	Maths	French	Maths	French	Maths	French
Model:	(1) High	(2) High	(3) Low	(4) Low	(5)	(6)
Variables						
Spring	0.0112***	0.0145***	0.0108***	0.0129***	0.0199***	0.0224***
	(0.0015)	(0.0017)	(0.0021)	(0.0026)	(0.0019)	(0.0022)
Availability	0.0020	-0.0190*	-0.1671***	-0.2498***	-0.1886***	-0.2781***
	(0.0079)	(0.0101)	(0.0217)	(0.0313)	(0.0235)	(0.0341)
Month of birth	-0.0306***	-0.0314***	-0.0352***	-0.0365***	-0.0335***	-0.0350***
	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Spring × Availability	0.0201***	0.0220***	0.0241*	0.0223	0.0181	0.0159
	(0.0056)	(0.0057)	(0.0129)	(0.0162)	(0.0112)	(0.0134)
high PCS cadre sup ins					0.1715***	0.2393***
					(0.0054)	(0.0077)
Spring × high PCS cadre sup ins					-0.0167***	-0.0175***
					(0.0024)	(0.0026)
Availability × high PCS cadre sup ins					0.2099***	0.2833***
					(0.0244)	(0.0346)
Spring × Availability × high PCS cadre sup ins					0.0016	0.0058
					(0.0123)	(0.0143)
Fixed-effects						
Department	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,682,646	1,686,890	1,659,086	1,665,474	3,443,226	3,454,353
DV mean	0.09649	0.13203	-0.09062	-0.13540	-0.00810	-0.01645

Clustered (municipality level) standard-errors in parentheses

Table 7.35: First stage regression: heterogeneity based on school % of manual workers and unemployed parents, defining it as "high" is above the median, "low" if below.

Dependent Variable:	Daycare		
Model:	(1) High % manual workers	(2) Low % manual workers	(3)
Variables			
(Intercept)	0.0808***	0.1212***	0.1104***
	(0.0090)	(0.0144)	(0.0133)
Spring	0.0192***	-0.0010	0.0039
	(0.0063)	(0.0126)	(0.0122)
Availability	0.2157***	0.3248***	0.3251***
	(0.0546)	(0.0745)	(0.0744)
Month of birth	-0.0019**	-0.0049***	-0.0034***
	(0.0009)	(0.0010)	(0.0007)
Spring × Availability	0.0160	0.1660**	0.1657**
	(0.0289)	(0.0712)	(0.0711)
high % manual workers			-0.0189
			(0.0140)
Spring × high % manual workers			0.0104
			(0.0130)
Availability × high % manual workers			-0.1092
			(0.0924)
Spring × Availability × high % manual workers			-0.1500*
			(0.0768)
Fit statistics			
DV mean	0.09285	0.15569	0.12155
F-test	3.9429	3.5460	5.3217

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

Notes: Median = 20

Table 7.36: Reduced form regression: heterogeneity based on school % of manual workers and unemployed parents, defining it as "high" is above the median, "low" if below.

Dependent Variables:	Maths	French	Maths	French	Maths	French
Model:	(1) High	(2) High	(3) Low	(4) Low	(5)	(6)
Variables						
Spring	0.0087***	0.0094***	0.0121***	0.0169***	0.0041**	0.0073***
	(0.0025)	(0.0031)	(0.0016)	(0.0018)	(0.0017)	(0.0018)
Availability	-0.2120***	-0.3091***	0.0138*	-0.0019	0.0303***	0.0183
	(0.0244)	(0.0341)	(0.0074)	(0.0094)	(0.0089)	(0.0114)
Month of birth	-0.0352***	-0.0364***	-0.0307***	-0.0314***	-0.0335***	-0.0350***
	(0.0002)	(0.0003)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Spring × Availability	0.0409**	0.0445**	0.0141**	0.0121*	0.0139**	0.0119*
	(0.0163)	(0.0208)	(0.0058)	(0.0062)	(0.0063)	(0.0065)
high PCS workers unempl					-0.1680***	-0.2312***
					(0.0055)	(0.0075)
Spring × high PCS workers unempl					0.0143***	0.0122***
					(0.0029)	(0.0034)
Availability × high PCS workers unempl					-0.2604***	-0.3505***
					(0.0278)	(0.0390)
Spring × Availability × high PCS workers unempl					0.0179	0.0222
					(0.0171)	(0.0214)
Fixed-effects						
Department	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,659,563	1,666,047	1,682,232	1,686,381	3,443,226	3,454,353
DV mean	-0.09004	-0.13341	0.09597	0.13018	-0.00810	-0.01645

Clustered (municipality level) standard-errors in parentheses

Table 7.37: First stage regression: heterogeneity based on school median income, defining it as "high" is above the median, "low" if below.

Dependent Variable:	Daycare		
Model:	(1) High median income	(2) Low median income	(3)
Variables			
(Intercept)	0.1267***	0.0705***	0.0815***
	(0.0127)	(0.0087)	(0.0075)
Spring	0.0138	0.0164*	0.0114
	(0.0085)	(0.0089)	(0.0086)
Availability	0.2470***	0.3821***	0.3818***
	(0.0584)	(0.0454)	(0.0456)
Month of birth	-0.0050***	-0.0020**	-0.0035***
	(0.0010)	(0.0009)	(0.0007)
Spring × Availability	0.0743*	0.0586	0.0587
	(0.0418)	(0.0712)	(0.0712)
high Median income			0.0342***
			(0.0108)
Spring × high Median income			0.0074
			(0.0117)
Availability × high Median income			-0.1348*
			(0.0740)
Spring × Availability × high Median income			0.0157
			(0.0825)
Fit statistics			
DV mean	0.13893	0.10436	0.12173
F-test	4.3347	3.9495	4.5728

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

Notes: Median = 19724.19

Table 7.38: Reduced form regression: heterogeneity based on school median income, defining it as "high" is above the median, "low" if below.

Dependent Variables:	Maths	French	Maths	French	Maths	French
Model:	(1) High	(2) High	(3) Low	(4) Low	(5)	(6)
Variables						
Spring	0.0149***	0.0211***	0.0117***	0.0131***	0.0194***	0.0214***
	(0.0023)	(0.0026)	(0.0027)	(0.0030)	(0.0027)	(0.0030)
Availability	-0.0116	-0.0393***	-0.1476***	-0.2139***	-0.1760***	-0.2518***
	(0.0095)	(0.0125)	(0.0183)	(0.0244)	(0.0193)	(0.0257)
Month of birth	-0.0316***	-0.0333***	-0.0355***	-0.0378***	-0.0340***	-0.0365***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Spring × Availability	0.0082	0.0074	0.0097	0.0169	0.0058	0.0102
	(0.0101)	(0.0104)	(0.0146)	(0.0157)	(0.0150)	(0.0164)
high Rev Med Etab					0.1563***	0.2149***
					(0.0050)	(0.0064)
Spring × high Rev Med Etab					-0.0114***	-0.0089**
					(0.0036)	(0.0039)
Availability × high Rev Med Etab					0.1809***	0.2358***
					(0.0213)	(0.0279)
Spring × Availability × high Rev Med Etab					0.0032	-0.0031
					(0.0182)	(0.0192)
Fixed-effects						
Department	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	677,431	680,322	667,606	671,237	1,375,602	1,382,210
DV mean	0.07416	0.18371	-0.08998	-0.04593	-0.01370	0.06063

Clustered (municipality level) standard-errors in parentheses

Table 7.39: First stage regression: heterogeneity based on municipality type.

Dependent Variable:	Daycare			
Model:	(1) Urban	(2) Isolated	(3) Rural	(4)
Variables				
(Intercept)	0.0911***	0.0996***	0.0625***	0.0920***
	(0.0164)	(0.0117)	(0.0067)	(0.0084)
Spring	-0.0353	0.0115	0.0126*	0.0149
	(0.0219)	(0.0136)	(0.0065)	(0.0133)
Availability	0.4209***	0.4158***	0.1230***	0.4154***
	(0.1119)	(0.0379)	(0.0247)	(0.0379)
Month of birth	-0.0041***	-0.0046***	-0.0009	-0.0035***
	(0.0014)	(0.0012)	(0.0007)	(0.0007)
Spring × Availability	0.3446***	0.1209*	-0.0123	0.1211*
	(0.1282)	(0.0703)	(0.0269)	(0.0702)
Urban				-0.0052
				(0.0182)
Isolated city				-0.0311**
				(0.0125)
Rural				-0.0104
				(0.0074)
Spring × Urban				-0.0484**
				(0.0231)
Spring × Isolated city				-0.0073
				(0.0220)
Spring × Rural				-0.0109
				(0.0144)
Availability × Urban				0.0054
				(0.1181)
Availability × Isolated city				0.0429
				(0.0807)
Availability × Rural				-0.2930***
				(0.0452)
Spring × Availability × Urban				0.2236
				(0.1459)
Spring × Availability × Isolated city				-0.1347
				(0.1471)
Spring × Availability × Rural				-0.1330*
				(0.0751)
Fit statistics				
DV mean	0.15882	0.14183	0.06242	0.12147
F-test	1.5535	2.7447	2.4096	3.2527

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 7.40: Reduced form regression: heterogeneity based on municipality type.

Dependent Variables:	Maths	French	Maths	French	Maths	French	Maths	French
Model:	(1) Rural	(2) Rural	(3) Suburban	(4) Suburban	(5) Urban	(6) Urban	(7)	(8)
Variables								
Spring	0.0139***	0.0157***	0.0156***	0.0163***	0.0222***	0.0274***	0.0185***	0.0199***
	(0.0016)	(0.0018)	(0.0020)	(0.0023)	(0.0037)	(0.0039)	(0.0020)	(0.0023)
Availability	-0.0039	-0.0096	0.1353***	0.1607***	0.0861***	0.0174	0.1374***	0.1611***
	(0.0055)	(0.0067)	(0.0194)	(0.0255)	(0.0287)	(0.0452)	(0.0186)	(0.0243)
Month birth	-0.0293***	-0.0307***	-0.0335***	-0.0347***	-0.0341***	-0.0346***	-0.0327***	-0.0336***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Spring × Availability	0.0098*	0.0035	0.0003	0.0081	-0.0222	-0.0196	0.0003	0.0075
	(0.0058)	(0.0062)	(0.0079)	(0.0093)	(0.0163)	(0.0166)	(0.0078)	(0.0091)
urbanization 4 catC							-0.0635***	-0.0748***
							(0.0089)	(0.0127)
urbanization 4 catI							0.0393***	0.0503***
							(0.0079)	(0.0103)
urbanization 4 catR							0.1050***	0.1391***
							(0.0052)	(0.0069)
Spring × urbanization 4 catC							0.0090**	0.0115**
							(0.0041)	(0.0045)
Spring × urbanization 4 catI							-0.0109**	-0.0092**
							(0.0043)	(0.0047)
Spring × urbanization 4 catR							-0.0162***	-0.0142***
							(0.0025)	(0.0028)
Availability × urbanization 4 catC							-0.0806**	-0.1857***
							(0.0398)	(0.0536)
Availability × urbanization 4 catI							-0.1019***	-0.1331***
							(0.0341)	(0.0442)
Availability × urbanization 4 catR							-0.1352***	-0.1586***
							(0.0193)	(0.0250)
Spring × Availability × urbanization 4 catC							-0.0234	-0.0286
							(0.0182)	(0.0190)
Spring × Availability × urbanization 4 catI							0.0139	0.0097
							(0.0218)	(0.0228)
Spring × Availability × urbanization 4 catR							0.0099	-0.0036
							(0.0097)	(0.0108)
Fixed-effects								
Department	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	719,731	721,540	1,426,254	1,430,708	1,080,663	1,084,740	3,524,306	3,535,476
Dependent variable mean	0.10120	0.13808	-0.00688	-0.01935	-0.04606	-0.06795	0.00723	0.00429

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

Clustered (municipality level) standard-errors in parentheses

Table 7.41: First stage regression: heterogeneity based on women's labor force participation, defining it as "high" is above the median, "low" if below.

Dependent Variable:	Daycare		
Model:	(1) High WLFP	(2) Low WLFP	(3)
Variables			
(Intercept)	0.1108***	0.0932***	0.1031***
	(0.0106)	(0.0137)	(0.0127)
Spring	0.0073	0.0224***	0.0180**
	(0.0079)	(0.0076)	(0.0072)
Availability	0.3158***	0.2410***	0.2409***
	(0.0558)	(0.0825)	(0.0825)
Month of birth	-0.0048***	-0.0021**	-0.0035***
	(0.0010)	(0.0009)	(0.0007)
Spring × Availability	0.1200**	0.0141	0.0140
	(0.0519)	(0.0320)	(0.0319)
high LFP (Women 25-54)			-0.0021
			(0.0136)
Spring × high LFP (Women 25-54)			-0.0062
			(0.0100)
Availability × high LFP (Women 25-54)			0.0749
			(0.0996)
Spring × Availability × high LFP (Women 25-54)			0.1059*
			(0.0609)
Fit statistics			
DV mean	0.12867	0.11372	0.12147
F-test	6.8934	2.4696	4.7277

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). The median women LFP is 87.4% Standard errors are heteroskedasticity robust and clustered at the municipality level are reported in parentheses.

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

Table 7.42: Reduced form regression: heterogeneity based on women's labor force participation, defining it as "high" is above the median, "low" if below.

Dependent Variables:	Maths	French	Maths	French	Maths	French
Model:	(1) High WLFP	(2) High WLFP	(3) Low WLFP	(4) Low WLFP	(5)	(6)
Variables						
Spring	0.0127***	0.0159***	0.0142***	0.0170***	0.0213***	0.0242***
	(0.0013)	(0.0015)	(0.0019)	(0.0022)	(0.0018)	(0.0021)
Availability	-0.0082	-0.0298***	0.0204	0.0007	0.0338**	0.0163
	(0.0078)	(0.0099)	(0.0149)	(0.0197)	(0.0164)	(0.0210)
Month birth	-0.0306***	-0.0316***	-0.0347***	-0.0357***	-0.0327***	-0.0337***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Spring × Availability	0.0155***	0.0163***	0.0114	0.0131	0.0104	0.0118
	(0.0049)	(0.0056)	(0.0083)	(0.0093)	(0.0083)	(0.0093)
high LFP women 25 54					0.1598***	0.2203***
					(0.0044)	(0.0060)
Spring × high LFP women 25 54					-0.0156***	-0.0154***
					(0.0023)	(0.0026)
Availability × high LFP women 25 54					-0.0456**	-0.0482**
					(0.0192)	(0.0245)
Spring × Availability × high LFP women 25 54					0.0049	0.0041
					(0.0096)	(0.0108)
Fixed-effects						
Department	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,743,148	1,747,757	1,781,128	1,787,689	3,524,276	3,535,446
Dependent variable mean	0.08185	0.11269	-0.06580	-0.10169	0.00723	0.00429

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

Table 7.43: First stage regression: heterogeneity based on school % of secondary sector worker parents, defining it as "high" is above the median, "low" if below.

Dependent Variable:	Daycare		
Model:	(1) High Sec	(2) Low Sec	(3)
Variables			
(Intercept)	0.0872***	0.1069***	0.1048***
	(0.0082)	(0.0126)	(0.0104)
Spring	0.0096	0.0157**	0.0167**
	(0.0096)	(0.0071)	(0.0069)
Availability	0.3711***	0.2508***	0.2508***
	(0.0311)	(0.0653)	(0.0653)
Month of birth	-0.0032***	-0.0038***	-0.0035***
	(0.0008)	(0.0011)	(0.0007)
Spring × Availability	0.1126**	0.0542	0.0541
	(0.0556)	(0.0472)	(0.0471)
high secondary sector			-0.0153
			(0.0099)
Spring × high secondary sector			-0.0081
			(0.0116)
Availability × high secondary sector			0.1203*
			(0.0723)
Spring × Availability × high secondary sector			0.0584
			(0.0729)
Fit statistics			
DV mean	0.12223	0.12106	0.12164
F-test	3.7930	5.4355	4.6051

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

Notes: Median = 0.048

Table 7.44: Reduced form regression: heterogeneity based on school % of secondary sector worker parents, defining it as "high" is above the median, "low" if below.

Dependent Variables:	Maths	French	Maths	French	Maths	French
Model:	(1) High Sec	(2) High Sec	(3) Low Sec	(4) Low Sec	(5)	(6)
Variables						
Spring	0.0161***	0.0188***	0.0125***	0.0161***	0.0115***	0.0149***
	(0.0016)	(0.0018)	(0.0014)	(0.0017)	(0.0015)	(0.0019)
Availability	0.0308**	0.0228	-0.0014	-0.0179	-0.0107	-0.0502**
	(0.0135)	(0.0182)	(0.0104)	(0.0141)	(0.0109)	(0.0212)
Month birth	-0.0330***	-0.0340***	-0.0323***	-0.0332***	-0.0327***	-0.0336***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Spring × Availability	0.0061	0.0101	0.0160***	0.0139**	0.0164***	0.0140**
	(0.0064)	(0.0072)	(0.0062)	(0.0064)	(0.0063)	(0.0071)
high industry					-0.0667***	-0.0929***
					(0.0058)	(0.0078)
Spring × high industry					0.0058**	0.0054**
					(0.0023)	(0.0026)
Availability × high industry					0.0382**	0.0861**
					(0.0175)	(0.0384)
Spring × Availability × high industry					-0.0103	-0.0039
					(0.0088)	(0.0100)
Fixed-effects						
Department	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,757,566	1,763,463	1,766,011	1,771,281	3,523,577	3,534,744
Dependent variable mean	-0.01211	-0.01964	0.02648	0.02811	0.00723	0.00429

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

Table 7.45: First stage regression: heterogeneity based on school % of temporary worker parents, defining it as "high" is above the median, "low" if below.

Dependent Variable:	Daycare		
Model:	(1) High Temp	(2) Low Temp	(3)
Variables			
(Intercept)	0.0824***	0.0996***	0.0960***
	(0.0106)	(0.0084)	(0.0073)
Spring	-0.0125	0.0160**	0.0176***
	(0.0157)	(0.0067)	(0.0064)
Availability	0.4418***	0.2037***	0.2038***
	(0.0540)	(0.0451)	(0.0451)
Month of birth	-0.0030***	-0.0040***	-0.0035***
	(0.0011)	(0.0009)	(0.0007)
Spring × Availability	0.3068***	0.0330	0.0331
	(0.1207)	(0.0273)	(0.0278)
% temporary workers			-0.0066
			(0.0100)
Spring × % temporary			-0.0513*
			(0.0209)
Availability × % temporary			0.2360***
			(0.0702)
Spring × Availability × % temporary			0.2740*
			(0.1234)
Fit statistics			
DV mean	0.15698	0.08907	0.12164
F-test	3.2460	4.9530	5.5029

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

Notes: Median = 0.055

Table 7.46: Reduced form regression: heterogeneity based on school % of temporary worker parents, defining it as "high" is above the median, "low" if below.

Dependent Variables:	Maths	French	Maths	French	Maths	French
Model:	(1) High Temp	(2) High Temp	(3) Low Temp	(4) Low Temp	(5)	(6)
Variables						
Spring	0.0202***	0.0210***	0.0135***	0.0163***	0.0086***	0.0120***
	(0.0030)	(0.0034)	(0.0012)	(0.0013)	(0.0012)	(0.0013)
Availability	0.3249***	0.3724***	-0.0051	-0.0187**	-0.0040	-0.0152*
	(0.0382)	(0.0487)	(0.0063)	(0.0079)	(0.0066)	(0.0083)
Month birth	-0.0343***	-0.0351***	-0.0312***	-0.0324***	-0.0327***	-0.0336***
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Spring × Availability	-0.0185	-0.0016	0.0128***	0.0088*	0.0128***	0.0087*
	(0.0124)	(0.0136)	(0.0049)	(0.0053)	(0.0049)	(0.0052)
High temporary					-0.1772***	-0.2333***
					(0.0081)	(0.0108)
Spring × High temporary					0.0175***	0.0143***
					(0.0031)	(0.0035)
Availability × High temporary					0.3074***	0.3593***
					(0.0365)	(0.0459)
Spring × Availability × High temporary					-0.0318**	-0.0113
					(0.0133)	(0.0145)
Fixed-effects						
Department	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,646,085	1,651,924	1,877,492	1,882,820	3,523,577	3,534,744
Dependent variable mean	-0.05235	-0.08005	0.05948	0.07828	0.00723	0.00429

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

Table 7.47: First stage regression: heterogeneity based on school % of tertiary sector worker parents, defining it as "high" is above the median, "low" if below.

Dependent Variable:	Daycare		
Model:	(1) High Ter	(2) Low Ter	(3)
Variables			
(Intercept)	0.0865***	0.0921***	0.0952***
	(0.0102)	(0.0083)	(0.0071)
Spring	-0.0084	0.0138**	0.0124**
	(0.0159)	(0.0063)	(0.0061)
Availability	0.4589***	0.1919***	0.1918***
	(0.0513)	(0.0413)	(0.0413)
Month of birth	-0.0039***	-0.0031***	-0.0035***
	(0.0011)	(0.0009)	(0.0007)
Spring × Availability	0.2219***	-0.0081	-0.0080
	(0.0849)	(0.0255)	(0.0255)
high other tertiary sector			-0.0118
			(0.0097)
Spring × high other tertiary sector			-0.0194
			(0.0159)
Availability × high other tertiary sector			0.2670***
			(0.0659)
Spring × Availability × high other tertiary sector			0.2302***
			(0.0886)
Fit statistics			
DV mean	0.15920	0.08801	0.12164
F-test	3.1522	4.1225	5.8130

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

Notes: Median = 0.094

Table 7.48: First stage regression: heterogeneity based on school % of tertiary sector worker parents, defining it as "high" is above the median, "low" if below.

Dependent Variables:	Maths	French	Maths	French	Maths	French
Model:	(1) High Ter	(2) High Ter	(3) Low Ter	(4) Low Ter	(5)	(6)
Variables						
Spring	0.0207***	0.0223***	0.0127***	0.0162***	0.0093***	0.0135***
	(0.0023)	(0.0026)	(0.0013)	(0.0014)	(0.0013)	(0.0014)
Availability	0.1581***	0.1663***	-0.0173**	-0.0315***	-0.0135*	-0.0240**
	(0.0185)	(0.0246)	(0.0076)	(0.0096)	(0.0081)	(0.0104)
Month birth	-0.0337***	-0.0345***	-0.0316***	-0.0328***	-0.0327***	-0.0336***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Spring × Availability	-0.0137	-0.0029	0.0123**	0.0076	0.0124**	0.0079
	(0.0086)	(0.0096)	(0.0060)	(0.0065)	(0.0060)	(0.0064)
High stable tertiary					-0.1121***	-0.1441***
					(0.0063)	(0.0086)
Spring × High stable tertiary					0.0149***	0.0117***
					(0.0026)	(0.0030)
Availability × High stable tertiary					0.1649***	0.1757***
					(0.0200)	(0.0259)
Spring × Availability × High stable tertiary					-0.0255**	-0.0102
					(0.0105)	(0.0115)
Fixed-effects						
Department	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,757,764	1,763,792	1,765,813	1,770,952	3,523,577	3,534,744
Dependent variable mean	-0.02809	-0.04576	0.04240	0.05413	0.00723	0.00429

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

7.3.10 Longitudinal specification and counterfactual type of care

Table 7.49: Margins of adjustment of changes in daycare availability and changes in the instrument

Dependent Variables:	Daycare	Childminder	Parents	Grandparents
Model:	(1)	(2)	(3)	(4)
Panel A: Only availability				
Variables				
(Intercept)	0.0813***	0.2964***	0.5354***	0.0642***
	(0.0077)	(0.0105)	(0.0070)	(0.0021)
Availability	0.3065***	-0.2843***	-0.0480	-0.0335***
	(0.0590)	(0.0620)	(0.0363)	(0.0107)
Fit statistics				
DV mean	0.12016	0.28026	0.51515	0.05657
F-test	32.663	15.920	0.34324	0.74251
Panel B: Instrument				
(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

Clustered (municipality level) standard-errors in parentheses

Table 7.50: Robustness of the robust to the exclusion of the year when parental care was not still available (2013).

Dependent Variables:	Maths mean	French mean	Maths mean	French mean	Math mean	French mean	Math mean	French mean
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Availability	0.0080	0.0158**	0.0056	0.0148*				
	(0.0063)	(0.0065)	(0.0073)	(0.0078)				
Daycare avail. (EPCI)					0.0527*	0.2064***	0.0552*	0.2071***
					(0.0309)	(0.0609)	(0.0313)	(0.0612)
Fixed-effects								
insee commune	Yes	Yes	Yes	Yes				
siren epci 16					Yes	Yes	Yes	Yes
Fit statistics								
Observations	69,579	69,580	66,876	66,877	69,043	69,043	68,357	68,357
Dependent variable mean	0.09046	0.06380	0.09048	0.06399	0.04519	0.00256	0.04509	0.00236

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

Table 7.51: Municipality fixed effects specifications: Reduced form evidence of the daycare openings and closings instrument

Dependent Variables:	Maths mean		French mean	
Model:	(1)	(2)	(3)	(4)
Variables				
Δ daycare avail. for openings or closing	-0.0338	-0.0311	-0.0512**	-0.0520**
	(0.0243)	(0.0253)	(0.0202)	(0.0208)
Parental		-0.0145*		-0.0358***
		(0.0078)		(0.0088)
Fixed-effects				
Municipality	Yes	Yes	Yes	Yes
Fit statistics				
Observations	69,635	66,921	69,636	66,922
DV mean	0.09041	0.09043	0.06379	0.06395

Clustered (municipality level) standard-errors in parentheses

Table 7.52: Robustness of the municipality fixed effect specification to the measure of skills: using ranks

Dependent Variables:	MathsRanks	French Ranks	MathsRanks (EPCI)	French Ranks (EPCI)
Model:	(1)	(2)	(3)	(4)
Variables				
Daycare avail.	-0.0005	0.0038*		
	(0.0016)	(0.0021)		
Parental	0.0018	-0.0102***		
	(0.0015)	(0.0024)		
Daycare avail. (EPCI)			$4.62 \times 10^{-5***}$	$-6.31 \times 10^{-5***}$
			(3.42×10^{-6})	(9.79×10^{-6})
Parental (EPCI)			0.0396***	-0.1014***
			(0.0044)	(0.0085)
Fixed-effects				
Municipality	Yes	Yes		
EPCI			Yes	Yes
Fit statistics				
Observations	66,876	66,877	68,881	68,881
DV mean	0.34317	0.44200	0.33471	0.42619

Clustered (municipality level) standard-errors in parentheses

Table 7.53: Robustness of the municipality fixed effect specification to the time dimension: using year FE, excluding tests in September 2020, using serially correlated standard errors

Dependent Variables:	Maths mean	French mean	Maths mean	French mean	Maths mean	French mean
Model:	(1) Year FE	(2) Year FE	(3) No 2020	(4) No 2020	(5) Serial corr.	(6) Serial corr.
Variables						
Daycare avail.	0.0005	0.0040	0.0097	0.0181***	0.0056	0.0148
	(0.0071)	(0.0084)	(0.0091)	(0.0069)	(0.0078)	(0.0099)
Parental	-0.0021	-0.0044	-0.0121	-0.0362***	-0.0142	-0.0358**
	(0.0077)	(0.0083)	(0.0091)	(0.0102)	(0.0077)	(0.0085)
Fixed-effects						
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
year birth	Yes	Yes				
Fit statistics						
Observations	66,876	66,877	49,702	49,702	66,876	66,877
DV mean	0.09048	0.06399	0.10357	0.08827	0.09048	0.06399

Clustered (municipality level) standard-errors in parentheses

Table 7.54: Robustness of the EPCI fixed effect specification to the time dimension: using year FE, excluding tests in September 2020, using serially correlated standard errors

Dependent Variables:	Maths mean	French mean	Maths mean	French mean	Maths mean	French mean
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Daycare avail. (EPCI)	-0.0447**	0.0050	0.0407	0.1604***	0.0372	0.1564***
	(0.0219)	(0.0186)	(0.0296)	(0.0505)	(0.0174)	(0.0237)
Parental (EPCI)	0.0337*	0.0113	-0.1176***	-0.3441***	-0.1190***	-0.3361***
	(0.0198)	(0.0215)	(0.0232)	(0.0335)	(0.0099)	(0.0126)
Fixed-effects						
EPCI	Yes	Yes	Yes	Yes	Yes	Yes
year birth	Yes	Yes				
Fit statistics						
Observations	68,357	68,357	51,069	51,069	68,357	68,357
DV mean	0.04509	0.00236	0.05877	0.02644	0.04509	0.00236

Clustered (municipality level) standard-errors in parentheses

Table 7.55: Municipality fixed effect specification: aggregating test scores for children born in the municipality or EPCI in spring or not.

Dependent Variables:	Maths mean in spring	French mean in spring	Maths mean not in spring	French mean not in spring	Maths mean in spring	French mean in spring	Maths mean not in spring	French mean not in spring
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Daycare avail.	-0.0137	0.0098	0.0082	0.0169**				
	(0.0129)	(0.0185)	(0.0088)	(0.0071)				
Parental	-0.0153	-0.0225*	-0.0124	-0.0400***				
	(0.0117)	(0.0131)	(0.0089)	(0.0098)				
Daycare avail. (EPCI)					0.0634**	0.2217***	0.0283	0.1402**
					(0.0298)	(0.0598)	(0.0322)	(0.0556)
Parental (EPCI)					-0.1198***	-0.2851***	-0.1261***	-0.3571***
					(0.0328)	(0.0437)	(0.0240)	(0.0324)
Fixed-effects								
Municipality	Yes	Yes	Yes	Yes				
EPCI					Yes	Yes	Yes	Yes
Fit statistics								
Observations	61,763	61,777	66,602	66,603	68,317	68,317	68,355	68,355
DV mean	0.17480	0.14997	0.06373	0.03602	0.13557	0.09585	0.01625	-0.02745

Clustered (municipality level) standard-errors in parentheses

Table 7.56: Municipality fixed effect specification: checks for skewness of the daycare availability variable.

Dependent Variables:	Maths mean	French mean	Maths mean	French mean	Maths mean	French mean	Maths mean	French mean	Maths mean	French mean
Model:	(1) Baseline	(2) Baseline	(3) Log	(4) Log	(5) Asinh	(6) Asinh	(7) No 0.001% outliers	(8) No 0.001% outliers	(9) No 0.01% outliers	(10) No 0.01% outliers
Variables										
Daycare avail.	0.0056	0.0148^{*}					0.0328^{*}	0.0418^{***}	0.0328^{*}	0.0418^{***}
	(0.0073)	(0.0078)					(0.0179)	(0.0144)	(0.0179)	(0.0144)
Parental	-0.0142^{*}	-0.0358^{***}	-0.0142^{*}	-0.0358^{***}	-0.0142^{*}	-0.0358^{***}	0.0002	-0.0204	0.0002	-0.0204
	(0.0078)	(0.0088)	(0.0078)	(0.0088)	(0.0078)	(0.0088)	(0.0154)	(0.0169)	(0.0154)	(0.0169)
log(Daycare avail.+1)			0.0192	0.0541^{**}						
			(0.0224)	(0.0221)						
asinh(Daycare avail.)					0.0152	0.0434^{**}				
					(0.0181)	(0.0180)				
Fixed-effects										
Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics										
Observations	66,876	66,877	66,876	66,877	66,876	66,877	17,683	17,683	17,683	17,683
DV mean	0.09048	0.06399	0.09048	0.06399	0.09048	0.06399	0.04354	0.00294	0.04354	0.00294

Clustered (municipality level) standard-errors in parentheses

Table 7.57: EPCI fixed effect specification: checks for skewness of the daycare availability variable.

Dependent Variables:	Maths mean	French mean	Maths mean	French mean	Maths mean	French mean	Maths mean	French mean	Maths mean	French mean
Model:	(1) Baseline	(2) Baseline	(3) Log	(4) Log	(5) Asinh	(6) Asinh	(7) No 0.001% outliers	(8) No 0.001% outliers	(9) No 0.01% outliers	(10) No 0.01% outliers
Variables										
Daycare avail. (EPCI)	$-7.7 \times 10^{-5***}$	-0.0002^{***}					-0.0002^{***}	-0.0004^{***}	-0.0004^{**}	-0.0013^{***}
	(1.37×10^{-5})	(3.2×10^{-5})					(3.41×10^{-5})	(7.11×10^{-5})	(0.0002)	(0.0005)
Parental (EPCI)	-0.1247^{***}	-0.3502^{***}	-0.1247^{***}	-0.3503^{***}	-0.1246^{***}	-0.3501^{***}	-0.1354^{***}	-0.3609^{***}	-0.1350^{***}	-0.3608^{***}
	(0.0215)	(0.0304)	(0.0215)	(0.0304)	(0.0215)	(0.0304)	(0.0263)	(0.0386)	(0.0264)	(0.0389)
log(Daycare avail. +1), EPCI			-0.0011	-0.0018						
			(0.0024)	(0.0077)						
asinh(Daycare avail.), EPCI					-0.0012	-0.0023				
					(0.0018)	(0.0059)				
Fixed-effects										
EPCI	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics										
Observations	68,881	68,881	68,881	68,881	68,881	68,881	60,086	60,086	60,024	60,024
DV mean	0.04435	0.00122	0.04435	0.00122	0.04435	0.00122	0.03989	-0.00485	0.03989	-0.00485

Clustered (municipality level) standard-errors in parentheses

Table 7.58: Municipality fixed effect specification: dividing the sample by type of urbanization.

Dependent Variables:	Maths mean	French mean	Maths mean	French mean	Maths mean	French mean
Model:	(1) Rural	(2) Rural	(3) Suburban	(4) Suburban	(5) Urban	(6) Urban
Variables						
Daycare avail.	0.0050	0.0125	0.0105	0.0085	-0.0307	0.1830***
	(0.0079)	(0.0084)	(0.0130)	(0.0145)	(0.0536)	(0.0642)
Parental	-0.0062	-0.0234**	-0.0297*	-0.0692***	-0.0343*	-0.0426*
	(0.0101)	(0.0113)	(0.0165)	(0.0185)	(0.0181)	(0.0218)
Fixed-effects						
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	41,613	41,614	15,587	15,587	5,597	5,597
DV mean	0.11081	0.09350	0.07594	0.04118	0.01030	-0.04951

Clustered (municipality level) standard-errors in parentheses

Table 7.59: Municipality fixed effect specification: dividing the sample by high and low women aged 25-54 labor force participation.

Dependent Variables:	Maths mean	French mean	Maths mean	French mean
Model:	(1) High FL FP	(2) High FLFP	(3) Low FLFP	(4) Low FLFP
Variables				
Daycare avail.	0.0072	0.0115	0.0048	0.0165
	(0.0084)	(0.0102)	(0.0100)	(0.0110)
Parental	-0.0139	-0.0448***	-0.0146	-0.0279**
	(0.0115)	(0.0126)	(0.0107)	(0.0123)
Fixed-effects				
Municipality	Yes	Yes	Yes	Yes
Fit statistics				
Observations	33,415	33,416	33,446	33,446
DV mean	0.13062	0.12222	0.05035	0.00579

Clustered (municipality level) standard-errors in parentheses

Table 7.60: Municipality fixed effect specification: dividing the sample by above and below the median population municipalities.

Dependent Variables:	Maths mean	French mean	Maths mean	French mean
Model:	(1) Above median	(2) Above median	(3) Below median	(4) Below median
Variables				
Daycare avail.	0.0232*	0.0550***	0.0027	0.0082
	(0.0132)	(0.0212)	(0.0078)	(0.0086)
Parental	-0.0266***	-0.0532***	-0.0054	-0.0238*
	(0.0089)	(0.0106)	(0.0118)	(0.0130)
Fixed-effects				
Municipality	Yes	Yes	Yes	Yes
Fit statistics				
Observations	33,825	33,825	33,028	33,029
DV mean	0.06447	0.02857	0.11711	0.10027

Clustered (municipality level) standard-errors in parentheses

Table 7.61: 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.

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 7.62: 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 7.63: 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 7.64: 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 7.65: Reduced form regression: using more granular skills for Maths.

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

Clustered (municipality level) standard-errors in parentheses

Table 7.66: Reduced form regression: using more granular skills for French.

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

Clustered (municipality level) standard-errors in parentheses

Table 7.67: 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 7.11: 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 7.26: Reduced form regression: quantile regression using the continuous definition of availability (Equation 3).

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)