Three essays in Health and Labour Economics

A thesis submitted for the degree of Doctor of Philosophy in Economics

by

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Declarations

No part of this thesis has been submitted for another degree.

Chapter 3 is co-authored with Dr. Birgitta Rabe. The other chapters in this thesis are exclusively mine.

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Summary

This thesis contains three studies that focus on childcare availability, maternal labour supply and children's health.

Chapter 1 analyses the impact of extending childcare availability on maternal labour outcomes in Russia. I exploit a substantial variation in childcare availability across regions over time. Based on survey data linked to administrative data on the number of enrolled children at each age in every region, I find that an increase in childcare availability has a positive and significant effect on maternal employment both at the intensive and the extensive margins. I also find that the effect of childcare availability on labour force participation of single mothers is significantly lower than on mothers with partners.

Chapter 2 investigates the effect of maternal employment on childhood obesity in Russia. I use a plausibly exogenous variation in childcare availability for the youngest child in the household as an instrumental variable for maternal employment to estimate the effect of maternal employment on the weight outcomes of older children. The results show that maternal employment leads to an increase in children's BMI z-score and probabilities to become overweight and obese. Exploring potential underlying mechanisms, I find that maternal employment is related to less physical activity and poorer dietary habits.

Chapter 3 estimates whether providing parents information about the weight status of their child has its intended effects – increasing physical activity, reducing sedentary activity, increasing consumption of healthy food and consequently reducing obesity rates – or whether it has unintended consequences. Based on the National Child Measurement Programme, we find that in the short-run feedback letters do not reach their intended effects, but instead cause adverse effects such as a tendency to skip breakfast and feeling tired and unhappy at school among overweight children, especially among overweight children from low socio-economic background.

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Introduction

Over the past decades, many developed countries have introduced policies to increase public childcare provision and availability. There are two main goals behind this: first, to help mothers maintain a work-family life balance and, subsequently, to increase their labour force participation and, second, to promote early childcare education and development. Indeed, in many countries, research shows that an affordable and accessible childcare system can play a significant role in helping mothers of young children to increase their labour force participation (Cattan, 2016). In Russia, the childcare system has been facing many challenges over the past 25 years. After the disintegration of the USSR, the number of pre-school organisations offering childcare has decreased significantly from 87,573 in 1991 to 51,329 in 2000. This was partly due to a sharp reduction in the fertility rate and partly due to the financial and economic crisis in the country. In 2000, the fertility rate in Russia started recovering, but the reduction in childcare provision continued. This implied that the availability of childcare turned out to be one of the most important problems for families with small children.

Due to the large scale of the problem, the regional governments have put efforts into extending childcare availability. Thus, between 2000 and 2015, Russia experienced an increase in childcare enrolment from 55.0% to 66.3%, reflecting an increase in childcare availability that was rolled out unequally across the Russian regions - the enrolment rate has increased from less than 1% in some regions to almost 35% in other regions. In Chapter 1, I exploit this substantial variation in childcare availability across regions over time to evaluate the impact of extending childcare availability on mothers' labour outcomes. The analysis is based on individual-level data from the Russian Longitudinal Monitoring Survey – Higher School of Economics (RLMS-HSE), which is a national representative panel of households in Russia, and a unique dataset on the number of enrolled children at each age in every region. I find that an increase in childcare availability has a positive and significant effect on maternal employment both at the intensive and extensive margins. In particular, the estimates imply that in Russia between 2000 and 2015 the expansion of childcare availability increased maternal labour force participation by 3.4%, maternal employment by 2.8% and maternal full-time employment by 2.2%. The heterogeneity analysis shows that the effect on the labour force participation is smaller among single mothers while in some western countries an opposite effect has been found. A set of robustness checks confirm the validity of the identification strategy and the results.

In Chapter 2, I further investigate the increase in maternal employment in Russia and study the effect of maternal employment on childhood obesity. The prevalence of obesity among children is considered a major public health concern in many developing and developed countries. The statistics on childhood obesity in Russia are alarming. According to the Health Behaviour in School-aged Children (HBSC) survey (WHO, 2017), the level of obesity in Russia was the lowest in 2002 across HBSC countries[1]. However, it has had the highest grow both among girls and boys during the following next 12 years. According to the last estimates of the Ministry of Health of the Russian Federation, in Russia around 15-20% of children and adolescents are overweight and 5-10% are obese.

Another notable trend in Russia is an increase of employment among women over the past two decades. During the 1990s, after the collapse of the Soviet Union and emergence of the Russian Federation, the employment rate among women of prime working age dramatically diminished from 77.6% in 1992 to 63.5% in 1998. However, the overall economic growth in Russia in 2000s led to a significant increase in the female employment rate up to 73.4% in 2016. In this chapter, I investigate whether the increase in maternal employment has contributed to the increase in childhood overweight and obesity.

To address the endogeneity of maternal employment I use a plausibly exogenous variation in childcare availability across regions over time for the youngest child in the household as an instrumental variable for maternal employment to estimate the effect of maternal employment on the weight outcomes of older children. This approach is built on findings that mothers increase labour supply when their youngest child becomes eligible for or enroll in public school/childcare. The analysis is based on an individual level dataset, the Russian Longitudinal Monitoring Survey – Higher School of Economics (RLMS-HSE), which is a national representative panel of households in Russia. For the analysis, I construct a sample of children between 6 and 13 years old in the time-period between 2000 and 2017 who have at least one sibling and the youngest sibling's age falls in the 0-6 age range. The rich nature of the data also allows me to study the mechanisms, i.e. the income and time effects, through which maternal employment can affect children's weight outcomes. For this, I use physical activity, sedentary behaviour and healthy dietary habits outcomes.

The results suggest that maternal employment has a causal impact on children's weight in terms of BMI z-score and probabilities to become overweight and obese. The heterogeneity

[1] HBSC countries: Austria, Belgium, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, the Netherlands, Norway, Poland, Portugal, Russia, Slovenia, Spain, Sweden, Switzerland, Macedonia, Ukraine.

analysis shows that the effects seems to be driven by mothers of upper-middle socio-economic status, mothers with partners, mothers working full-time, and mothers whose families live in urban areas. Exploring potential underlying mechanisms, I find that maternal employment causes a higher consumption of prepared/semi-prepared meat and a higher probability of eating out as well as a decrease in physical activity. Thus, the findings suggest that both an unhealthy diet and a reduction in physical activity may explain the adverse effect of maternal employment on children's weight outcomes.

In Chapter 3, we study childhood overweight and obesity in England, where in the 2018/19 school year, almost one in four children was overweight or obese when they started school at age 4-5, and more than one in three children by the time they left primary school at age 11 (NHS Digital, 2019). The National Child Measurement Programme (NCMP) is an important element of the Government's strategy to tackle the rise in childhood obesity. Established in 2005 as a child-level health surveillance programme, the NCMP annually weighs and measures children in Reception Year (aged 4-5 years) and Year 6 (aged 10-11 years). From 2008, in order to raise awareness of unhealthy body weight, the programme began delivering feedback letters to all parents/carers. This includes information on child's height, weight, body weight status (underweight/healthy weight/overweight/very overweight), information on potential health risks of being overweight, and a wide range of additional information (a leaflet, a phone number to contact back school nurses, information about local weight management services and links to websites providing further information and advice).

In this chapter, we investigate whether providing parents information about the weight status of their children modifies children's health and health-related behaviour or has any adverse effects. In our main analysis, based on the Millennium Cohort Study (MCS), we provide comprehensive evidence on the impact of sending feedback letters on adiposity-related outcomes, behavioural outcomes related to energy balance (physical activity, sedentary behaviour and fruit intake), and adverse effects (psychological outcomes and unhealthy eating behaviours) of the intervention. We apply a difference-in-difference approach that takes advantage of the fact that one of the data collection years of the MCS took place when children were weighed and measured for the NCMP in their last year in primary school (Year 6). The research design relies on a comparison of the dates of the MCS interview and the dates at which children were measured in their schools through the NCMP. We assign every child either into a treatment or control group by comparing the date of interview and the date of the NCMP measurement: children who were weighed and measured through the NCMP in the time before the day of their MCS interview are in the treatment group because their parents will have received the weight information by the time of the interview, while children who are still to be weighed and measured at the point of the MCS interview are in the control group as their parents are yet to receive the letters.

Our main results show that in the short run the intended positive effects of the feedback letters do not show up in the outcome measures available to us: adiposity-related outcomes such as BMI, body fat percentage and overweight probability as well as behavioural outcomes related to energy balance such as physical activity, sedentary behaviour and fruit intake remain unaffected. However, we find that parents' feedback letter receipt leads overweight children to skip breakfast – they are 2.3 times more likely to skip breakfast at least once a week than overweight children whose parents have not received the letters. Investigating this effect by family background, we find that sending feedback letters causes skipping breakfast to rise even more among overweight children from families of low income and children of single mothers. We also find that sending feedback letters leads some groups of overweight children to report unhappiness and tiredness at school. The effects are particularly high among children in low socio-economic background families.

Chapter 1

Childcare availability and maternal labour supply in Russia

1.1 Introduction

In Russia, the employment rate of women has traditionally been high (in 2016, 73.4% among working-age women). However, like in most developed countries, childbirth interrupts a woman's career. So, after childbirth, a mother has a choice – either to enter/re-enter the labour market or be a stay-at-home parent. A number of factors influence women's decisions. On the one hand, as the child grows, supporting them becomes less time-consuming, but requires more financial investments (Becker, 1964; Mincer and Polachek, 1974). Thus, the need for women to return to the labour market may be caused by their family's level of financial stability. A wide range of studies have shown that in Russia children and families with children are at the highest risk of poverty (Pishnyak and Popova, 2011). Moreover, according to the Federal State Statistic Service of Russian Federation (FSSS), more than half of low-income households are households with children.[2] On the other hand, when taking the decision to enter/re-enter the

[2] Russian statistical yearbook, 2017. http://www.gks.ru/bgd/regl/b17_13/Main.htm

labour market, a woman faces a number of barriers. In Russia, in particular, there is a lack of part-time jobs or jobs with flexible working hours, mothers receive lower wages compared to childless women (Arzhenovskiy and Artamonova, 2007; Biryukova and Makarentseva, 2017), and there are difficulties with child placement in childcare centres, amongst other issues.

In many countries, the female labour force is significantly influenced by childcare policies. Over the past decades, many developed countries have introduced policies to increase public childcare provision and availability. There are two main goals behind this: first, to help mothers maintain a work-family life balance and, subsequently, to increase their labour force participation and, second, to promote early childcare education and development. Indeed, in many countries, research shows that an affordable and accessible childcare system can play a significant role in helping mothers of young children to increase their labour force participation (Cattan, 2016).

During the last 25 years, the Russian childcare system has been facing many challenges. After the disintegration of the USSR, the number of pre-school organisations offering childcare has decreased significantly from 87,573 in 1991 to 51,329 in 2000.[3] This was partly due to a sharp reduction in the fertility rate and partly due to the financial and economic crisis in the country. Under the Soviet Union, it was common that public sector employers had their own social services such as childcare. However, the crisis, which took place right after the end of the Soviet Union, forced public organisations to abandon social services. Thus, childcare became the responsibility of the local municipalities, and as they did not have enough funds, many nurseries were shut down.

In 2000, the fertility rate in Russia started recovering, but the reduction in childcare provision continued.[4] This implied that the availability of childcare turned out to be one of the most important problems for families with small children. The importance of this problem is reflected in the number of children who are waiting to get a place in childcare: in 2014, 2.8 out of 12.2 million children aged 0-6 were on a waiting list; that is about 1 in 4 children under the age of 6 years.

Due to the large scale of the problem, the government has put efforts into extending childcare availability. From 2000 to 2015, the share of children aged 0-6 covered by childcare services increased from 55.0% to 66.3% or, if these figures are broken down by age groups,

[3] Social and Economic indicators of the Russian Federation www.gks.ru/free_doc/doc_2016/year/pril-year_2016_eng.xls

[4] Social and Economic indicators of the Russian Federation www.gks.ru/free_doc/doc_2016/year/pril-year_2016_eng.xls

increased from 64.1% to 83.4% for children aged between 3 and 6 and slightly decreased from 20.9% to 18.4% for children under the age of 3 years.

The effect of childcare availability on maternal employment has been investigated in many European countries, as well as in the US, Argentina and Israel. However, the literature is scarce on Russia. The history of the USSR and contemporary Russia and its features such as lack of part-time jobs, low enforcement of employment rights for pregnant women and women with young children, relatively low family and maternal benefits and a critical shortage in childcare places make Russia a unique case study that differs from many western countries.

The aim of this paper is to provide new empirical evidence on the relevance of childcare for maternal labour supply in Russia. To evaluate the impact of childcare availability expansion on mothers' labour market outcomes, I rely on the fact that there were no centralised childcare policies in place regarding the increase in childcare availability at the national level and so the regions had to cope with this issue independently. In 2013, the Government launched a programme called "The Modernisation of Federal Preschool Childcare System" that mandated full enrolment for preschool education of children aged 3-7, but the regions were fully responsible for drawing federal subsidies and organisational implementation of it. This generated a large variation in childcare coverage, both between regions and across time – during the last 15 years enrolment rates have increased by less than 1% in some regions and up to 35% in other regions. However, it is important to emphasise that regional policy decision about extending childcare availability is a choice variable and potentially may be endogenous. To address this issue, I explore the variation across regions and over time in childcare availability conditioning on a rich set of regional socio-demographic and economic time-varying characteristics, including regional expenditures on different policies, demographic and labour market characteristics and generosity of regional welfare policies.

To measure childcare availability in the presence of shortages, I assume that childcare availability is equal to the enrolment rate (i.e. the number of children age 0 to 6 who are enrolled in childcare organisations, divided by the total number of children aged 0-6). Since the private childcare system is very marginal (in 2015, only 1.4% children covered by childcare were in private childcare), when mentioning childcare availability, I refer to the number of available places only in public childcare. To calculate the enrolment rates, I use a unique dataset on the number of enrolled children at each age in every region provided by the Federal State Statistic Service. Furthermore, the analysis is based on individual-level data from the Russian

Longitudinal Monitoring Survey – Higher School of Economics (RLMS-HSE)[5] which is a national representative split panel of households in Russia.

I find that an increase in childcare availability has positive and statistically significant effects on various maternal labour market outcomes. More precisely, the baseline specification suggests that a 10 percentage points growth in childcare enrolment leads to an increase in the probability of maternal labour force participation by 3.4 percentage points, the probability to be employed by 2.6 percentage points and the probability to be in full-time employment by 2.0 percentage points. In other words, the estimates imply that in Russia between 2000 and 2015 the expansion of childcare availability from 55.0% to 66.3% increased maternal labour force participation by 3.4%, maternal employment by 2.9% and maternal full-time employment by 2.2%. Interestingly, the effect on the labour force participation is smaller among single mothers while in some western countries an opposite effect has been found.

This paper adds to the existing literature in the following ways. First, it demonstrates the impact of childcare system expansion on female labour outcomes in the case of Russia. Second, as shown in Lovász (2016), the institutional background of Russia is similar to some Central and Eastern European countries, thus my results are likely to give some valuable insights for other post-socialist countries that are interested in childcare expansion. Third, I also argue that understanding the effects of childcare reforms on maternal employment is highly policy relevant as Russia is in a phase of rapid population ageing, which increases pressure on economic growth. Thus, understanding the potential consequences of changes in childcare policies can provide some insights into how mothers with young children can be brought back into the labour market that in turn can contribute to sustainable economic development.

The rest of this paper is organised as follows: Section 1.2 summarises the existing literature. Section 1.3 describes the institutional background of the female labour market, welfare benefits and childcare system in Russia. Section 1.4 and 1.5 present the dataset and the empirical strategy, respectively. Section 1.6 presents the results and heterogeneity analysis. Section 1.7 provides robustness checks, and Section 1.8 concludes.

[5] "Russia Longitudinal Monitoring survey, RLMS-HSE", conducted by National Research University "Higher School of Economics" and OOO "Demoscope" together with Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology of the Federal Center of Theoretical and Applied Sociology of the Russian Academy of Sciences. (RLMS-HSE web sites: http://www.cpc.unc.edu/projects/rlms-hse, http://www.hse.ru/org/hse/rlms)

1.2 Related Literature

Research on the effect of childcare on maternal labour supply faces an endogeneity problem, for example, women may have unobserved traits that make them both more likely to choose to use childcare and to work. To minimise the endogeneity problem, recent empirical studies use different quasi-experimental identification strategies that exploit exogenous variation in childcare availability and prices. There are two main approaches that are commonly used for these purposes. The first one is based on using day-of-birth cut-off rules for eligibility for educational programmes. The second one is based on variation in availability across geographic units over time, which usually comes from the different speed of expansion of childcare services. The existing evidence based on these approaches is mixed across time and countries.

One of the first studies based on a quasi-experimental strategy to estimate a causal effect of childcare enrolment on maternal labour supply was conducted by Gelbach (2002). Gelbach uses the access rule to free public preschool for five-year-old children and the quarter of birth of these children using the 1980 US Census. Comparing those who are just eligible for public school and those who are not because they were born just after the cut-off date, he finds a significant positive effect of public school enrolment on maternal labour supply for cases where the five-year-old child is the youngest child in the family. Later US studies show slightly different results. Cascio (2009), evaluating the staggered introduction of free childcare places for five-year-olds mainly in the 1960s and 1970s by using a difference-in-difference approach, finds a significant positive effect only for single mothers whose youngest child was five. Further, Fitzpatrick (2010, 2012) repeats Gelbach's identification strategy (Gelbach, 2002) but using younger cohorts from the 2000 US Census and finds effects of the availability of universal childcare on the maternal labour supply only for single mothers where the five-year-old child is the youngest child. Fitzpatrick suggests that the difference in the results among different studies arise due to demographical, labour market and lifecycle changes over time. These studies show us that the impact of childcare can vary between single and married women, over time within one country, and also depends on whether a child is the youngest or not.

Significant positive causal effects of childcare availability on maternal labour supply for both single and married mothers have been found in Argentina (Berlinski and Galiani, 2007; Berlinski et al., 2011), Quebec (Baker et al., 2008; Lefebvre and Merrigan, 2008; Lefebvre, Merrigan and Verstraete, 2009), Spain (Nollenberger and Rodriguez-Planas, 2015), Germany (Bauernschuser and Schlotter, 2015) and in the United Kingdom for full-day childcare (Brewer, Cattan, Crawford, Rabe, 2016). Evidence from France (Goux and Maurin, 2010) and Israel

(Schlosser, 2011) show that an increase in childcare availability has a significant positive effect only for some subgroups of mothers, for example, among single mothers or more educated mothers (in the case of France, the effect is positive and significant but very small). Finally, studies conducted in Sweden (Lundin, Mork and Ockert, 2008), the UK (Brewer and Crawford, 2010) and Norway (Havnes and Mogstad, 2011) demonstrate little, if any, effects of childcare availability on maternal labour outcomes.

Cattan (2016) summarises findings from different countries and argues that significant differences across countries and periods can be explained by policy parameters and the country-specific context. She suggests four main driving factors that affect the magnitude of the effect of childcare availability on maternal labour market outcomes. The first one is the initial maternal employment rate. The effect of childcare expansion can be substantial in those countries where the initial level of female employment is low. This argument generally works in absence of other barriers for female employment such as slow economic growth or lack of flexible and part-time work opportunities for mothers. The second factor is the difference in nonparental care use. The effect of the introduction of free preschool places can have no effect (or an effect that is smaller than the increase in childcare attendance) in countries where there is a well-developed private childcare system or parents intensively use informal childcare. In this case, parents switch from informal/unsubsidised to formal/subsidised childcare and we observe just a crowding out effect without significant changes in maternal labour market outcomes. The third driving factor behind the variation in results among countries is differences in mothers' non-labour income and welfare benefits. As described previously, single mothers can be affected more due to the fact that relatively smaller non-labour income forces them to join the labour market. Also, countries with more generous welfare systems for parents experience lower changes in maternal employment rate in response to expanding childcare availability because mothers have less financial need to come back into the labour market. Finally, one of the most obvious factors is the differences in policies. Policies in different countries are aimed at children of different ages, at different social groups, and provide different amounts of free education.

Post-socialist countries in Central and Eastern Europe are distinct along these 4 dimensions from Western European, Anglo-Saxon, Nordic and North American countries so that childcare availability could potentially have very different effects from those seen in these countries. However, the literature is scarce on Central and Eastern European countries. Lovász (2016) analyses potential childcare expansion and mothers' employment in post-socialist countries in Central and Eastern Europe. Whilst comparing backgrounds and experiences of different European countries, she argues that the maternal labour market in post-socialist countries could gain a lot from childcare expansion because of the current low labour force participation of mothers whose children are under three and low childcare coverage rates for children under three. However, Lovász emphasises that post-socialist countries have some common characteristics such as inflexible labour markets, very long or very short maternal leave and unsupportive social views on employment of mothers with young children that could prevent effective increase in maternal employment if childcare expansion occurs without any other policies changes. A study on Hungary, a post-socialist country, on the effect of childcare availability confirms Lovász's arguments (Lovász and Szabó-Morvai, 2013).

A few papers investigate the effect of childcare availability on female labour market outcomes in Russia. The majority of these studies estimates associations between childcare availability and maternal employment (Savinskaya, 2011; Karabchuk and Nagernyak, 2013) however some studies attempt to estimate the causal effect. Lokshin (2004) evaluates the childcare price elasticity of female labour supply. He shows that fully subsidizing family spending on pre-schools can increase the female employment rate by 11.4% from 50.0% to 55.7%. However, the paper is based on data from 1994-1996 and may not reflect the current situation in Russia. Levin and Oshchepkov (2013) investigate the relationship between using childcare and maternal employment based on a more recent and relevant time period (RLMS-HSE 2000-2009). To overcome the endogeneity problem, they use a system of two simultaneous probit equations (a probit-model for being employed and a probit-model for using childcare) with three instrumental variables in the second equation – a dummy variable for having a pre-school in a city/town/village, the number of enrolled children per 100 places (the pre-schools functioning capacity), and a dummy variable equal to one if the number of enrolled children per 100 places is more than 100. The results show that if all children that are on the waiting list get a place in childcare (around 35% of children in 2009) the probability to be employed for women increases by 8.5-12.5 percentage points.[6]

My paper differs from Levin and Oshchepkov (2013) in several aspects. Exploring the variation across regions and over time in childcare availability, I attempt to evaluate the effect of regional childcare expansion policies, which is a policy relevant parameter that can be useful for further childcare reforms. By implementing this empirical strategy, I avoid using the variable of childcare use which is underreported in the dataset I use. Also, I use a longer period

[6] A weakness of this analysis comes from using a variable of childcare use that is underreported. According to my estimates based on RLMS-HSE, childcare use is 20-25 percentage points lower than the federal statistics.

of time (2000-2015) and nine different labour market outcomes. In addition, I use a unique dataset on childcare enrolment for each age between 0 and 6 at the regional level that increases accuracy in measuring childcare availability.

1.3 Institutional background in Russia

This section reports the institutional background in Russia based on four points that Cattan (2016) finds to be the main driving factors that affect the way that expansion of childcare availability affects maternal labour market outcomes. In particular, this section describes the following aspects: the situation of the female labour market, the welfare benefits system in Russia, informal childcare use, the childcare system and the policy set up. An understanding of these key elements can provide valuable insights into the expected effects of childcare policy changes in the case of Russia.

1.3.1 Female labour market

The Soviet Union had high levels of female employment. The highest proportion of women aged 16 to 54 (the working age in the Soviet Union countries and in Russia until 2019) who were employed was 89.7% in 1970 (Shapiro, 1992). After the fall of the Soviet Union, due to the economic crisis the situation changed significantly – the employment rate for working-age women dramatically fell from 77.6% in 1992 to 63.5% in 1998. After that, the overall economic growth in Russia led to an increase in the female employment rate up to 72.6% in 2015.

Similarly to many countries, maternal employment in Russia varies considerably according to the age of youngest child. However, the gap between the employment rate of mothers whose youngest child is aged 0-2 and the employment rate of mothers whose youngest child is aged 3-6 is significantly larger than in most OECD countries (Figure 1.1). In 2014, the employment rate of Russian mothers whose youngest child was aged 3-6 was relatively high (78.4%) and Russia performed extremely well compared to OECD countries. At the same time, Russia was in the group of countries with the lowest employment rate of mothers whose youngest child was aged 0-2 – Russia with 25.7%, Estonia with 23.7%, Czech Republic with 22.3%, Turkey with 21.7%, Slovakia with 16.7% and Hungary with 13.4%. Thus, in Russia the gap in maternal employment between these two groups was 52.7 percentage points with only two counties such as Estonia and Hungary showing a larger gap (57.4 and 54.5 percentage points respectively). It is important to note that all these countries, with the exception of Turkey, are post-socialist countries of Central and Eastern Europe, which emphasizes some similarities between these countries.

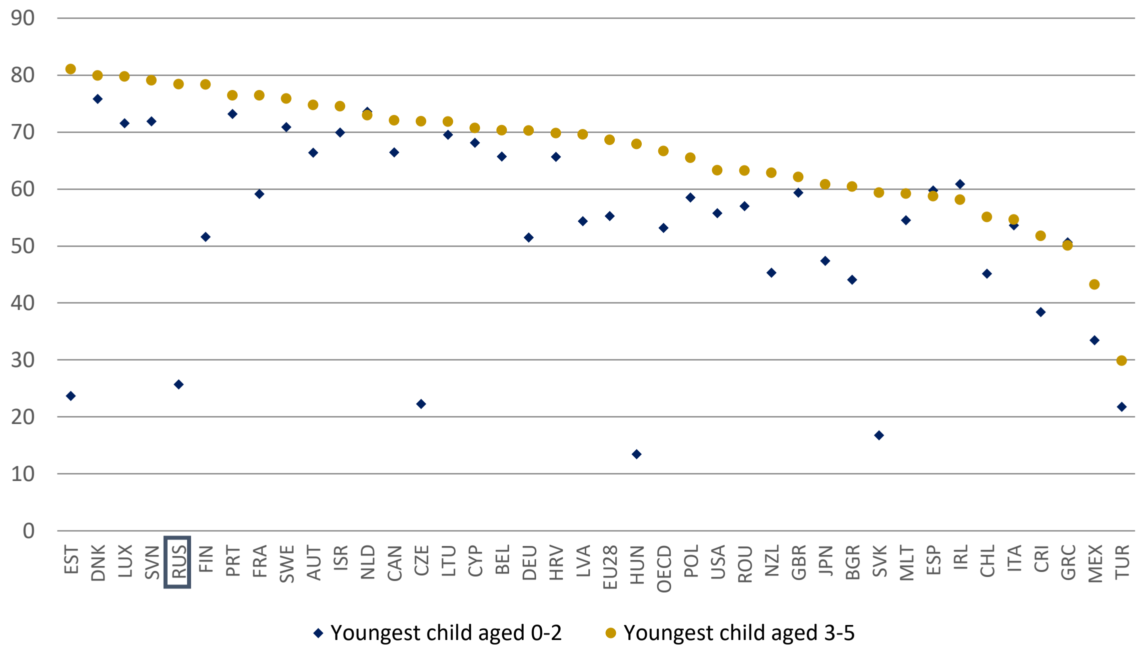

Figure 1.1 – Maternal employment (%) by age of youngest child in 2014

Notes: The employment rate of women 15-64 years old. For Russia the age of women is 16-54 since it is their working age. For Russia the children age groups are 0-2 and 3-6.
Source: OECD Family Dataset. Online at: http://www.oecd.org/els/family/database.htm; Chart LMF1.2.C. Employment rates for Russia is calculated by author.

Also of note is the difference in maternal employment between partnered and single mothers. Figure 1.2 shows substantial variation across countries in the employment rate of these two groups. Among OECD countries, around one third of the countries tend to have higher employment rate of single mothers than partnered, ranging from a massive gap of 31.3 percentage points in Mexico to 1.4 percentage points in Greece. Russia also demonstrates a significant gap of 6.7 percentage points between maternal employment of single and partnered women. Moreover, Russia is among the top countries showing the highest level of single mothers' employment rate – the employment rate of single mothers is equal to 86.3% in Switzerland, to 85.3% in Luxemburg and to 77.7% in Russia (versus 70.9% for partnered mothers).

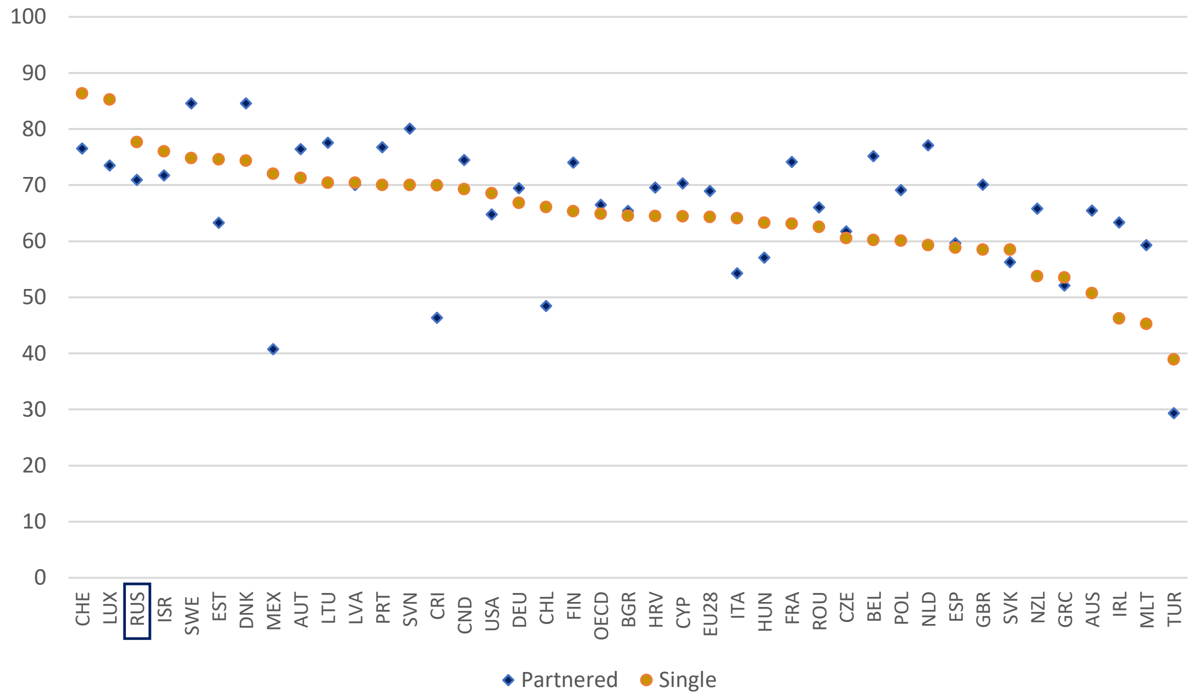

Figure 1.2 – Employment rates (%) for partnered mothers and single mothers with at least one child aged 0-14, 2014 or latest available

Notes: The employment rate of women 15-64 years old; for Sweden, women aged 15-74. Data for Denmark and Finland is to 2012, and for Chile, Germany, and Turkey to 2013. For Canada, children aged 0-15, for Sweden children aged 0-18, and for the United States children aged 0-17.
Source: OECD Family Dataset. Online at: http://www.oecd.org/els/family/database.htm; Chart LMF1.3.A.

One of the explanations of low maternal employment when the youngest child is under the age of 3 years is a low availability of part-time jobs. Like in most post-socialist countries, the Russian labour market is relatively inflexible. Part-time employment (less than 30 hours per week) is rare: in 2014, only 6.5% of working women had part-time jobs. This figure is even lower for childbearing age women – 5.2% in the 20-29 age group, 4.8% in the 30-39 age group and 5.3% in the 40-49 age group. Russia is significantly lagging behind other developed countries in this respect with only a few countries such as Bulgaria, Macedonia and Romania performing worse (Figure 1.3). Again, we can see that the right tale of the distribution is represented mainly by post-socialist countries, which indicates that there are institutional similarities between these countries.

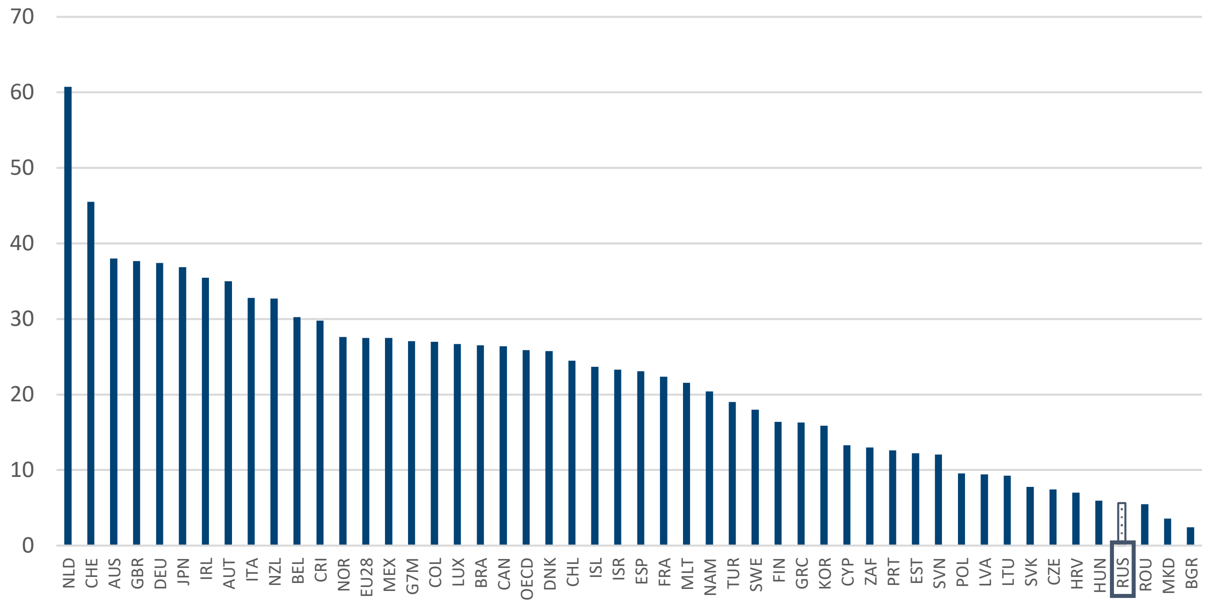

Figure 1.3 – Proportion of women employed part-time among all employed women, 2015

Notes: Part-time employment is defined as people in employment (whether employees or self-employed) who usually work less than 30 hours per week in their main job. Employed people are those aged 15 and over who report that they have worked in gainful employment for at least one hour in the previous week or who had a job but were absent from work during the reference week while having a formal job attachment.
Source: OECD (2017), Part-time employment rate (indicator). doi: 10.1787/f2ad596c-en (Accessed on 25 September 2017).

Also, it is important to mention that there is low enforcement of labour laws for pregnant women and women with young children. According to the Russian Labour Code, pregnant women and women with children under the age of 3 years have a rich set of social guarantees. For instance, employed pregnant women are provided with maternity (70 days before and 70 days after childbirth) and parental leave (three years after childbirth); for pregnant women and women with children under the age of 3 years it is prohibited to work at night, to do overtime work and go on business trips; women with children the age of 1.5 years have the right to take extra breaks during working hours to feed their children, which are included in working hours and paid in line with average earnings and so on (Sinyavskaya, O. *et al*., 2015). Although the Russian laws protect the employment rights of pregnant women and women with young children, these laws are rarely followed, especially in the private sector, and courts often dismiss claims of unfair treatment in the workplace (Sinyavskaya, O. *et al*., 2007; World Bank, 2014). In addition, although the Labour Code guarantees the same employment rights for pregnant women and women with children under 3, women face difficulties securing a job as employers are reluctant to hire women who have working restrictions (Karabchuk and Nagernyak, 2013).

1.3.2 Welfare benefits

In Russia, family and maternal financial support comes from both the State and regional governments. The main forms of support are maternity allowance, a lump-sum payment to women who register in a hospital during early stages of pregnancy, a lump-sum payment at the child's birth or in case of adoption, adoption of a disabled child, a monthly payment for child care, a monthly payment to disabled children, a payment to ensure healthy nutrition of pregnant women, breastfeeding mothers and children under the age of 3 years, a monthly payment to low income families, and a lump-sum payment to families with 3 and more children. Although the number of different types of social benefits for families with young children is huge, social benefits play a rather important role only for families with three or more children under the age of 18 years where the share of social benefits in total income is almost a fifth (Table 1.1).[7] For families with children under the age of 3 years the share is 16.6%. Single-parent families seem to be financially unprotected, with social benefits corresponding to just 8.1% of the total household income.

Table 1.1 – Household (HH) income composition by source of income in 2015, %

	Source of income				
	Wages	Income from properties	Pension	Social benefits (without pension)	Others
All HH	76.7	1.1	14.9	4.5	2.8
HH with families that have children under the age of 18 years	81.1	0.7	7.1	7.2	3.9
among them with					
1 child	85.2	0.7	7.6	3.1	3.5
2 children	77.0	0.9	6.1	11.8	4.2
3 and more children	67.6	0.6	7.4	19.1	5.3
HH with families that have children under the age of 3 years	71.6	0.6	6.8	16.6	4.4
HH with young families	87.7	0.2	3.5	4.3	4.2
HH with single-parent families	66.1	0.8	17.9	8.1	7.0
HH with families that do not have children up to 18 years old	74.1	1.3	19.7	2.8	2.1

Source: Statistical Survey of Income and Participation in Social Programmes 2016.

[7] Here total social benefits include all types of social support except pensions. Thus, the proportion of family and children benefits is even lower.

Investigating family benefits in Russia, Sinyavskaya et al. (2015) show that although the maximum post-natal leave is three years and the first 18 months are paid, most of these months are paid at a relatively low rate. Popova (2013) and Kolosnitsyna and Philippova (2017) have found that these benefits are not well targeted, the system suffers from leakages, significant gaps in coverage and low efficiency. Also, children and families with children have the highest risk of poverty among all socio-demographic groups and the risk of falling into poverty increases with the number of children in the family (Pishnyak and Popova, 2011). In 2015, 63% of poor households were households with children.

Comparing to other OECD countries, Russia is among those that spend less than 1% of GDP on benefits for families and children (Figure 1.4). In 2013, total family benefits were 0.9% of GDP. It is important to note that this figure includes spending on the Maternal Capital programme which is administrated in the form of certificates that can be used three years after a child is born or adopted on housing improvements, education and the mother's future funded pension (Elizarov and Levin, 2015). Expenditure on benefits for families and children without spending on the Maternal Capital programme is half as much and puts Russia even further away from other developed countries (in 2013 it was 0.5% of GDP).

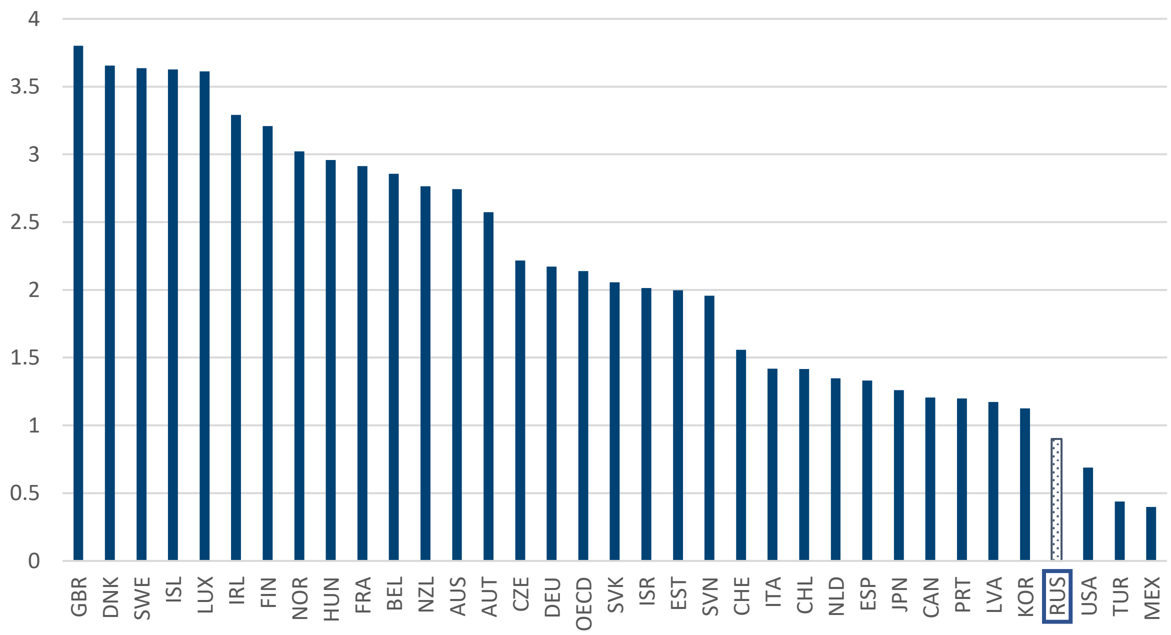

Figure 1.4 – Family and child benefits public spending in 2013, percentage of GDP

Notes: Family benefits spending refer to public spending on family benefits, including financial support that is exclusive for families and children. Spending recorded in other social policy areas, such as health and housing, which also assist families, but not exclusively, it is not included in this indicator.
Source: OECD (2017), Family benefits public spending (indicator). doi: 10.1787/8e8b3273-en (Accessed on 27 September 2017). FSSS (2014), Social provision and standards of living in Russia.

1.3.3 Informal childcare use

As discussed in the following section, the main features of the Russian childcare system are the place shortage in the formal public childcare system and a relatively small private childcare system. These force mothers to resort to informal childcare if they want to come back to the labour market. Informal childcare includes help from relatives that can live at the same or different household, friends, neighbours or other people who do not work in childcare. In Russia, traditionally, grandmothers tremendously facilitate combining mothers' work and their family obligations even though grandparents' assistance is becoming more irregular (Cherkashina, 2011). As an example, Table 1.2 shows how parents allocate childcare time by childcare providers in families with one child. Clearly, the amount of informal care depends on the child's age. Parents of very young children use only informal care and exclusive use of formal care does not exist. As a child grows, parents use less informal care and rely more and more on both types of childcare, but they still use some informal care. Very often, parents cannot fully exclude informal care because the majority of childcare organisations work until 5-6pm and parents have to make arrangements to pick up their children. Pelikh and Tyndik (2014) confirm that informal childcare compliments the formal provision rather than substitute it.

Table 1.2 – Consumption of informal and formal childcare by single-child households (2007)

Age	Only Informal Care	Only Formal Care	Both
Younger than 1.5	98.3	0	1.7
1.5-3	43.4	0	56.6
4-6	17.6	2.3	80.1

Source: Sukhova, 2011.

1.3.4 Childcare system

Main trends in childcare system

After the end of the Soviet Union in 1990, the fertility rate in Russia fell dramatically (DaVanzo and Farnsworth, 1996; The Demographic Yearbook of Russia, FSSS 2002, 2015): from 1.9 in 1990 to 1.3 in 1995 and to 1.2 in 2000 (Figure 1.5).[8] The decline in the fertility rate led to a sharp decrease in the number of preschool age children enrolled into childcare. Due to this

[8] The fertility rate decrease started much earlier than at the end of the USSR but the decrease during the previous 30 years was less significant than in 10 years after 1990 (from 2.5 in 1960 to 1.9 in 1990).

reduction, the number of childcare providers and the number of places in the public childcare system shrank. Moreover, at this time many childcare services were transferred from public organizations to municipalities, which were forced to close childcare services due to lack of funds. The total number of places in the childcare system fell from 8,109 thousand in 1991 to 5,232 thousand in 2000. From 2000, the fertility rate began to increase, and subsequently there was an increase in the number of children enrolled into childcare. However, the reduction in places in the childcare system continued until 2007 (Figure 1.5). While the number of places in childcare started increasing from 2008, it was not enough to cover demand.[9] In terms of childcarers, their number has been relatively stable with a slight increase of 1.7% between 2000 and 2005 and has grown significantly since 2005. From 2005 to 2015, the growth was 16.7%.

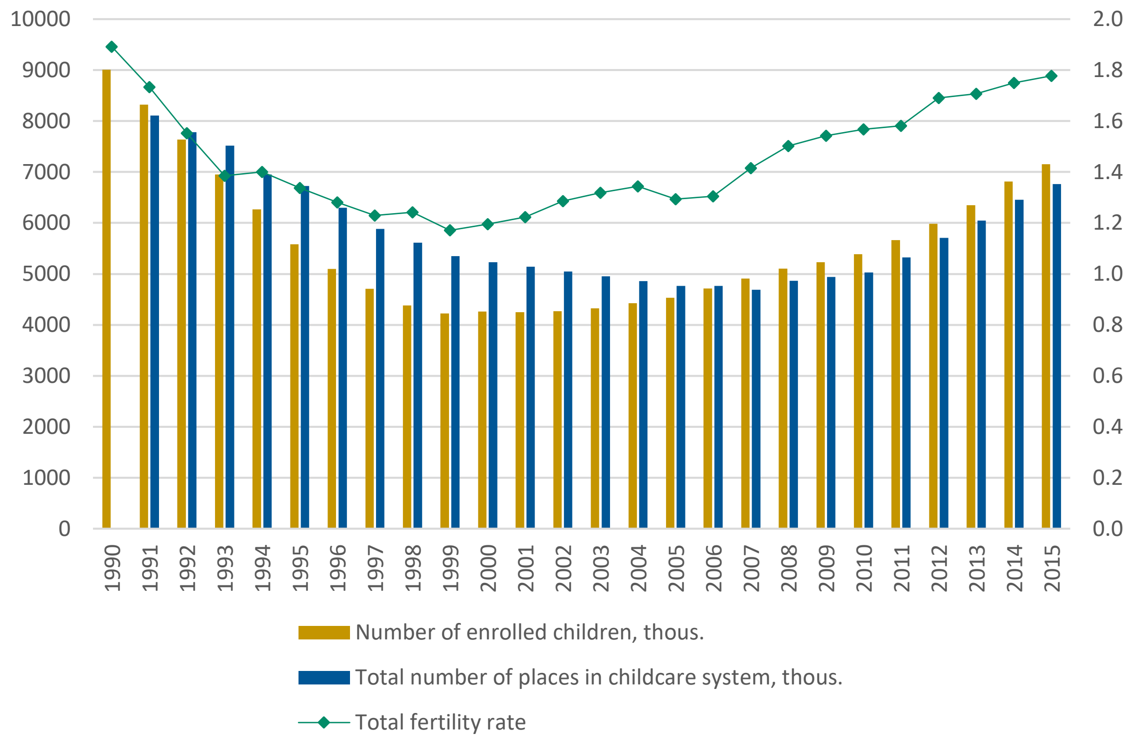

Figure 1.5 – Main trends in the childcare system in Russia

Notes: The left vertical axis corresponds to the number of children enrolled into childcare system and the number of places in childcare system. The right vertical axis corresponds to the total fertility rate.
Source: Country-level data from the Federal State Statistic Service of Russian Federation - Social provision and standards of living in Russia in 1999, 2015. Data on total number of places in childcare system is not available before 2000.

[9] It is worth noting that there was a lack of part-time public childcare – only 2.4% of children covered by childcare attended part-time nurseries in 2015. Indicators of Education in the Russian Federation: 2017. Data Book.

As a result of place shortages in the childcare system there are long waiting lists to get a place. Due to the lack of places, parents have to apply for a place straight after the child's birth, but even this does not guarantee getting a place on time. The number of children waiting for a place increased from 2.6% in 2000 to 23.3% in 2014 (Figure 1.6). The situation was exacerbated by a lack of private childcare. In 2015, among all childcare providers, only 2% were private organisations, which only covered 1.4% of children in childcare. One of the reasons for the lack of private providers is the strict requirements for buildings, equipment, qualifications of the staff and considerable bureaucratic barriers. After overcoming these obstacles, providers have to set high prices for childcare that parents mostly cannot afford.

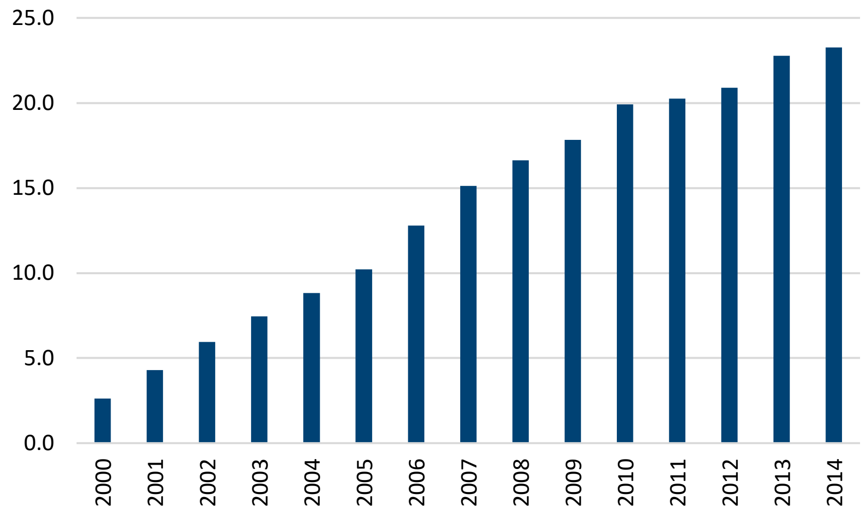

Figure 1.6 – Share of children aged 0-6 in the waiting list to get a place in kindergarten

Source: The indicator is calculated by author using country-level data on number of children in the waiting lists from the Federal State Statistic Service of Russian Federation.

Childcare availability expansion

The identification strategy used in this study is based on variation over time across regions in the childcare availability, measured by childcare enrolment (Section 1.4 explains why I choose childcare enrolment to measure childcare availability). Here I provide details on the childcare availability expansion over the period between 2000 and 2015.

Until 2013, there were no federal policies to solve the problem of the shortage in childcare places. Moreover, the childcare system was financed almost only from regional and municipality budgets – the share of federal spending on the childcare system in total spending was not more than 2% between 2000 and 2013.[10] In this situation every region had to expand

[10] Education in Russia 2014. Higher School of Economics Data Books.

public childcare in order to cope with an increase in demand without support from the central government. The intensity of the creation of new places in the childcare system varied considerably both across regions and over time, and depended on regional budget policies, financial priorities and on existing coverage. In order to describe the magnitude of childcare expansion by region, Figure 1.7 gives two maps, which show the enrolment rate in all the Russian regions in 2000 and 2015. In 2000 the enrolment rate varied from 3.8% to 80.7%. The increase in the enrolment rates over the time ranges from a minimum of 0.1 percentage points to a maximum of 34.6 percentage points. Thus, in 2015 the enrolment rates varied from 17.4% to 91.9%. In total, the proportion of children covered by the childcare system in Russia increased from 55% to 66.2%.[11]

There are three main mechanisms which were used to meet the high demand for childcare services in the circumstances of limited resources and lack of assistance from the government. First, it started by filling available places. Second, when all available places were taken, childcare providers began enrolling children above the childcare capacity.[12] As is apparent from Figure 1.5, from 2007 the total number of enrolled children exceeds the total number of places in the public childcare system. Notice that, despite the fact that at the country level this issue appeared only in 2007, over-enrolment has remained a concern in Russia both in urban and rural areas throughout the entire considered period of time (Table 1.3). An increasing load on childcare was also reflected in the number on children per childcarer. Between 2000 and 2009, there were 10 children per one childcarer but from 2011 this number began to increase and reached 14 children per childcarer in 2015.[13] The third mechanism that was involved in increasing childcare availability is the actual building of new childcarers.

Table 1.3 – Proportion of childcare organisations where the number of enrolled children is higher than the maximum ceiling, %

	2000	2005	2010	2011	2012	2013
Total	28.2	41.9	54.5	52.0	48.1	48.0
Urban area	39.3	58.3	71.6	66.8	61.0	60.1
Rural area	14.1	20.2	29.9	29.9	28.9	30.2

Source: Higher School of Economics Data Book on Education in Russia 2014.

[11] FSSS, Social provision and standards of living in Russia in 1999, 2015.

[12] Before 2010, the maximum number of children per class could not exceed 15 for children under the age of 3 years and 20 for 3- to 7-year-olds. In 2010, the maximum group size rules changed (Decree of the Chief State Sanitary Doctor of the Russian Federation from 22.07.2010 N91) such that the maximum number of children per class is calculated by building size – a childcare provider has to ensure that there are 2.5 square meters per child aged under 3 and 2 square meters per child aged 3-7. To calculate the number of potential places the whole surface area of a childcare organisation is included (bedrooms, dining rooms, play areas and so on).

[13] Education in Russia 2017. Higher School of Economics Data Books.

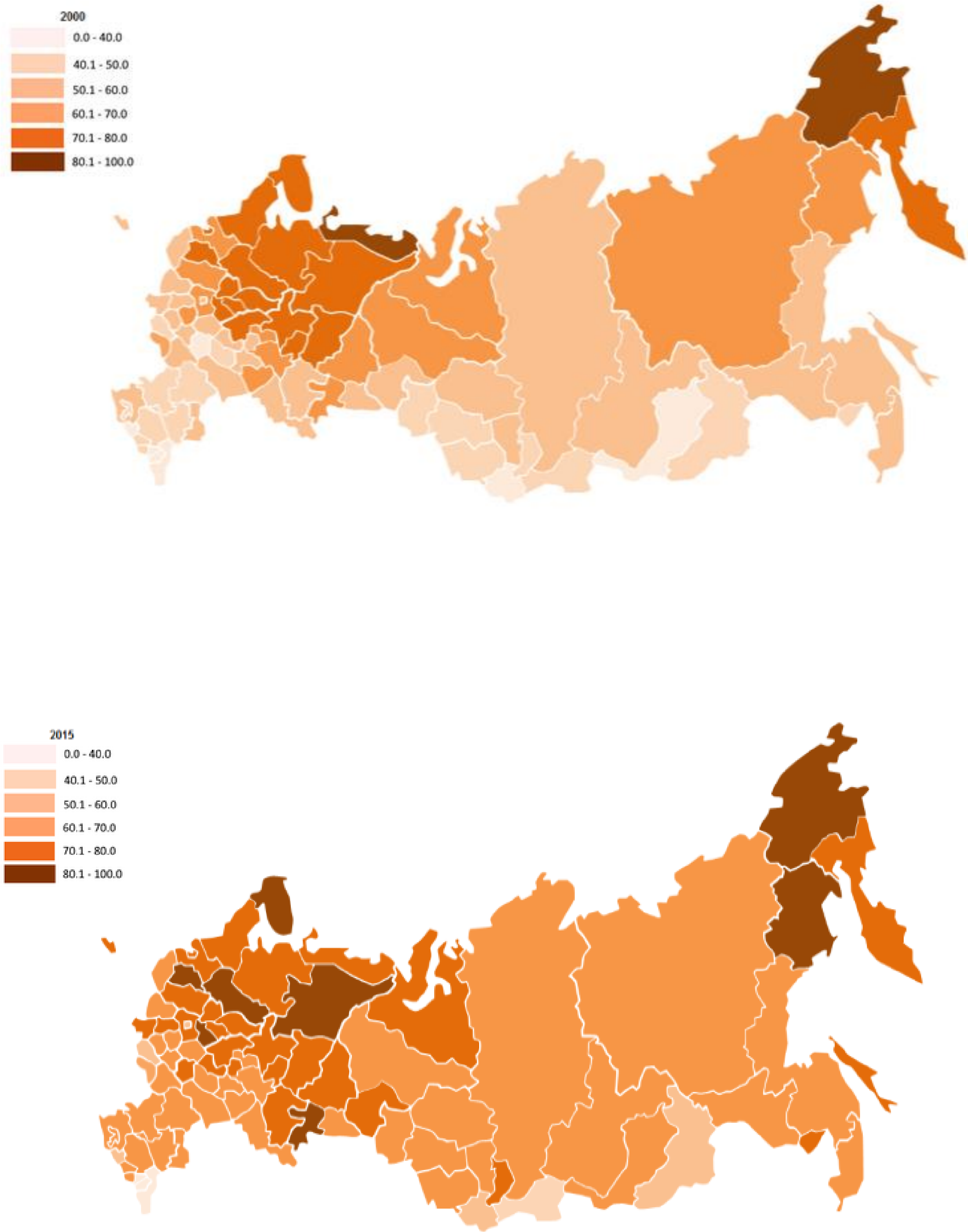

Figure 1.7 – Childcare enrolment rate among Russian regions in 2000 and 2015

Notes: Childcare enrolment rate varies from 0 to 100%. Darker colour means a higher level of enrolment rate.
Source: Country-level data from the Federal State Statistic Service of Russian Federation.

As an example, Table 1.4 presents the growth of childcare enrolment rates and the number of children per 100 places in childcare in ten regions, i.e. five regions with the highest growth of childcare enrolment and five regions with lowest growth of childcare enrolment between 2000 and 2015, and shows how the two mechanisms of the increase in childcare enrolment work. The table shows how much on average in a certain region the capacity of childcare is used (number of children per 100 places) and how, depending on this, the childcare enrolment rate varies. In the Tambov region, where we observe the biggest increase in childcare enrolment by 34.6 percentage points, to deal with a high demand for childcare, first there was a process of filling available places. The number of children per 100 places in 2000 was equal to 70 and reached 100 in 2010. After that, the childcare system in this region was used at full capacity and the number of children per 100 places was relatively stable. Oppositely, in the Kabardino-Balkar Republic, where the childcare in 2000 was already used at almost full capacity, we can observe a considerable over-enrolment after 2008 when the fertility rate started to grow significantly (Figure 1.5). In the Penza and Novosibirsk regions, to increase childcare enrolment, first, the available places were steadily introduced. When the regional childcare systems reached their full capacity, we see that the second mechanism of over-enrollment was involved. As a result, in 2015 there were 111 and 114 children per 100 places in the Penza and Novosibirsk regions, respectively. In Saint Petersburg, the childcare system in 2000 was already overcrowded, thus, we observe a decrease in childcare enrolment between 2000 and 2010 with even a higher level of over-enrollment by 2010. The Tomsk region is an example of a region where between 2000 and 2010 we observe a substantial increase in over-enrollment from 98 to 118 children per 100 places and a slight increase in childcare enrolment from 55.6 to 58.0 percent. However, in 2010, the childcare enrolment rate began to grow, and over-enrolment began to decrease. This is because in this region in 2010 the first childcare was built after a 20-year hiatus. Within next 5 years, more than 15 childcares were built in the region which helped to increase childcare enrolment and decrease over-enrolment.[14] The described differences in how regions coped with increased demand for childcare explains why the childcare availability grew more rapidly in some regions than others over the period between 2000 and 2015.

[14] http://niatomsk.ru/more/81564/

Table 1.4 – Childcare enrolment and number of children per 100 places, 2000-2015.

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total change
Tambov region	Childcare enrolment	39.8	42.1	44.3	45.9	46.1	45.8	47.6	49.0	50.0	49.0	53.0	55.7	60.1	62.1	67.2	74.4	**34.6**
	Children per 100 places	70	71	73	75	78	78	89	78	94	96	100	103	99	97	99	99	**29**
Chuvash Republic	Childcare enrolment	56.2	58.8	62.4	64.2	66.3	67.0	67.5	68.3	67.3	66.7	67.0	67.8	69.7	72.8	78.0	79.0	**22.8**
	Children per 100 places	59	60	62	84	89	92	93	92	95	96	99	93	95	99	99	100	**41**
Kabardino-Balkar Republic	Childcare enrolment	46.2	46.9	47.4	50.9	48.2	48.9	50.7	57.6	55.6	58.1	51.6	51.8	56.6	60.6	62.7	67.9	**21.7**
	Children per 100 places	98	100	97	97	88	92	93	92	100	100	113	113	117	120	115	114	**16**
Penza region	Childcare enrolment	47.2	48.7	50.6	50.8	50.1	50.9	51.3	53.1	54.2	54.0	55.4	58.6	60.2	62.1	65.7	68.4	**21.2**
	Children per 100 places	72	75	78	79	80	82	84	82	89	94	100	102	101	102	105	111	**39**
Novosibirsk region	Childcare enrolment	46.4	47.4	48.3	48.3	48.6	48.7	50.1	51.0	54.1	53.8	57.8	59.1	60.8	61.3	61.8	64.9	**18.5**
	Children per 100 places	71	71	72	74	89	98	101	98	107	110	114	115	117	112	112	114	**43**
Saint Petersburg	Childcare enrolment	73.3	74.2	73.6	70.5	68.3	67.1	67.2	69.4	69.1	68.3	75.2	78.7	77.1	75.9	75.4	73.4	**0.1**
	Children per 100 places	103	101	105	105	106	110	110	110	112	110	109	109	109	104	106	108	**5**
Republic of Tatarstan	Childcare enrolment	65.2	66.6	68.6	69.2	69.5	69.6	70.9	72.1	70.7	69.5	70.0	71.5	70.8	68.5	68.1	68.3	**3.1**
	Children per 100 places	97	98	100	101	101	102	105	102	108	107	110	108	112	115	113	111	**14**
Perm Krai	Childcare enrolment	70.3	72.0	73.2	72.7	71.3	70.2	69.7	70.1	69.9	66.5	67.1	65.9	65.3	66.0	70.9	74.4	**4.1**
	Children per 100 places	89	97	100	106	106	107	111	107	114	113	110	109	100	101	102	104	**15**
Komi republic	Childcare enrolment	79.1	80.6	80	81.6	80.4	78.2	78.3	78.8	78.7	78.1	82.5	83.0	84.3	84.4	85.3	85.9	**6.8**
	Children per 100 places	84	85	86	88	91	93	95	93	102	98	98	96	95	94	95	93	**9**
Tomsk region	Childcare enrolment	55.6	55.2	57	57.4	57.8	54.7	57.6	57.7	58.6	57.5	58.0	60.4	62.9	64	64.5	66.5	**10.9**
	Children per 100 places	98	101	106	110	113	112	116	112	116	116	118	106	105	103	101	100	**2**

Notes: The table presents the growth of childcare enrolment rates and the number of children per 100 places in childcare in ten regions, i.e. five regions with the highest growth of childcare enrolment and five regions with lowest growth of childcare enrolment between 2000 and 2015.

As the childcare availability increased at different rates across the country, one might be concerned about confounding the effect of childcare expansion with other regional policy choices taking place at the same time that could also have affected the female labour market outcomes or that there are other significant differences between regions that experienced a large childcare expansion and regions that did not.

To get an idea as to how much regions differ and consequently to check the assumption that childcare expansion is independent of other regional characteristics that vary over time and across regions that might affect our outcomes, I follow Havnes and Mogstad (2011) and Blanden *et al.* (2016) in defining treatment and comparison regions (but for the main analysis I rely on a continuous variable of childcare availability extention and do not use a binary categorisation). According to this strategy, I divide all regions in Russia into two groups depending on the percentage point increase in enrolment rates. The 50% of regions with the highest increase are in the treatment group while the 50% of regions with the lowest increase are in the comparison group. For this analysis, I use only the 32 regions presented in the dataset I use for this study (see Section 1.4 for more details) in order to be confident that the assumptions hold for this sub-sample. Figure 1.8 shows the trends in childcare coverage in the treatment and comparison groups. The expansion started in 1998 but for reasons of survey data availability I focus on the period from 2000.[15] The expansion of childcare between 2000 and 2015 was 16.3 percentage points in the treatment group and 7.1 percentage points in the comparison group. It is clear that the higher level of childcare expansion in the treatment group corresponds to lower levels of initial childcare enrolment.

Figures 1.9-1.12 show trends in the main regional characteristics in the treatment and comparison groups and, in particular, in factors that can affect mothers' labour outcomes. More specifically, I look at regional expenditures on different policies, regional demographic characteristics, labour market characteristics and region's wealth and generosity characteristics. As shown, the treatment and comparison groups experience similar trends in most regional socio-demographic and economic characteristics between 2000 and 2015. An exception is expenditure on professional training. However, in this case it is not an issue as expenditure is lower in the treatment group. It is particularly important to emphasise that expenditures on family and childhood security policies are the same in the two groups and this means that work incentives do not differ. Between-region migration should also be considered.

[15] The survey data I use in this study has been collected from 1994 but due to the financial and economical crisis in the country the survey did not run in 1997 and 1999.

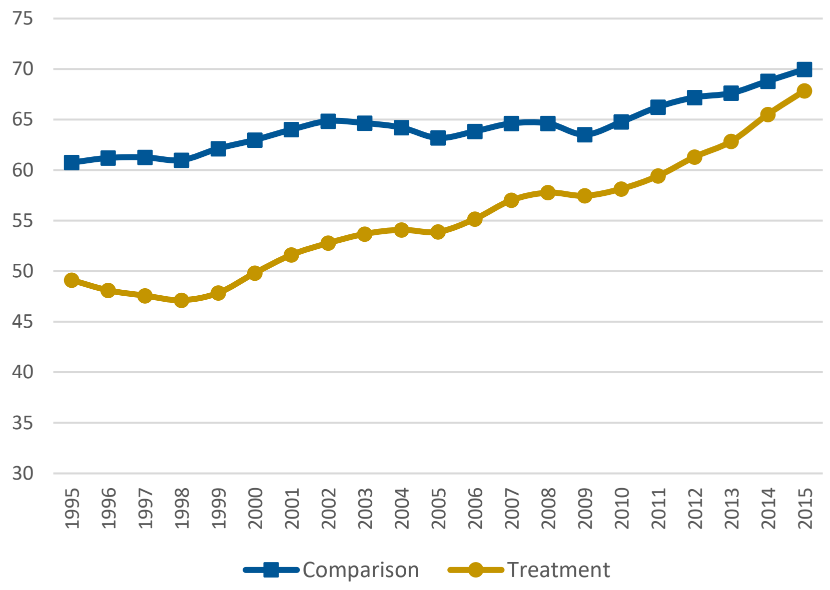

Figure 1.8 – Expansion of childcare enrolment across Russia, 2000-2015

Notes: The graph shows expansion of childcare enrolment in treatment and comparison groups. The treatment group is the top 50% regions with the highest increase in enrolment rate while the comparison group is the bottom 50% between 2000 and 2015. Enrolment rate is a proportion of children aged 0-6 in total number of children at this age group. Enrolment rate varies from 0 to 100%.
Source: Regional-level data from the Federal State Statistic Service of Russian Federation.

One of the potential issues is sorting of families into regions with higher childcare availability that could lead to a correlation between childcare availability and mothers' labour outcomes. Comparing between-region migration in the treatment and control groups displays very similar trends, which means that regions with higher childcare availability do not attract more families.[16] Additionally, Figure 1.13 shows the difference between treatment and control groups in the number of children per 100 places in childcare. As we can see, after 2007 the level of children per 100 places was much higher in the treatment group that in the control. As it was discussed before, enrolling more children than childcare capacity was one of the main mechanisms to expand childcare availability in the circumstances of limited resources and lack of assistance from the government and this mechanism was actively used in the regions that experienced a large childcare expansion.

[16] Also, the literature on interregional migration in Russia does not allocate childcare availability as a separate potential factor that affects migration flows. This indirectly confirms that people do not adjust the place they live according to childcare availability expansion.

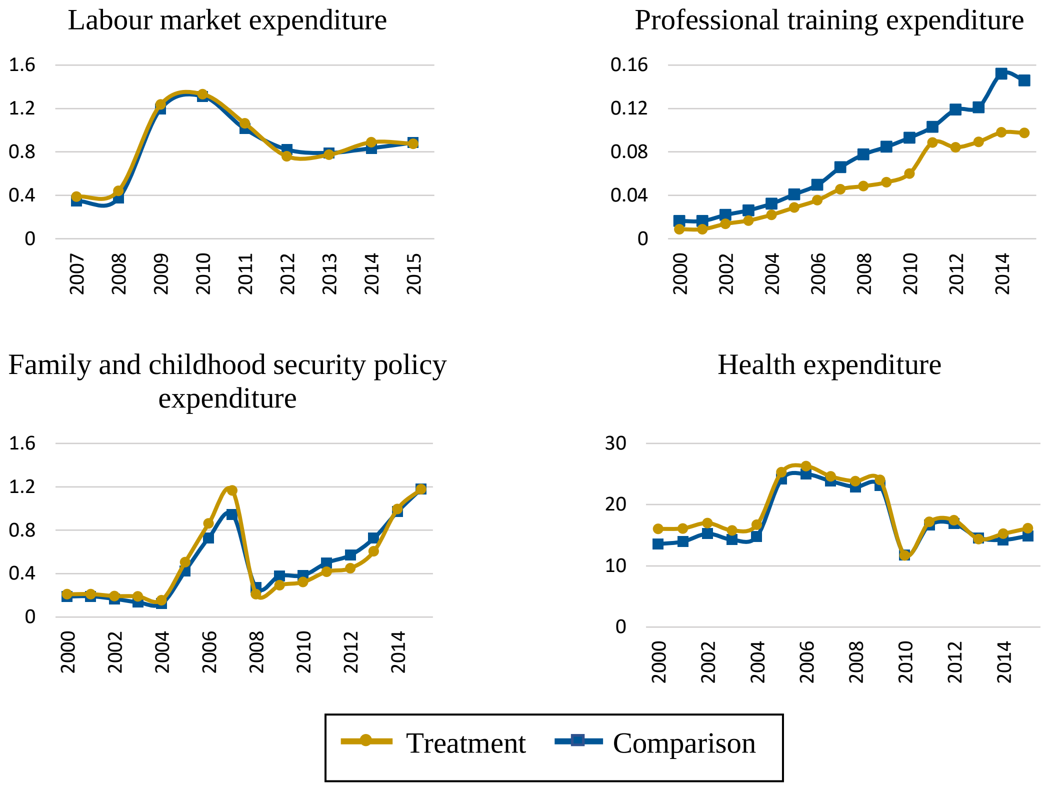

Figure 1.9 – Dynamics of regional expenditures on different policies in treatment and comparison groups (thousand rubbles per capita)

Notes: See notes to Figure 1.8 for the definition of treatment and comparison groups.
Source: Author's calculations based on the region-level data on budgets accounts from the Federal Treasury.

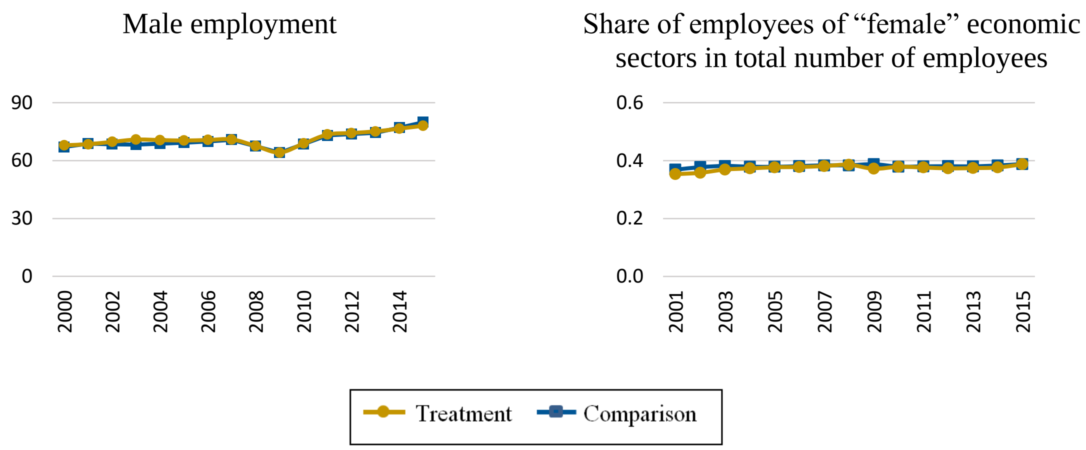

Figure 1.10 – Dynamics of regional labour market characteristics in treatment and comparison groups

Notes: See notes to Figure 1.8 for the definition of treatment and comparison groups. Male employment is presented for working age people (16-59 years old in Russia). In 2015, the "female" economic sectors with corresponding proportions of women in these sectors in parentheses are Education (82%), Health and Social Services (79%), Hotels and Restaurants (76%), Other Public and Social Services (68%), Wholesale and Retail Trade (61%). These five sectors covered 58.3% of employed women in 2015.
Source: Regional-level data from the Federal State Statistic Service of Russian Federation.

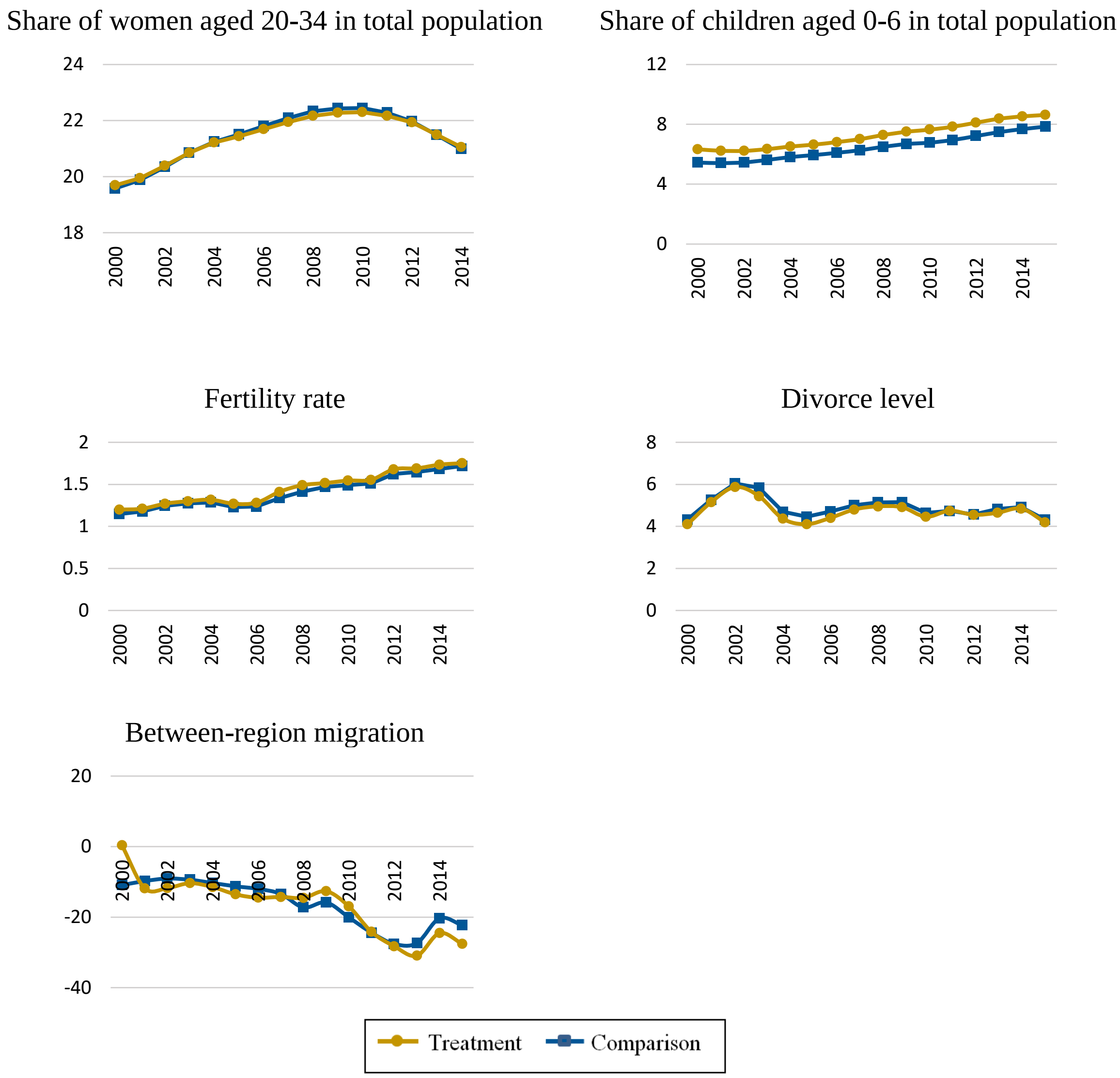

Figure 1.11 – Dynamics of regional demographic characteristics in treatment and comparison groups

Notes: See notes to Figure 1.8 for the definition of treatment and comparison groups. Divorce level shows the number of divorces per 1000 people. Between-region net migration rate shows the difference between the number of persons entering and leaving a region during the year, per 10,000 persons.
Source: Regional-level data from the Federal State Statistic Service of Russian Federation.

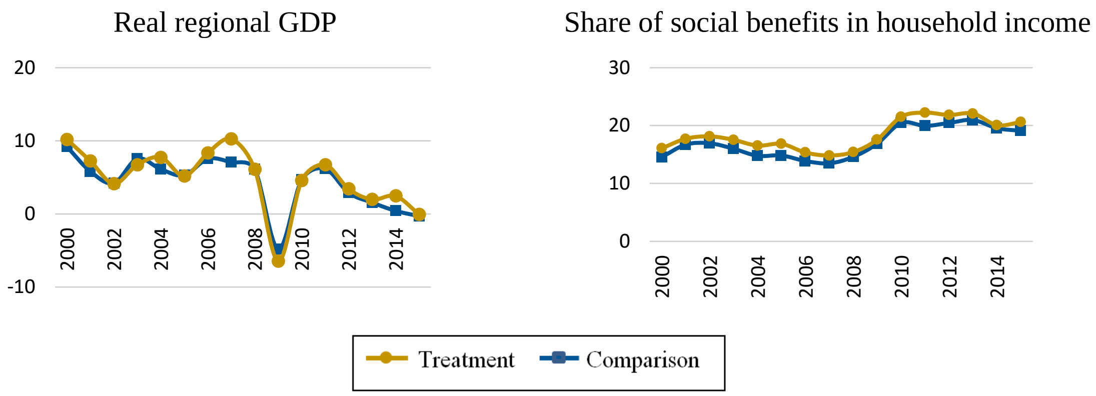

Figure 1.12 – Dynamics of region’s wealth and generosity characteristics in treatment and comparison groups

Notes: See notes to Figure 1.8 for the definition of treatment and comparison groups. The real regional GDP is measured in growth rates compared to previous years. Social benefits include all type of benefits as well as pensions, scholarships, insurance compensations and others.
Source: Country-level data from the Federal State Statistic Service of Russian Federation.

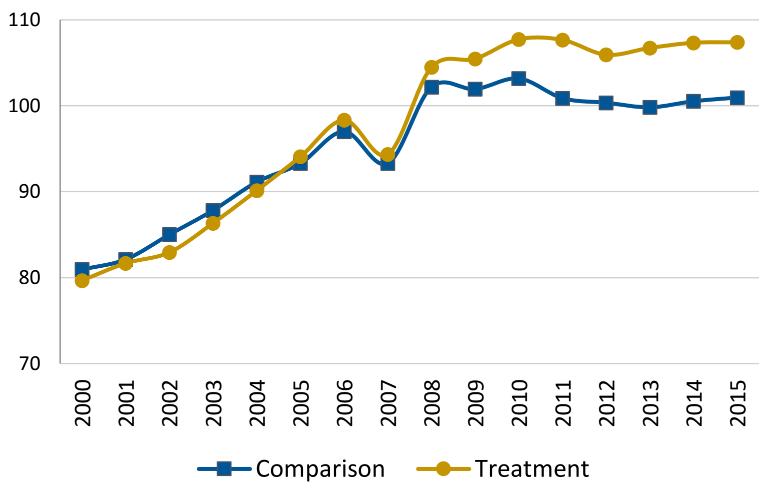

Figure 1.13 – Number of children per 100 places in childcare system in treatment and comparison groups

Notes: See notes to Figure 1.8 for the definition of treatment and comparison groups.
Source: Country-level data from the Federal State Statistic Service of Russian Federation.

Lastly, I also investigate trends in maternal employment before and during childcare expansion. Unfortunately, the Federal State Statistic Service started to collect the data on maternal employment at the country and regional levels only since 2009, thus, to check the maternal employment trends I rely on the survey data. Figure 1.14 shows levels of maternal employment among women aged 20-49 whose youngest child is 0-6 years old in the treatment and control groups; the red vertical line indicates the year in which we observe the increase in childcare enrolment. We can see that maternal employment follows approximately parallel trends in years before the increase in childcare enrolment. The trends continue to follow relatively similar trends through the expansion years. However, the level of maternal employment increased by 4.0 percentage points in the control group and by 7.2 in the treatment group over the studying period between 2000 and 2015. Overall, the difference in the maternal employment levels between the two groups decreased by 1.5 times.

Overall, this descriptive analysis of the childcare expansion does not indicate that there is a need to be concerned about different trends in socio-demographic and economic time-varying characteristics, although I will control for all these regional variables in the regression analysis.

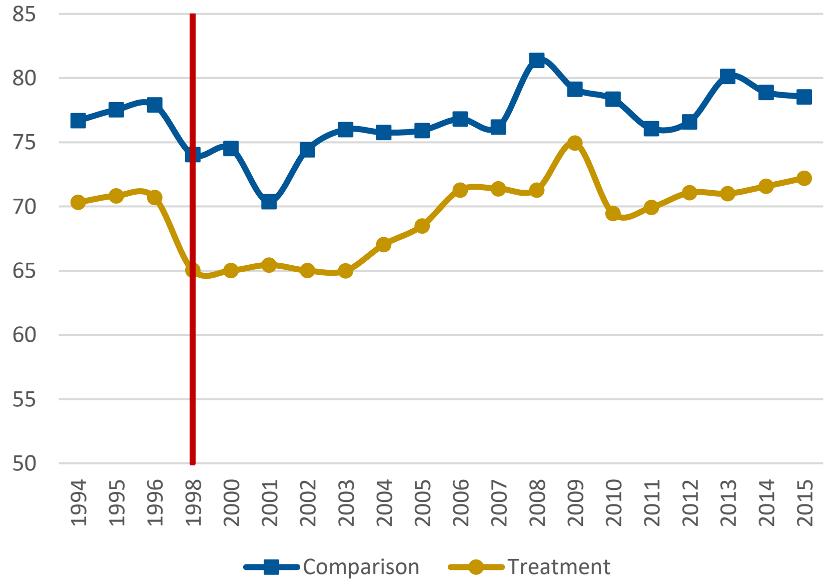

Figure 1.14 – Maternal employment among women aged 20-49 whose youngest child is 0-6 years old

Notes: See notes to Figure 1.8 for the definition of treatment and comparison groups.
Source: Author's calculations based on Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

Childcare prices

According to the Federal Law No. 273-FZ "Education in Russian Federation", the childcare system can provide two types of services – early child education and childcare. Public childcare providers offer a combination of educational and childcare services. While the educational part is free for children of all ages, childcare services are not. The childcare services cost includes the cost of essential needs like food or personal hygiene. The government is involved not only in the provision of public childcare services but also in controlling service prices in the public market. The regional government sets municipality-level price ceilings and public childcare providers form the price according to the price ceilings ones a year. The government provides federal subsidies to help parents to afford childcare. Before 2013, parents were responsible only for 20% of the actual cost of provided services and 80% of childcare costs were subsidized by federal and local governments. Since 2013, parents pay the full price but later the government pays back 20% of childcare fees for the first child, 50% for the second child, and 70% for the third and subsequent children.

The price of childcare can play important role in understanding the effect of childcare on maternal labour supply if prices are high and represent a significant barrier for women who want to enter/re-enter the labour market. However, in this paper, I do not take childcare prices into account due to several reasons. First, the price of public childcare in Russia is relatively small. In 2015, the average monthly price of childcare was 1,870 rubles which was equal to approximately 5.6% of the average income (or around £20 per month).[17,18] Second, childcare prices are based on only essential goods (like food) that parents would pay anyway. Third, parents receive a "discount" in the form of federal subsidies. Morover, according to Table 1.5 that shows the distribution of children aged between 3 and 6 who did not attend childcare in 2014 by reasons of non-attendance in Russia and across federal districts, it appears that the price of childcare is the last reason not to attend childcare (4.5%). In total, around 36.0% of children had to stay at home due to the lack of places or childcare providers around, and in every federal district the absence of places or childcare providers is a more acute problem than are high prices.

[17] Education in Russia 2017. Higher School of Economics Data Books.
[18] https://tradingeconomics.com/russia/wages

Table 1.5 – Distribution of children aged between 3 and 6 who did not attend childcare in 2014 by reasons of non-attendance, %

	No places	High prices	No childcare providers around	It is better to stay at home	Due to health issues	Other reasons
Russian Federation	23.4	4.5	12.6	38.9	6.4	14.3
Central federal district	13.9	2.3	15.8	42.0	9.8	16.2
North-West federal district	7.9	1.5	3.3	78.2	3.4	5.8
South federal district	24.3	2.2	15.9	34.4	8.4	14.9
North Caucasus federal district	14.7	3.0	7.0	54.1	4.9	16.4
Volga federal district	27.6	11.6	9.2	36.2	6.4	9.1
Ural federal district	38.9	7.1	3.0	24.7	5.8	20.5
Siberia federal district	34.7	6.0	10.1	25.4	6.1	17.7
Far East federal district	24.6	0.6	14.0	38.6	5.0	17.3

Source: Russian Comprehensive monitoring of living conditions in 2014.

Summing up the different aspects of the institutional background in Russia described above, I highlight the main features and some speculations about expected effects of childcare expansion in these circumstances. First, maternal employment varies substantially with the age of youngest child, with the employment rate of mothers whose youngest child is 0-2 years old being very low (25.7%), and that of mothers whose youngest child is 3-6 years old being very high (78.4%). The employment rate is considerably higher among single mothers and relatively high in comparison to other countries. Low maternal employment of mothers whose youngest child is aged 0-2 can be partly explained by the very low availability of part-time jobs and also by low enforcement of labour laws for pregnant women and women with young children. Expanding childcare availability should generate an increase in maternal employment, particularly for mothers whose youngest child is aged 0-2. However, the inflexibility of the labour market can dampen the effect.

Second, family and child benefits in Russia are relatively low and the welfare system is not very efficient. It is theoretically possible to find positive effects on maternal employment rate because in this case work incentives are high and financial needs can force mothers to join the labour market, especially single mothers. However, these single mothers already show high employment rates and this can reduce the potential effect.

Third, parents intensively use informal childcare. In this case, expanding childcare availability could motivate parents to shift from informal childcare arrangements to subsidised formal ones, which would lead to crowding out effect without significant changes in maternal employment.

Last, the current childcare system is characterized by a tremendous lack of places and an absence of private and part-time providers. All else equal, by providing more subsidized childcare places, the theoretical effects of childcare expansion on the extensive margin are unambiguously non-negative: the maternal rate should not fall and would likely rise. But all the circumstances described above can prevent effective increases in maternal employment. Thus, it is ambiguous how maternal employment would react to childcare expansion – different dimensions could strengthen or hinder the effectiveness of the policy.

As mentioned above, the case study of Russia can be beneficial for other post-socialist countries that have some similarities related to the institutional background that may affect the impact of childcare expansion on maternal employment. Table 1.6 shows some of these key characteristics for 11 post-socialist countries from Central and Eastern Europe and for Russia. While there is a substantial variation in some characteristics, there are some similarities. With the notable exception of Slovenia and Lithuania, in most post-socialist countries maternal employment rates are relatively low. Like in Russia, in the Czech Republic, Estonia, Hungary and the Slovak Republic there is a significant gap between maternal employment rates of mothers whose youngest child is aged 0-2 and whose youngest child is aged 3-5. The labour markets of these countries can be characterized as inflexible due to the small proportion of women employed part-time. In all countries except Hungary and the Czech Republic, family benefits are lower than the average of OECD countries. The last common characteristic is low levels of childcare coverage for children under the age of three. Despite these similarities, it is important to note that the results for Russia cannot be directly applied for other countries due to different historical contexts, different views on traditional gender roles, and cultural norms that also influence the formation of preferences regarding work and use of childcare. The results from this paper can give some insight into direction of childcare availability expansion that should be cautiously interpreted.

Table 1.6 – Institutional characteristics in post-socialist countries

	Maternal employment (%), 2014		Proportion of women employed part-time (%), 2015	Family benefits public spending in 2013, percentage of GDP	Formal childcare coverage (%), 2014	
	Youngest child aged 0-2	Youngest child aged 3-5			Under age 3	Ages 3-5
Bulgaria	44.1	60.4	2.4	n/a	11.2	82.1
Croatia	65.7	69.8	7.0	n/a	16.9	56.7
Czech Republic	22.3	71.9	7.4	2.2	5.6	80.5
Estonia	23.7	81.1	12.2	2.0	23.2	89.6[b]
Hungary	13.4	67.9	5.9	2.9	14.5	89.7
Latvia	54.4	69.6	9.4	1.2	24.0	91.0
Lithuania	69.5	71.8	9.3	n/a	28.8	82.6
Poland	58.5	65.5	9.6	1.2[a]	11.0	74.1
Romania	57.0	63.2	5.5	n/a	12.4	84.2
Russia	**25.7**	**78.4**	**5.6**	**0.9**	**18.0**	**83.4**
Slovak Republic	16.7	59.4	7.8	2.0	6.4	73.0
Slovenia	71.9	79.1	12.0	1.9	40.3	87.2

Notes: a. 2012, b. 2013. For Russia the children age groups are 0-2 and 3-6.
Source: OECD Family database.

1.4 Data

This paper is based on data from the Russian Longitudinal Monitoring Survey – Higher School of Economics (RLMS-HSE). The RLMS-HSE is a nationally representative split panel[19] of households in the Russian Federation. Although the dataset includes only 32 regions out of 89, the dataset represents the country well in terms of gender, education and type of settlement. The survey was designed to monitor the effects of Russian reforms on the health and economic welfare of households and individuals in the Russian Federation. The RLMS-HSE is conducted by the National Research University Higher School of Economics and ZAO “Demoscope” together with Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS.

Data has been collected from 1994 until now. On average, every year the dataset includes around 12,000 individuals from approximately 4,000 households. It includes variables such as socio-demographical information and family structure, precise measurement of household-level expenditures and service utilization, and a collection of relevant community-level data, including region-specific prices and community infrastructure data.

[19] Split (supplemental) panel surveys are a combination of a panel and a repeated panel survey. These surveys are designed to follow a particular group of sample units for a specified period of time and to introduce new groups of sample units at each time point during the specified period.

For the analysis, I construct a sample of mothers aged 20-49 who have at least one child aged between 0 and 6 in the period between 2000 and 2015. The unit of observation is the mother. I adopt this strategy because I ultimately want to investigate the impact of the childcare expansion at the region level on maternal labour market outcomes. For the period between 2000-2015, I have a sample of 17,575 mother-year observations. Of these 17,575 observations I lost 131 observations (0.7%) due to missing information on the explanatory variables, so the final sample was reduced to 17,444 mother-year observations.

In addition, I use data from the Federal State Statistic Service of Russian Federation that provides a vast range of regional characteristics for every year and every region and also a unique dataset on the number of enrolled children at each age in every region. Moreover, I use data from the Federal Treasury on detailed regional budget accounts linked to survey by region.

Key treatment variable

According to the existing literature, the number of children covered by childcare (or the enrolment rate) is the most appropriate way to measure childcare availability in the presence of shortages in the availability. For the case of Russia, the use of enrolment rates can be doubted because as shown in Figure 1.5 during some years the number of enrolled children is less than the total number of places. It suggests that not all available places were taken. However, the main reason to justify using enrolment rates to measure childcare availability in Russia is that waiting lists have operated in every region and in every year. From 2000, in every region there were parents who wanted to use childcare services but had to wait for a place (Figure 1.6). This could be because there is an allocation rule under which parents can apply to only three (in some regions, five) childcare organisations within their municipality. This means that if parents apply to three childcare organisations where there are no free places this application goes to the waiting list even if places are available at other childcare organisations. It may be that some parents avoid this allocation rule by direct informal communication to childcare organisation's director. However, available places must be within accessible distance; it may be impossible to reallocate children from one village/town without free childcare places to another village/town with available places. Distance is an important factor, especially in rural areas where towns and villages are often located very far from each other. Thus, even if there are some available places in the suburb, municipality, or region, these places are not always available to people due to the allocation rule or distance from home to childcare facilities, which leads to the child being put on the waiting list. Due to these reasons, the childcare enrolment rate appears to be an appropriate measure for childcare availability. Yet, in Section 7, I check my results by excluding the period between 2000-2006 from the analysis when the number of enrolled children was less than the total number of places. Enrolment rates are equal to the proportion of children aged between 0 and 6 that are actually enrolled in the childcare system and varies from 0 to 100%.

Data for enrolment rates has been provided by the Federal State Statistic Service of Russian Federation for every region and every year between 2000 and 2015. Moreover, from 2007 there is more detailed information on the enrolment rate – for every region there is information on how many children at each age from 0 to 6 were enrolled. With the exception of some fluctuations for the children aged 2 and for the period of time after starting the national programme on childcare system modernisation, the increase in the childcare enrolment was uniformly distributed across the age groups (Figure 1.15). Thus, to get more detailed data before 2007, I assume that pre-2007 years had the same distribution as in 2007. I use age-specific enrolment rates in 2007 and total regional enrolment rates during each year between 2000-2006 and apply age proportions observed in 2007 backwards to the previous years. In section 1.7, I show that my estimates are robust to excluding the 2000-2006 time period from the analysis.

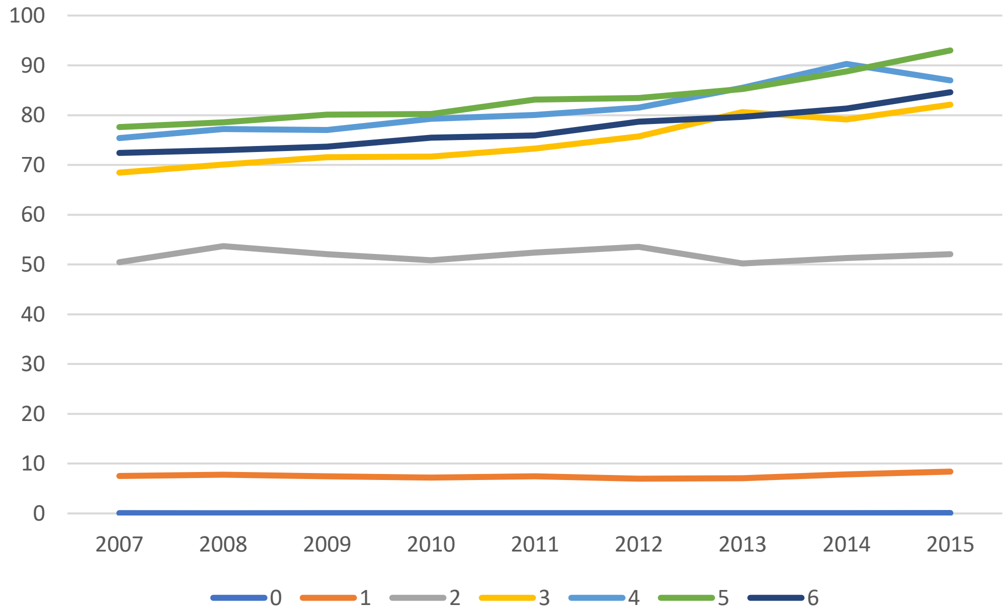

Figure 1.15 – Average age-specific enrolment rates for the period 2007-2015

Notes: Average age-specific enrolment rates for the period 2007-2015 for the regions presented in the dataset.
Source: Federal State Statistic Service of Russian Federation.

Labour market outcomes

I use a wide range of labour market outcomes in order to capture the impact of changes in childcare availability, defined as follows:

- Labour force participation (LFP) is a dummy variable equal to 1 if the mother is currently employed or unemployed or 0 otherwise.
- Employment is a dummy variable equal to 1 if the mother is currently working or is on paid/unpaid leave (except maternity or parental leave) or 0 otherwise.
- Hours of work: (1) Hours of work per week is a continuous variable equal to a duration of usual work week (the question is "how many hours is your usual work week"); (2) Part-time job is a dummy variable equal to 1 if the mother is currently working up to 30 hours per week or 0 otherwise; (3) Full-time job is a dummy variable equal to 1 if the mother is currently working 31-45 hours per week or 0 otherwise; (4) Over-employment is a dummy variable equal to 1 if the mother is currently working more than 45 hours per week or to otherwise. These variables take a value zero if the mother does not work.
- Informal employment is a dummy variable equal to 1 if in the last 30 days the mother was engaged in some kind of work for which she was paid (or will be paid) except her primary work (for example, sewed someone a dress, gave someone a ride in a car, assisted someone with apartment or car repair, looked after a sick person, sold purchased food or goods in a market or on a street and so on) or 0 otherwise.
- Job search is a dummy variable equal to 1 if in the last 30 days the mother applied anywhere or asked anyone for a job or 0 otherwise.
- Training is a dummy variable equal to 1 if during the last 12 months the mother studied or is studying now courses for the improvement of professional skills, or any other courses, including courses of foreign language and education at the work place, or 0 otherwise.

Descriptive statistics

Table 1.7 provides main descriptive statistics for the final sample. 57.3% of women are in the labour force and 53.1% are currently working while 4.7% are looking for a job.[20] On average, women work 21.1 hours per week but among those who are actually in work, the average

[20] These numbers are lower than national averages. For example, the maternal employment rate (mothers aged 20-49) was 64% in 2015.

duration of working week is 41.4 hours. Women more often work full-time (63%) and a quarter of employed women are overemployed. Interestingly, only 12.1% of employed mothers with young children work part-time. Only 4.6% of all women are doing some work that can be identified as informal employment and 6.0% are either taking some courses now or were enrolled during the last year to improve their professional skills. On average, women are 29.4 years old and the majority of them have a partner (87.2%). Around half of women estimate their health as satisfactory, the second half as good. More often women have higher education (32.9%) and a little less often secondary school (29.4%) or vocational training education (27.1%). The rest of the women did not finish secondary education. On average, there are 1.15 children aged up to 6 in a family. The average age of the youngest child is 2.9 years. There is at least one unemployed female relative older than 18 except an unemployed grandmother in 16.2% of households. I take into account these two variables because this could be a source of informal help within the household.

Figure 1.16 shows that women who have at least one preschool age child work less compared to those who do not have children of this age. However, the gap is significantly different between women whose youngest child is aged 0-2 and women whose youngest child is aged 3-6. The employment rate is 50-55 percentage points less for women with children aged 0-2 compared to women without young children. For women with children aged 3-6 the employment rate is on average 4 percentage points lower compared to women without young children with a bigger gap (around 7 pp) present during 2000-2004 that narrowed to 2-4 percentage points after 2004. Also, the employment rate considerably varies by age of the youngest child and by socio-economic group (Figure 1.17). It significantly increases with age of the youngest child until the child reaches the age of 4; after that, the employment rate is fairly stable. This relationship is similar for both single and low-educated mothers. Single mothers work particularly more when the age of the youngest child is less than 3 years. In total, when the youngest child reaches the age of 6, the employment rate is equal to 80% among all mothers and to 85% and 73% among single and low-educated mothers, respectively.

Table 1.7 – Descriptive statistics of the final sample

	Mean	SD	N
In labour force	0.573	0.495	17,570
In work	0.531	0.499	17,570
Part-time work (1-30 hrs/wk)	0.062	0.241	16,817
Full-time work (31-45 hrs/wk)	0.322	0.467	16,817
Overemployment (46+ hrs/wk)	0.126	0.332	16,817
Usual weekly hours	21.12	22.41	16,817
Looking for work	0.047	0.217	17,570
Informal employment	0.046	0.211	17,563
Training	0.060	0.237	16,896
Mother's age	29.37	5.453	17,444
Mother's has a partner	0.872	0.334	17,444
Very bad health	0.001	0.031	17,444
Bad health	0.025	0.155	17,444
Satisfactory health	0.487	0.500	17,444
Good health	0.470	0.499	17,444
Very good health	0.020	0.135	17,444
Incomplete secondary education	0.106	0.308	17,444
Secondary school education	0.294	0.455	17,444
Vocational training education	0.271	0.445	17,444
Higher education	0.329	0.470	17,444
Age of youngest child	2.853	1.928	17,444
Number of children 0-6	1.146	0.399	17,444
Number of children 7-10	0.185	0.418	17,444
Number of children 11-18	0.183	0.390	17,444
Unemployed female relatives older than 18 in HH	0.162	0.427	17,444
Regional center	0.396	0.489	17,444
City	0.284	0.451	17,444
Town	0.055	0.228	17,444
Village	0.265	0.441	17,444
Labour marker characteristics for those who are in work			
Part-time work (1-30 hrs/wk)	0.121	0.326	8,585
Full-time work (31-45 hrs/wk)	0.630	0.483	8,585
Overemployment (46+ hrs/wk)	0.249	0.431	8,585
Usual weekly hours	41.38	12.07	8,585

Notes: Sample consists of mothers aged 20-49 who have at least one pre-school age child (0-6 years old) between 2000 to 2015.
Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

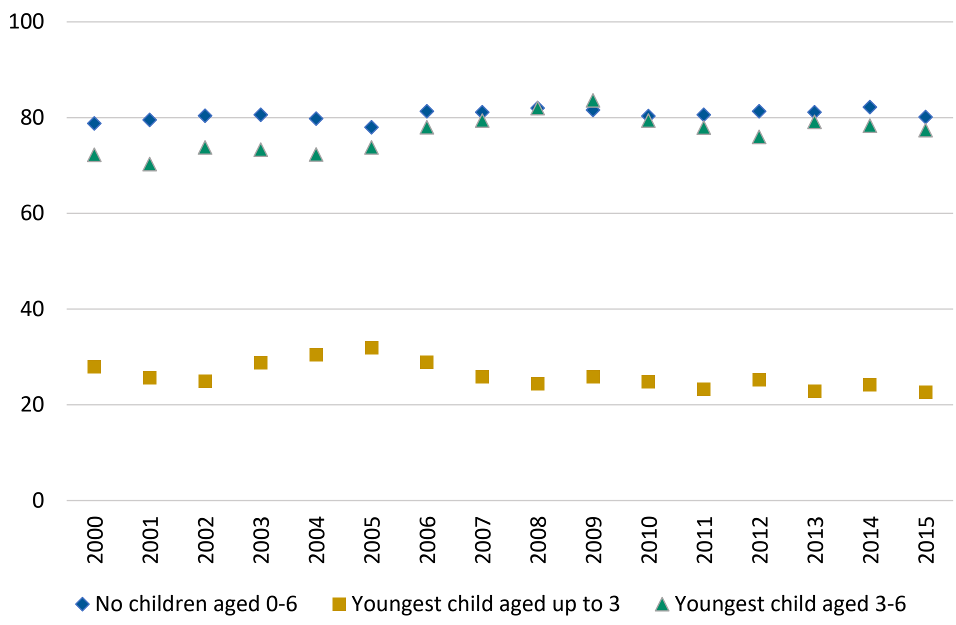

Figure 1.16 – Percentage of women in work with and without children aged 0-6

Notes: Woman is defined "in work" if she is currently working or is on paid/unpaid leave except maternity or parental leave
Source: Author's calculations based on Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

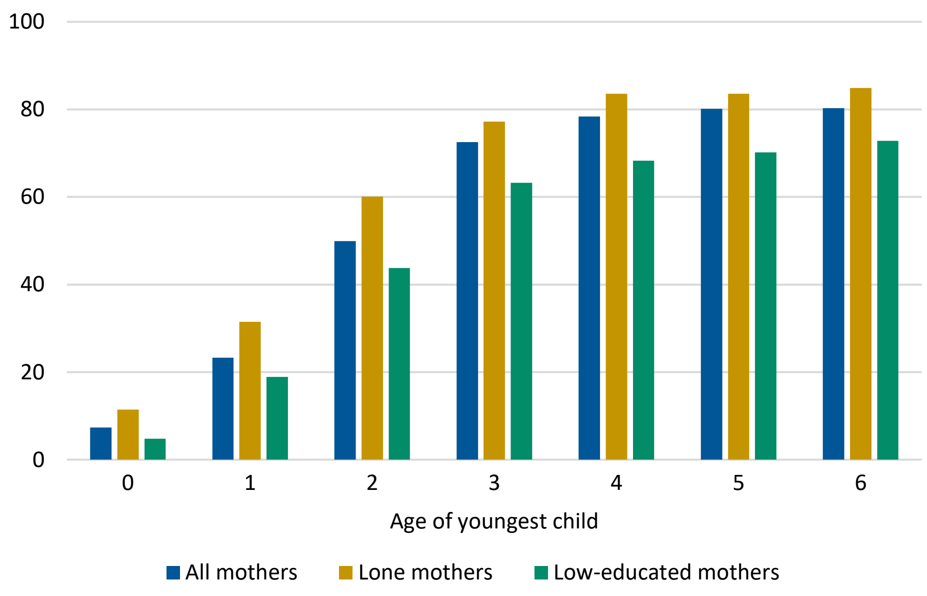

Figure 1.17 – Percentage of mothers in work by age of youngest child

Notes: Mother is defined as single if she is not married and does not have a partner. Mother is defined as having low education if her highest qualification is secondary school education or below.
Source: Author's calculations based on Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

1.5 Empirical strategy

To identify the effect of childcare availability on mothers' labour outcomes, I explore geographic and temporal variations in childcare coverage caused by the fact that the availability of public childcare system developed at different rates in different regions. The main assumption behind this method is that the expansion of childcare across regions and over time is independent to other time-varying and region-specific characteristics that might affect labour market outcomes. To implement this strategy, I use a generalised difference-in-difference technique that allows me to use a continuous treatment variable.

In the absence of good quality data on childcare usage in the RLMS-HSE[21], the strategy I use allows me to estimate the Intention-To-Treat effect of expansion of childcare availability on maternal labour market outcomes. The existing literature shows that any effects of public childcare should be stronger among mothers for whom the child getting childcare is the youngest one (Berlinski et al., 2011, Nollenberger and Rodriguez-Planas, 2015, Bauernschuser and Schlotter, 2015). In the main part of the analysis I consequently estimate the impact of childcare availability for the youngest child in the household. Further in Section 1.7, I present the results of the same model for mothers of children aged 0-6 who are not the youngest in the household.[22]

My main specification is defined at the mother-level and presented as follows:

$$Y_{itr} = \beta_1 Availability_{tr(age)} + \beta_2 X_{it} + \beta_3 Z_{tr} + \eta_t {*} Availability2000_{r(age)} + \mu_r + \eta_t + \xi_{itr} \quad (1)$$

where:

- Y_{itr} is one of the labour market outcome for woman *i* in region *r* in year *t;*
- $Availability_{tr(age)}$ is an indicator of childcare availability in year *t* and region *r* for the youngest child in the family. To measure childcare availability, I use age-specific enrolment rates which vary from 0 to 100%;
- $\boldsymbol{X}_{it}$ is a vector of mother's individual and family characteristics: age, education, health, marital status, number of children in the age bands 0-6, 7-10, 11-15, age of the youngest

[21] According to my estimates, childcare use is significantly underreported in the RLMS-HSE.
[22] Berlinski et al. (2011) suggest to estimate the model separately for those who are the youngest in the household and for those who are not the youngest in the household because the effect of childcare attendance on maternal labour market outcomes could differ between these two groups.

child, a dummy variable for the presence of unemployed female members in household (except unemployed grandmothers) as well as settlement type;

- $\boldsymbol{Z}_{tr}$ is a vector of region-specific characteristics that may affect mother's labour market outcomes and vary over the time;
- $\eta_t*Availability2000_{r(age)}$ is an interaction between year dummies and levels of childcare availability (enrolment rate) in 2000 which is the first year of the studied time period. Including these interaction terms allows to control for primary regional levels of childcare availability;
- μ_r is a region fixed effect which controls for time-invariant unobserved region characteristics;
- η_t is a year fixed effect capturing year-specific differences;
- ξ_{itr} is an error term.

I use a rich set of regional socio-demographic and economic characteristics, $\boldsymbol{Z}_{tr}$, because one might be concerned about confounding the effect of childcare expansion with other regional policy choices taking place at the same time that could also have affected the female labour market outcomes. It includes information on a region's population age structure (share of women aged 20-34, share of women aged 35-54, share of children under the age of 6 years), between-region migration, rate of marriages[23] and divorces[24] to capture local demographics; information on male employment and share of employees of the "female" economic sectors[25] in total number of employees to capture local labour market circumstances. I also include a wide range of regional expenditure on different policies per capita to capture time-varying difference in local public finance, which reflect current regional priorities, such as expenditure on health system, on higher education, on professional training, on youth policy[26], on social security, on family and childhood security policy[27] and on labour market support. Furthermore,

[23] Level of marriages shows number of marriages per 1000 people.
[24] Level of divorces shows number of divorces per 1000 people.
[25] In 2015, the "Female" economic sectors (with corresponding proportions of women in these sectors in parentheses) are Education (82%), Health and Social Services (79%), Hotels and Restaurants (76%), Other Public and Social Services (68%), Wholesale and Retail Trade (61%). These five sectors covered 58.3% of employed women in 2015.
[26] Youth policy is system of priorities and measures aimed at creating conditions and opportunities for successful socialisation and effective self-realisation of young people, to develop their potential for the benefit of the socio-economic and cultural development of the country, ensuring their competitiveness and enhancing national security.
[27] Family and childhood security is the system of measures aimed at ensuring the health of mothers and children, strengthening families, promoting motherhood, creating the most favourable conditions for the children upbringing, their physical, intellectual and moral development.

I control for the GDP per capita in period *t-1* and average proportion of social benefits in household income to capture region's wealth and generosity. Controlling for this set of different regional characteristics helps to minimise the problem of confounding the effect of other regional policies and exploit only the growth in childcare availability.

1.6 Results

Table 1.8 shows my main results based on Eq. (1), where each row shows the result of a separate regression for the nine labour market outcomes while columns correspond to different specifications of the main equation. Column (1) presents results of a model that controls for year and region fixed effects as well as individual and family characteristics. In column (2) I add regional time trends. In column (3) I additionally control for mother's individual and family characteristics. In column (4) I control for the interaction of year fixed effects with childcare availability during the first year of the observation period and in column (3) I add regional controls capturing regional socio-demographic and economic conditions and regional policy decisions on how to distribute regional budgets among different policies. In all specifications, I cluster standard errors at the regional level. The model that includes all listed covariates is used as a baseline specification. For the baseline model, I adjust the p-values for multiple inference correction following Anderson (2008), Table A1.

Column (1) shows that when I control only for year and region fixed effects the effect of the childcare expansion on LFP, employment, full-time job and hours of work is relatively high and statistically significant while the effect on part-time job, over-employment, informal employment, job search and training is also statistically significant but small. These results rely on the identification assumption that there are no omitted time-varying and region-specific effects correlated with the childcare expansion. Column (2) shows that adding regional time trends does not change the results. In Column (3), I add mother's individual and family characteristics. This decreases the magnitude of the effects but the differences are not statistically significant. Column (4) shows the results of a model that takes into account that the allocation of childcare in regions could be an explicit function of the childcare availability in the region in 2000, the first year of the studied time period. Including the interactions of year fixed effects with starting levels of childcare availability in the regions in 2000 makes most estimates smaller, suggesting that starting levels of childcare availability are correlated with the childcare availability expansion. In Column (5), I add in region-level controls which do not change point estimates much. Overall, the results change only between Columns (3) and (4).

This indicates the importance of controlling for starting levels of enrolment rates because it may be correlated with the childcare expansion and affect labour market outcomes.

The baseline specification, displayed in Column (5), shows positive and statistically significant effects of childcare expansion on some maternal labour market outcomes. More specifically, if there is a 10 percentage points increase in childcare enrolment, the probability of maternal labour force participation increases by 3.4 percentage points and the probability to be employed increases by 2.8 percentage points. These results are statistically significant at the 1% and 5% levels, respectively. This magnitude of expansion in childcare availability also leads to increase the extensive margin of full-time employment by 2.2 percentage points but this effect is statistically significant only at the 10% level. The intensive margin of maternal labour supply reacts by 1.24 hours increase per week in response to a 10 percentage points growth of childcare availability. The result is statistically significant at the 5% level.

To assess the magnitude of these results, I consider a total increase in childcare availability from 55% to 66.2% between 2000 and 2015 which is equal to 11.2 percentage points. Assuming linearity of the results, I argue that overall childcare expansion increased the total maternal labour force participation by an average of 3.8%, an extensive margin of maternal employment by an average of 3.1%, an extensive margin of full-time employment by an average of 2.4% and an intensive margin of maternal labour supply by an average of 1.4 hours per week between 2000 and 2015.

Table 1.9 shows that the estimated impact varies across different groups of mothers. Panel A displays the difference in the impact between single and partnered mothers; Panel B shows the difference between low- and high-educated mothers; and Panel C reports the difference between the group of mothers whose youngest child is aged 0-2 and the group of mothers whose youngest child is aged 3-6. By low-educated mothers, I consider those who at most have secondary education. For every difference I adjust the p-values for multiple inference correction following Anderson (2008), Table A2.

Panel A shows results that diverge from the existing literature, which often underlines that childcare growth has significantly higher effect for single mothers or the effect exists only for single mothers. In the case of Russia, the effect of childcare availability on the labour force participation of single mothers is significantly lower than on mothers with partners. We observe that a 10 percentage points growth in childcare enrolment increases labour force participation

Table 1.8 – Effect of childcare availability on mothers' labour market outcomes

	(1)	(2)	(3)	(4)	(5)	N
Labour force participation	0.0087***	0.0088***	0.0063***	0.0033**	0.0034***	17,084
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	
Employment	0.0084***	0.0084***	0.0056***	0.0026**	0.0028**	17,084
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	
Part-time job	0.0007***	0.0007***	0.0005***	0.0001	0.0001	16,358
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Full-time job	0.0057***	0.0057***	0.0040***	0.0019	0.0022*	16,358
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	
Over-employment	0.0020***	0.0020***	0.0011***	0.0004	0.0005	16,358
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	
Hours of work	0.355***	0.356***	0.232***	0.114**	0.124**	16,358
	(0.009)	(0.008)	(0.015)	(0.047)	(0.045)	
Informal employment	0.0003***	0.0003***	0.0000	0.0006	0.0007	17,076
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	
Job searching	0.0004***	0.0004***	0.0007***	0.0007	0.0006	17,084
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Training	0.0007***	0.0007***	0.0005***	0.000	0.0001	16,436
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	
Year fixed effect	Yes	Yes	Yes	Yes	Yes	
Region fixed effect	Yes	Yes	Yes	Yes	Yes	
Regional time trends	No	Yes	Yes	Yes	Yes	
Individual and family characteristics	No	No	Yes	Yes	Yes	
Availability2000*Year FE	No	No	No	Yes	Yes	
Regional characteristics	No	No	No	No	Yes	

Notes: The sample includes mothers aged 20-49 whose youngest child is aged between 0 and 6. All regressions are linear regressions. Key treatment variable is enrolment rate that varies from 0 to 100%. The first column regression includes year and regional fixed effects. In the second column, the regional time trends are added. The third column regression additionally includes a vector of mothers' individual and family structure characteristics such as age, education, health, marital status, number of children in the age bands 0-2, 3-6, 7-10, 11-15, age of youngest child, dummy for unemployed female members in the household. In the fourth column, regression interaction between year dummies and levels of childcare availability (enrolment rate) in 2000 is also added. The fifth column specification includes all previous controls plus regional characteristics such as male employment, share of employees of "female" economic sectors in total number of employees, regional migration, level of marriages, level of divorces, share of women aged 20-34, share of women aged 35-54, share of population under the age of 6 years, regional expenditure on health per person, regional expenditure on higher education per person, regional expenditure on professional training per person, regional expenditure on youth policy per person, regional expenditure on social security per person, regional expenditure on family policy per person, regional expenditure on labour market support per person, average proportion of social benefits in household income at the regional level, GDP per capita in period t-1, settlement type. The fifth specification that includes all listed covariates is used as a baseline specification. The regression sample sizes are sometimes slightly different from column to column. This is because there is different amount of missing data for different variables. As a rule, for each specification I drop observation that is either missing the dependent variable or missing all of the independent variables. The last column shows the number of observations for the final specification. Standard errors are clustered at the regional level. *p<0.10, **p<0.05, ***p<0.01.

by 3.1 percentage points among mothers with partners and by 2.1 percentage points among single mothers. One potential explanation for this is that single mothers experience higher financial needs, which force them to come back to the labour market even in the absence of public childcare. As a consequence, these mothers have to find alternative methods of childcare for their children. Also, there is a minor but significant difference in terms of probability to be employed and informal employment between these groups of mothers.

Panel B demonstrates that there are also some significant differences between low- and high-educated mothers in the effect of childcare availability. It seems that childcare expansion affects low-educated mothers less than high-educated ones in terms of labour force participation, employment and working full-time. But, again, these differences are indistinguishable from zero except the probability of having a full-time job. A 10 percentage points growth in childcare enrolment increases probability of being employed full-time by 3.0 percentage points among high-educated mothers while for low-educated mothers the effect is equal to 1.3 percentage points and is not statistically significant. At the same time it is observed that there is a minor positive and statistically significant effect on over-employment among low-educated mothers whereas there is no effect on over-employment among high-educated mothers.

Panel C shows some differences in the effect of childcare availability between the group of mothers whose youngest child is aged 0-2 and the group of mothers whose youngest child is aged 3-6. For example, the effect on labour force participation is bigger for mothers whose youngest child is aged 0-2, but the probability to work full-time is higher among those mothers whose youngest child is aged 3-6. However, these differences are not statistically significant.

Table 1.9 – Heterogeneity analysis: Effect of childcare availability on mothers' labour market outcomes

	Panel A			Panel B			Panel C		
	Partnership status			Education			Youngest child age is 0-2		
	Single	Partnered	Δ	Low	High	Δ	0-2	3-6	Δ
Outcome:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LFP	0.0021*	0.0031**	-0.0010**	0.0031**	0.0037**	-0.0007**	0.0036**	0.0024**	-0.0012
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Employment	0.0022**	0.0029**	-0.0006*	0.0024**	0.0032**	-0.0008**	0.0029**	0.0024**	-0.0005
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Part-time job	-0.0006	-0.0001	-0.0005**	-0.0002	-0.0001	-0.0001	0.0001	-0.0007	-0.0009***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Full-time job	0.0021*	0.0022*	-0.0001	0.0013	0.0030**	-0.0017***	0.0016	0.0026**	0.0010
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Over-employment	0.0006	0.0005	0.0001	0.0010*	0.0002	0.0008**	0.0007	0.0002	-0.0005
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Hours of work	0.1137**	0.1252**	-0.0115	0.1164**	0.1331**	-0.0169	0.1219**	0.1109**	-0.0110
	(0.044)	(0.046)	(0.016)	(0.045)	(0.045)	(0.011)	(0.051)	(0.036)	(0.034)
Informal employment	0.0004	0.0007	-0.0004**	0.0008	0.0006	0.0001	0.0009	0.0007	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Job searching	0.0002	0.0007	-0.0005**	0.0007	0.0005	0.0002**	0.0008*	-0.0002	-0.0010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Training	-0.00008	-0.00005	-0.00003	-0.0004	0.0003	-0.0007***	0.0000	-0.0003	-0.0003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)

Notes: See notes to Table 1.8Table 1.6 for details in baseline specification. All regressions are linear regressions. Key treatment variable is enrolment rate that varies from 0 to 100%. Mother is defined as single if she is not married and does not have a partner. Mother is defined as having low education if at most she has secondary school education. *p<0.10, **p<0.05, ***p<0.01.

1.7 Robustness checks and extension

Table 1.10 reports a number of robustness checks based on the Eq. (1), demonstrating that the effect of childcare availability on maternal labour market outcomes is very similar to the baseline results (Column (1)) across different specifications. For every specification test I adjust the p-values for multiple inference correction following Anderson (2008), Table A3.

More precise control for regional time-varying characteristics

The main assumption for the strategy I use in this paper is that the expansion of childcare across all regions in Russia and over time is independent of other possible region-specific and time-varying characteristics that could potentially affect maternal labour market behaviour. Even after controlling for the rich set of regional characteristics this still might be an issue. Thus, I follow Duflo (2001) and add interactions between all regional characteristics at the starting point in 2000 and year fixed-effect. Column (2) of Table 1.10 shows that after controlling for this extra set of regional characteristics results stay very similar to the baseline that are reported in Column (1).

Excluding 2014 and 2015 from the analysis

There are two reasons to exclude 2014 and 2015 from the analysis. The first is that in 2013 the government launched the programme on preschool childcare system modernisation and regions began to get federal subsidies. Thus, exclusion of 2014 and 2015 from the analysis shows the effect of the childcare expansion without taking the national programme into account.

The second reason is methodological. In 2014, the methodology for data collection on childcare providers changed. Before 2014 all information on childcare providers was based only on those organisations that provide childcare exclusively. In 2014, the number of organisations that were obliged to provide information expanded. Since that time it is not only those organisations that specialise in providing childcare services but also those organizations that specialise in the formal education in general (schools, colleges, universities and so on) and additionally provide services for preschool age children. This should not change the derivation of the dataset for the enrolment rate because all children covered by the childcare system should be taken into account regardless of whether they attend just childcare or a college that additionally provides childcare services. To be sure that this does not affect the results, I estimate the baseline model without these two years. Column (3) of Table 1.10 demonstrates that the effect of the childcare expansion on maternal labour outcomes is nearly the same for all outcomes except full-time job.

Excluding the 2000-2006 time period from the analysis

There are two reasons to exclude the period of time between 2000 and 2006. First, as mentioned in Section 1.3, between 2000 and 2007 the number of enrolled children was less than the total number of places in the childcare system. It means that not all available places were taken and it can affect the method I use to define childcare availability. Second, as described in Section 1.4, detailed information on the enrolment rate by age exists only from 2007. To fill the gap between 2000 and 2007, I use the existing information on enrolment rates by age in 2007 and apply this backwards in time to the total regional enrolment rates during the period of 2000-2006. To check whether the results are sustainable I drop this time period and run the baseline model only for the period of 2007-2015. Column (4) of Table 1.10 reports that the results do not change.

Excluding five regions with extremely large increases in the female employment rate

During the period of 2000-2015, there are five regions that experienced a very high female employment growth – 43.0 percentage points in the Krasnoyarsk region, 23.0 percentage points in the Nizhny Novgorod region, 21.7 percentage points in the Penza region, 16.6 percentage points in the Orenburg region and 13.5 percentage points in the Republic of Chuvash. I drop these regions from the analysis to be sure that the main results are not driven by these outliers. Column (5) of Table 1.10 shows that the results are robust to this check.

Excluding rural areas from the analysis

Despite the fact that the over-enrolment problem was always a concern both in urban and rural areas (see Table 1.3), in rural areas the average number of enrolled children per 100 places was less than 100 between 2000 and 2015. These contradictory circumstances possibly arise because of the distance issue which is described in Section 1.4. The fact that the total number of available places was higher than the total number of enrolled children could put into question the use of the definition of childcare availability that is equal to enrolment rates. Although in Section 1.4 I describe why I still could use enrolment rates as a measure of childcare availability, I drop rural areas at the sub-regional level from the analysis as a robustness check. Column (6) of Table 1.10 reports that the results do not change much.

Probit model estimation

So far I have used OLS regressions for all outcomes. Nevertheless, because 8 out of 9 labour market outcomes are binary variables, I estimate Eq. (1) as a probit regression model. Column (7) of Table 1.10 reports marginal effects what look very similar to the baseline results with small change in the probability to have a full-time job which is 1 percentage points higher with a higher level of statistical significance.

Panel data estimation

The longitudinal nature of the data allows controlling for mother fixed effects that enable the removal of any time-invariant difference in labour market outcomes between mothers from different regions with different level of childcare exposure. The results from Column (8) of Table 1.10 show that using mother fixed effects is in line with the baseline results, indicating unobservable characteristics are not an issue.

Analysis for mothers of children who are not the youngest in the household

All previous results are based on the model which estimates the impact of childcare availability expansion for the youngest child in the households. Theoretically the effect could be different for those who are the youngest in the household and for those who are not the youngest in the household. Column (9) of Table 1.10 presents results based on the same baseline model, but for mothers of children aged between 0 and 6 who are not the youngest in the household. There are some significant effects on a mode of work (part-time/full-time/overemployment) but these coefficients are extremely small. In general, in line with the previous literature there is no evidence of changes in employment or hours of work in response to childcare availability expansion for children who are not the youngest in the household.

Table 1.10 – Robustness checks: alternative specifications and samples

	Baseline model (1)	Economic controls2000 * year FE (2)	Without 2014 and 2015 (3)	Without 2000-2006 (4)	Without five regions (5)	Only urban area (6)	Probit-model (7)	Mother FE (8)	Not the youngest children in HH (9)
Labour force participation	0.0034***	0.0039**	0.0034**	0.0032**	0.0039**	0.0038**	0.0032**	0.0037***	0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Employment	0.0028**	0.0035**	0.0030**	0.0029**	0.0031**	0.0033**	0.0030**	0.0032***	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Part-time job	0.0001	0.0001	0.0002	-0.0002	0.0001	-0.0006	0.0000	0.0003	0.0004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Full-time job	0.0022*	0.0023*	0.0013	0.0021*	0.0022*	0.0021**	0.0030***	0.0018**	-0.0013**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Over-employment	0.0005	0.0008	0.0010	0.0006	0.0005	0.0015**	0.0005	0.0007	0.0008**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Hours of work	0.124***	0.1573**	0.1306**	0.1425**	0.1323**	0.1915**	-	0.1320***	0.0035
	(0.045)	(0.051)	(0.052)	(0.050)	(0.052)	(0.061)	-	(0.042)	(0.021)
Informal employment	0.0007	0.0007	0.0005	0.0006	0.0006	0.0003	0.0006	0.0006	0.0005*
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Job searching	0.0006	0.0005	0.0005	0.0004	0.0009*	0.0005	0.0003	0.0004	0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Training	0.0001	0.0002	0.0003	0.0001	0.0005	-0.0001	0.0003	0.0004	0.0002
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
N	17,084	17,084	14,395	11,784	14,551	11,579	17,084	17,084	2,086

Notes: See notes to Table 1.8 for details in baseline specification. All regressions are linear regressions. A key treatment variable is enrolment rate that varies from 0 to 100%. Results in Column (1) are baseline model. Results in Column (2) control more precise for regional time-varying characteristics adding interactions between all regional characteristics at the starting point in 2000 and year fixed effects. Results in Column (3) are without 2014 and 2015 years. Results in Column (4) are without 2000-2006 time period. Results in Column (5) are without five regions with extremely high increase in female employment rate. Results in Column (6) are without rural area. Results in Column (7) use probit model instead of OLS. Results in Column (8) are with mother fixed effects. Results in Column (9) are for mothers of children who are not the youngest in the household. Standard errors are clustered at the regional level. *p<0.10, **p<0.05, ***p<0.01

1.8 Conclusion

This paper provides the first evidence of the effects of public childcare expansion on maternal labour market outcomes in Russia. While in many countries during the last decades childcare expansion was on the top of the policy agenda, the Russian government until recently did not pay much attention to this issue. This led to a substantial excess demand for childcare. In this context, Russian regions had to solve the problem without financial support from the central government, which resulted in significant variations in childcare availability across regions over time. I exploit this variation, conditioning on a rich set of economic time-varying regional characteristics, to establish causality.

Using a wide range of labour market outcomes, the estimates reveal that there is a significant positive effect of childcare expansion. A 10 percentage points growth in childcare availability increases the probability to participate in the labour force by 3.4 percentage points, the probability to be employed by 2.8 percentage points and the probability to have a full-time job by 2.2 percentage points among mothers whose youngest child is under the age of 6 years. In addition, it leads to increase hours of work by 1.4 hours per week. Several robustness checks corroborate the validity of these results. The effects are significantly smaller for single mothers and this is in line with extremely high level of employment among single mothers in Russia. According to these findings, half of the total rise in maternal employment, which was equal to 6.2 percentage points between 2000 and 2015, is due to the increase in childcare availability.

It is difficult to compare the size of my effects to the effect identified in other studies due to several reasons. Firstly, different studies are based on different identification strategies and though present different effect, e.g. intention-to-treat effects or (local) average treatment effects. Secondly, different policies focus on different groups of population, sometimes very specific groups. For example, Cascio (2009) evaluates the introduction of free childcare places for five-year-olds, Bauernshuser and Schlotter (2015) focus on mothers whose youngest child is three or four, Nollenberger and Rodriguez-Planas (2015) study the effects of full-time public childcare for three-year-olds. In this study I focus on a wider group of mothers whose youngest child is between 0 and 6. This means that the effect of public childcare for this group theoretically should be less strong than the effect of public childcare for a narrower group of mothers. Thirdly, different reforms offer different conditions such as it could be totally free or party subsidised part-time or full-time public childcare. Taking these issues into account, in comparison with other countries where parents of pre-school age children are supported by free full-time childcare, the size of my point estimates of the effect of childcare expansion in Russia are close, but still smaller, to those found in Germany (Bauernshuser and Schlotter, 2015) and in the UK (Brewer, Cattan, Crawford, Rabe, 2016).

Similarities between Russia and other post-socialist countries in Central and Eastern Europe, such as low maternal labour supply rates, lack of part-time jobs and low childcare coverage rates of children under the age of three, suggest a potential positive effect of childcare expansion on maternal employment in these countries as well. However, it is crucial to keep in mind that mothers' labour market behaviour is a complex phenomenon and that to help mothers to join the labour market other changes are required. This could include creating flexible and part-time job opportunities or increasing the quality and flexibility (such as more flexible hours) of childcare.

To sum up, the results show that an expansion of public childcare is an effective policy to increase employment of mothers of young children. The demographic processes that are currently taking place in Russia, the ageing population in particular, increase the share of pensioners in the country while the share of working people is declining. This results in high risks for the Russian social system. Under these circumstances, the creation of appropriate conditions for maternal employment is one of the potential mechanisms in mitigating these problems. At the same time, it is important to remember about a potential drawback as expanding childcare can compromise its quality which further can affect child development. In this respect, one of the potential focuses of government work could be to stimulate private childcare by simplifying the process of its opening, making them more affordable to more people.

Appendices

Appendix A1 – Adjusted p-values

Table A1 – Effect of childcare availability on mothers' labour market outcomes - Table of p-values and q-values.

Outcome	P-values of the baseline model
Labour force participation	**0.008**
	0.045
	0.048
Employment	**0.016**
	0.066
	0.055
Part-time job	0.703
	0.749
	0.499
Full-time job	**0.071**
	0.124
	0.090
Over-employment	0.386
	0.389
	0.209
Hours of work	**0.010**
	0.045
	0.048
Informal employment	0.151
	0.168
	0.126
Job searching	0.277
	0.389
	0.209
Training	0.822
	0.994
	0.635

First row: standard p-values.

Second row: q-values introduced by Benjamini and Hochberg (1995).
Third row: sharpened two-stage q-values introduced by Benjamini, Krieger, and Yekutirli (2006).

Notes: This is a table of p-values and q-values corresponding to Column (5) of Table 1.8. Q-values are p-values that are adjusted for the number of multiple hypotheses being tested. I adjust them considering all hypotheses tested in Table 1.8, following Anderson (2008).

Table A2 – Heterogeneity analysis: Effect of childcare availability on mothers' labour market outcomes - Table of p-values and q-values.

	Difference between single and partnered mothers	Difference between low- and high-educated mothers	Difference between mothers whose youngest child aged 0-2 and 3-6
LFP	**0.001**	**0.008**	0.166
	0.036	**0.011**	0.327
	0.038	**0.007**	0.341
Employment	**0.087**	**0.002**	0.551
	0.177	**0.003**	0.569
	0.113	**0.002**	0.485
Part-time job	**0.006**	0.264	**0.008**
	0.036	0.311	**0.045**
	0.038	0.116	**0.042**
Full-time job	0.652	**0.000**	0.109
	0.816	**0.001**	0.327
	0.570	**0.001**	0.341
Over-employment	0.681	**0.001**	0.223
	0.816	**0.003**	0.407
	0.570	**0.002**	0.463
Hours of work	0.482	0.140	0.748
	0.792	0.143	0.739
	0.544	0.050	0.686
Informal employment	**0.042**	0.309	0.371
	0.102	0.311	0.539
	0.073	0.116	0.485
Job searching	**0.023**	**0.017**	**0.000**
	0.057	**0.017**	**0.001**
	0.047	**0.010**	**0.001**
Training	0.817	**0.000**	0.478
	0.816	**0.001**	0.539
	0.570	**0.001**	0.485

First row: standard p-values.

Second row: q-values introduced by Benjamini and Hochberg (1995).

Third row: sharpened two-stage q-values introduced by Benjamini, Krieger, and Yekutirli (2006).

Notes: This is a table of p-values and q-values corresponding to Column (3), (6) and (9) of Table 1.9. Q-values are p-values that are adjusted for the number of multiple hypotheses being tested. I adjust them considering all hypotheses tested in Table 1.9, following Anderson (2008).

Table A3 – Robustness checks: alternative specifications and samples - Table of p-values and q-values.

	Baseline model	Economic controls2000 * year FE	Without 2014 and 2015	Without 2000-2006	Without five regions	Only urban area	Probit-model	Mother FE	Not the youngest children in HH
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(7)	(9)
Labour force participation	**0.008**	**0.008**	**0.029**	**0.027**	**0.015**	**0.022**	**0.012**	**0.000**	0.511
	0.045	**0.030**	0.159	0.129	**0.068**	**0.099**	**0.035**	**0.001**	0.723
	0.048	**0.031**	0.190	0.133	**0.073**	**0.097**	**0.034**	**0.001**	0.671
Employment	**0.016**	**0.008**	**0.033**	**0.028**	**0.030**	**0.019**	**0.013**	**0.000**	0.642
	0.066	**0.030**	0.159	0.129	**0.099**	**0.099**	**0.035**	**0.001**	0.723
	0.055	**0.031**	0.190	0.133	**0.084**	**0.097**	**0.034**	**0.001**	0.671
Part-time job	0.703	0.884	0.638	0.783	0.817	0.279	0.994	0.461	**0.064**
	0.749	0.884	0.638	0.806	0.817	0.419	0.994	0.461	0.144
	0.499	0.418	0.483	0.559	0.373	0.229	0.816	0.258	0.127
Full-time job	**0.071**	**0.053**	0.217	**0.070**	**0.099**	**0.094**	**0.004**	**0.034**	**0.011**
	0.124	0.120	0.326	0.158	0.179	0.170	**0.032**	**0.065**	**0.059**
	0.090	**0.087**	0.278	0.149	0.135	0.119	**0.034**	**0.046**	**0.063**
Over-employment	0.386	0.186	0.159	0.250	0.342	**0.047**	0.284	0.298	**0.013**
	0.389	0.279	0.326	0.375	0.385	0.106	0.450	0.382	**0.059**
	0.209	0.184	0.278	0.264	0.217	0.104	0.323	0.205	**0.063**
Hours of work	**0.010**	**0.004**	**0.016**	**0.007**	**0.017**	**0.004**	-	**0.002**	0.868
	0.045	**0.030**	0.159	0.117	**0.068**	**0.054**	-	**0.003**	0.868
	0.048	**0.031**	0.190	0.133	**0.073**	**0.058**	-	**0.003**	0.932
Informal employment	0.158	0.144	0.335	0.149	0.258	0.555	0.122	0.130	**0.053**
	0.168	0.260	0.326	0.225	0.191	0.481	0.244	0.165	0.144
	0.126	0.169	0.278	0.177	0.146	0.272	0.180	0.146	0.127

Continued on next page

Table A3 – continued from previous page

Job searching	0.151	0.274	0.313	0.359	0.054	0.291	0.393	0.362	0.546
	0.389	0.331	0.522	0.467	0.174	0.590	0.450	0.382	0.723
	0.209	0.225	0.483	0.291	0.131	0.356	0.323	0.205	0.671
Training	0.822	0.728	0.630	0.806	0.211	0.964	0.392	0.339	0.587
	0.994	0.819	0.630	0.806	0.272	0.964	0.450	0.328	0.723
	0.635	0.387	0.483	0.559	0.021	0.720	0.323	0.205	0.671

First row: standard p-values.
Second row: q-values introduced by Benjamini and Hochberg (1995).
Third row: sharpened two-stage q-values introduced by Benjamini, Krieger, and Yekutirli (2006).

Notes: This is a table of p-values and q-values corresponding to Table 1.10. Q-values are p-values that are adjusted for the number of multiple hypotheses being tested. I adjust them considering all hypotheses tested in Table 1.10, following Anderson (2008).

Chapter 2

Maternal employment and childhood obesity in Russia

2.1 Introduction

Childhood obesity is considered a major public health concern in many developing and developed countries. The level of overweight and obesity among children and adolescents aged 5-19 has risen tenfold in the past four decades (Ezzati et al. 2017). Among the consequences of childhood obesity are low self-esteem, anxiety, depression (Daniels, 2006; Forste and Moore, 2012) and a higher risk of obesity in adulthood, leading to higher risks of morbidity, disability and premature mortality in adult life. The main obesity-related diseases that can develop during childhood and adolescence are cardiovascular diseases, type 2 diabetes, asthma, musculoskeletal disorders and cancers of the endometrium, breast and colon (WHO, 2018).

The statistics on childhood obesity in Russia are alarming. According to the Health Behaviour in School-aged Children (HBSC) survey[28] (WHO, 2017), the level of obesity in Russia was the lowest in 2002 across HBSC countries[29]. However, it has had the highest growth both among girls and boys during the following 12 years. According to the last estimates of the Ministry of Health of the Russian Federation, in Russia around 15-20% of children and adolescents are overweight and 5-10% are obese. Doctors highlight that the disease becomes an epidemic (Loria et al., 2018).

Another notable trend is an increase of employment among women. In the former Soviet Union, more women participated in the labour force than in almost any other country in the industrialised world (Lokshin, 2004). In the 1980s, the highest proportion of women of prime working age (aged 16-54) who were employed was recorded at 89.7% (Shapiro, 1992). During the 1990s, after the collapse of the Soviet Union and emergence of the Russian Federation, reforms launched by the Russian government led to dramatic changes in the socio-economic environment that caused employment to shrink. The employment rate among women of prime working age dramatically diminished from 77.6% in 1992 to 63.5% in 1998. However, the overall economic growth in Russia in the 2000s led to a significant increase in the female employment rate up to 73.4% in 2016 (Federal State Statistic Service of Russian Federation).

In this paper, I investigate whether the increase in maternal employment has contributed to the increase in childhood overweight and obesity over the past two decades. An increase in maternal employment typically involves two types of effects, on time and on income, both of which can affect children's weight. The time effect can affect children's weight through both a change in energy intake and expenditure. First, working mothers have less time to supervise their children than stay-at-home mothers. This can lead children to adopt a more sedentary lifestyle such as watching more television and playing computer games. Additionally, due to time constraints that working mothers face, organizing children's physical activity and sports can be more difficult (for example, bring/pick up children from sport classes). Second, maternal employment can lead children to develop unhealthy eating. As working mothers have less time for cooking, this may lead to higher consumption of processed and ready-to-cook food or eating

[28] The Health Behaviour in School-aged Children survey is a WHO collaborative cross-national study that monitors the health behaviours, health outcomes and social environments of boys and girls aged 11,13 and 15 years every four years across Europe and North America.

[29] HBSC countries: Austria, Belgium, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, the Netherlands, Norway, Poland, Portugal, Russia, Slovenia, Spain, Sweden, Switzerland, Macedonia, Ukraine.

out of home, which is a risk factor for higher energy and fat intake and lower micronutrient intake (Lachat et al., 2012; Alkerwi et al., 2015). Also, children can make poor nutritional choices such as consuming unhealthy after-school snacks due to less supervision. Taken together, these factors decrease children's energy expenditure and increase energy intake, affecting the energy balance and leading to weight gain. Thus, from a theoretical point of view the time effect is always negative.

Maternal employment will increase family income. The effect of an increase in income is indeterminate. On the one hand, parents may use the additional income to switch away from cheap processed food towards healthier and higher quality options that can decrease energy intake and improve children's health and weight. Parents also may use the additional income on children's physical activities such as sports clubs. This can increase energy expenditure and again improve children's weight. On the other hand, higher income can make families eat out more or may increase the amount of unhealthy food such as chocolate/sweets/biscuits which may have been unavailable to them before due to tighter budget constraints. This can result in an increase in children's energy intake and weight. Therefore, theoretically, the income effect is indeterminate. In this paper, I investigate both the time and income effects.

The main issue of estimating a causal effect of maternal employment on child's obesity is the endogeneity of maternal employment. A mother's employment decision is not exogenous to her child's health. A mother who decides to work may differ systematically from non-working mothers due to unobserved characteristics which affect both her labour supply and her decision on how to care for her children. For example, mothers who are more intelligent or have higher ambitions may have a higher probability to work but at the same time they have better understanding of how to prevent their children from becoming obese. Omitting these personal characteristics would lead to a downward bias of the OLS estimate. Another issue is a reverse causality. Children's obesity may affect maternal employment – mothers either can exit the labour market to take care of their obese child or enter the labour market to earn extra income for treating health issues.

To deal with the endogeneity issue I follow Courtemanche et al. (2017) who suggest an instrumental variable strategy based on the idea that the opportunity cost of working is substantially reduced when the youngest child in the family is attending childcare.[30] This approach is built on findings that mothers increase labour supply when their youngest child

[30] The Courtemanche et al. (2017) approach is based on Morrill (2011) who uses the youngest child's kindergarten eligibility as an instrument to show that maternal employment increases the probability of older siblings in the household experiencing overnight hospitalization, asthma episodes, and injuries/poisonings.

becomes eligible for or enroll in public school/childcare (Gelbach, 2002; Berlinski and Galiani, 2007; Baker et al., 2008; Lefebvre and Merrigan, 2008; Lefebvre, Merrigan and Verstraete, 2009; Cascio, 2009; Fitzpatrick, 2010, 2012; Nollenderger and Rodrigues-Planas, 2015; Brewer et al., 2016).

Based on using plausibly exogenous substantial variation in childcare availability across regions over time, the first chapter of this thesis shows that in Russia, like in many other countries, there is an increase in maternal employment in response to an increase in childcare availability.[31] Building on these results, in this paper I use the same variation in childcare availability for the youngest child in the household as an instrumental variable for maternal employment to estimate the effect of maternal employment on the weight outcomes of older siblings. This approach is based on the assumption that childcare availability for the youngest sibling does not affect the weight outcomes of the older sibling, other than through maternal employment. I focus on the role of maternal employment and do not consider paternal employment because in Russia it is still mostly mothers who bear the bulk of responsibilities for child-rearing, and fathers' employment is hardly affected by having children or childcare availability. For example, in 2015, fathers in only 2% of families took paternal leave.[32]

The analysis is based on an individual level dataset, the Russian Longitudinal Monitoring Survey – Higher School of Economics (RLMS-HSE)[33], which is a nationally representative panel of households in Russia. For the analysis, I construct a sample of children between 6 and 13 years old in the time-period between 2000 and 2017 who have at least one sibling and the youngest sibling's age falls in the 0-6 age range. The rich nature of the data also allows me to study the mechanisms, i.e. the income and time effects, through which maternal employment can affect children's weight outcomes. For this, I use physical activity (training sessions with a coach and active games outdoor), sedentary behaviour (watching TV and playing computer games) and healthy dietary habits outcomes.

The results suggest that maternal employment has a causal impact on children's weight in terms of BMI z-score and probabilities to become overweight and obese. A mother's

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[31] The first chapter of this thesis is also published as a working paper in the Institute for Social and Economic Research Working Paper Series.

[32] SuperJob.ru Research Center https://superjob.ru/research/articles/111910/rossijskie-muzhchiny-v-dekret-ne-hodyat/

[33] "Russia Longitudinal Monitoring survey, RLMS-HSE", conducted by National Research University "Higher School of Economics" and OOO "Demoscope" together with Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology of the Federal Center of Theoretical and Applied Sociology of the Russian Academy of Sciences.
(RLMS-HSE web sites: http://www.cpc.unc.edu/projects/rlms-hse, http://www.hse.ru/org/hse/rlms)

decision to enter the labour market leads to a 0.216 units increase in BMI z-score, a 5.0 percentage points increase in the probability to become overweight and a 3.2 percentage points increase in the probability to become obese. Due to potential measurement error in weight and height, I interpret these findings cautiously by saying that the results provide suggestive evidence that maternal employment increases child weight. Further, I find that maternal employment causes a higher consumption of prepared/semi-prepared meat and a higher probability of eating out as well as a decrease in physical activity. Thus, the findings suggest that both an unhealthy diet and a reduction in physical activity may explain the adverse effect of maternal employment on children's weight outcomes.

This study adds to the existing literature in the following ways. First, to my knowledge, I present the first evidence on the relationship between maternal employment and children's weight in Russia. The problem of childhood obesity in Russia is becoming very acute. However, the issue remains insufficiently investigated and there are no studies on the contribution of maternal employment. Second, in order to deal with the selection into maternal employment, I provide the first application of a two-stage least squares (2SLS) instrumental variable approach based on geographical and temporal variation in childcare availability, building on Courtemanche et al. (2017) who use the youngest child's age-based eligibility as an instrument for maternal employment. My final contribution is that my rich data allows me to study how the mechanisms, i.e. the income and time effects, underlay the effect of maternal employment, using physical activity, sedentary behaviour and dietary habits outcomes.

The rest of this paper is organised as follows: Section 2.2 summarises the existing literature. Section 2.3 describes the data and data quality, followed by the empirical strategy in Section 2.4. Section 2.5 presents the main findings, robustness checks, heterogeneity analysis and the results on potential mechanisms. Section 2.6 concludes.

2.2 Literature

There is a growing literature on the effect of maternal employment on children's weight. The majority of these studies estimates an association between maternal employment and childhood obesity. However, several studies attempt a credible identification strategy to estimate a causal effect and mainly find a positive effect of maternal employment on children's weight. Anderson et al. (2003) first attempt to estimate a causal relationship for the US by using several techniques to address endogeneity concerns including fixed effects and various instrumental variables such as a variation between states and over time in the local unemployment rates, child care regulations, wages of child care workers, welfare benefit levels, and the status of welfare reform. They demonstrate that children aged 3 to 11 years were 1 percentage point more likely to become overweight if their mothers worked an extra ten hours per week, and this effect comes from mothers of higher socio-economic status. Using different samples of US children, several follow-up studies based on instrumental variable and/or fixed effects approaches mainly confirm these findings. For example, similar results have been found by Ruhm (2008) applying sibling fixed effect and propensity score models and by Courtemanche (2009) using a long differences approach. Results of higher magnitudes are obtained by Liu et al. (2009) and Courtemanche et al. (2017). Based on parametric, semi-parametric, and non-parametric methods, Lui et al. (2009) find that full-time maternal employment increases a child's body mass index by around half a unit and probability of being obese by 12%.[34] Courtemanche et al. (2017) exploit plausibly exogenous variation from the youngest sibling's school eligibility and show that ten additional parental work hours per week increase BMI z-score by 0.15-0.19 units, probability of being overweight by 6.6-8.1 percentage points, and probability of being obese by 4.9-6.0 percentage points.

Several non-US studies attempt a credible identification strategy to estimate the causal relationship between maternal employment and children's weight. A positive impact of maternal employment on children's BMI and on excess weight has been found in the UK (von Hinke Kessler Scholder, 2008; Fitzsimons and Pongiglione, 2019), Germany (Meyer, 2016), Australia (Li et al., 2017), Ireland (McDonnell and Doyle, 2019) and Canada (Chia, 2008) while a negative effect has been found in Denmark (Greve, 2011). In the case of Denmark, the effect of increased maternal work hours on a reduction of childhood obesity is explained by higher quality of Danish childcare and by a significant contribution of fathers to children's health.

Few studies investigate whether children from different socio-economic background are affected differently by maternal employment. The findings show that adverse effects of maternal employment on child obesity are concentrated among children from higher socio-economic background – there is an effect on children of mothers with higher levels of education and earnings but no effect on children of mothers with lower education and earnings (Anderson, 2003; Ruhm, 2008; Courtemanche et al., 2017; McDonnell and Doyle, 2019). McDonnell and

[34] In the parametric and semi-parametric methods, Lui et al. (2009) use an endogenous switching model to allow for joint dependence between a mother's full-time employment and a child's BMI equations and behavioural changes when external conditions change.

Doyle (2019), studying the joint impact of maternal employment and childcare during infancy on childhood overweight at ages 3 and 5, suggest that the adverse effect for children of better educated mothers can be explained by a lower quality of “replacement” care compared to parental care.

Descriptive empirical evidence on mechanisms through which increased employment may affect children’s weight is scant and mixed. Crepinsek et al. (2004), Fertig et al. (2009), Morrissey et al. (2011) and Gwozdz et al. (2013) find little or no evidence that maternal employment is related to an unhealthy diet and activity behaviour. In contrast, Hawkins et al. (2009) show that children of working mothers are more likely to consume sweetened drinks, use the TV/computer at least 2 hours per day, and consume less fruit and vegetables. Cawley and Liu (2012) find that employed mothers spend less time on cooking and eating with their children and have a higher likelihood of purchasing prepared food. Little causal evidence on mechanisms suggests that maternal full-time employment induces poorer eating habits including a higher consumption of prepared food and sweetened drinks, a lower consumption of vegetables and fruit and likely increases sedentary behavior such as watching TV and playing video games (Meyer, 2016; Fitzsimons and Pongiglione, 2019).

To my knowledge, there is only one paper investigating the relationship between maternal employment and childhood obesity in Russia. Nazarov and Zhuravleva (2018) explore the effect of formal childcare and maternal employment on childhood obesity. To overcome the endogeneity issue, they use a multi-equation framework and jointly estimate childcare and maternal employment along with a child’s physical production function which indicates the probability of having an obese child. Based on a sample of pre-school age children, they find that formal childcare and maternal employment increase the child’s probability of becoming obese. However, it is still an open question whether the effect comes from using childcare or directly from maternal employment.

Yet, there are several descriptive papers on obesity trends and the effect of the transition to market economy on overweight and obesity in Russia that can give insights into some mechanisms related to obesity. Based on the Russian Longitudinal Monitoring Survey, Huffman and Rizov (2007) find that dietary factors had a strong effect on the dramatic growth of obesity in adults during transition from a planned to a market economy. Income is among other important factors positively associated with higher weight and BMI for both females and males. Although the total calory intake did not change over the transition period, there were significant changes in consumption patterns such as shifting away from a healthy and balanced diet comprising fruit and vegetables towards fatty and sugary products and excessive consumption of potatoes. Thus, the authors conclude that during the transition in Russia, Russian households responded to the income and price shocks by shifting the composition of their diets towards cheaper foods. Several studies report an income gradient for the intake of energy, food groups and weight status. Dore et al. (2003) find that during an unstable period between 1994 and 2000, children in low-income households had a constant energy intake while children from high-income families increased their energy intake. Overall, this literature shows that dietary factors such as consumption patterns and calory intake are affected by economic conditions and that different reactions to economic conditions may occur depending on household's socio-economic status.

2.3 Data

2.3.1 Dataset

The analysis is based on survey data linked to official regional statistics. The survey data is the Russian Longitudinal Monitoring Survey – Higher School of Economics (RLMS-HSE), a nationally representative split panel[35] of households in the Russian Federation. Although the dataset includes only 32 regions out of a total of 89 the dataset represents the country well in terms of gender, education and type of settlement. The survey was designed to monitor the effects of Russian reforms on the health and economic welfare of households and individuals in the Russian Federation. The RLMS-HSE is conducted by the National Research University Higher School of Economics and ZAO "Demoscope" together with the Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS.

Data has been collected from 1992 until now. On average, every year the dataset includes around 12,000 individuals from approximately 4,000 households. It includes variables on individuals such as detailed socio-demographical information and family structure, precise measurement of household-level spendings and service utilization, and collection of relevant community-level data, including region-specific prices and community infrastructure data. The information on children I use in this paper is based on parental assessment for the 2000-2017 time period.

[35] Split (supplemental) panel surveys are a combination of a panel and a repeated panel survey. These surveys are designed to follow a particular group of sample units for a specified period of time and to introduce new groups of sample units at each time point during the specified period.

In addition, I use data from the Federal Sate Statistics Services of Russian Federation that provides a vast range of regional characteristics for every year and every region and also a unique dataset on the number of enrolled children at each age in every region. Moreover, I use data from the Federal Treasure on detailed regional budget accounts linked to survey be region.

2.3.2 Measures

Child BMI z-score and overweight and obesity status

The outcome measures are body mass index (BMI) z-score, probability to become overweight/obese and probability to become obese. The outcomes are constructed based on children's BMI. BMI is based on the responses of the main respondent about the height and weight of their children and defined as weight in kilograms divided by squared height in meters. Because children's healthy weight range varies by age and gender, the Centers for Disease Control and Prevention recommends using BMI z-score – a standardized measure of BMI using age-and-gender specific BMI distribution. I use the 2007 World Health Organization Growth Reference for school-aged children and adolescents. The probabilities to become overweight and obese are dummy variables that are equal to 1 if a child's BMI is higher than the WHO reference overweight and obesity cut-off points, respectivly. The cut-off points are gender and age (in month) specific.

Maternal employment and hours of work

A mother is defined to be employed if she reports to be currently working or if she is on paid/unpaid leave except maternity leave. As an alternative measure of maternal employment, I use weekly working hours. I assign zero hours to non-working mothers.

Childcare enrolment

To instrument maternal employment, I use childcare availability which I measure by the number of children covered by childcare or in other words enrolment rates for the youngest child in the family. The first chapter of the thesis (Section 1.4) comprehensively describes why the use of enrolment rates can be doubted as a measure of childcare availability in Russia and justifies why it is nevertheless a suitable measure. Based on the number of enrolled children, I calculate the enrolment rates which are equal to the proportion of children aged between 0 and

6 who are enrolled in the public childcare system and varies from 0 to 100%. Unfortunately, age-specific data on the number of enrolled children exists from 2007. To derive age-specific enrolment data before 2007, I rely on the fact that from 2007 the increase in the childcare enrolment was uniformly distributed across the age groups with the exception of some fluctuations for the children aged 2 and for the period of time after starting the national programme on childcare system modernization in 2014 (Figure 1.15 in section 1.4). Thus, I assume that pre-2007 years had the same distribution as in 2007. I use age-specific enrolment rates in 2007 and total regional enrolment rates during each year between 2000-2006 and apply age proportions observed in 2007 backwards to the previous years.

Covariates

I include a detailed set of control variables. The first set of control variables relate to the child's and mother's individual and family characteristics. Child characteristics include age in months and a gender indicator. Maternal characteristics include the mother's age in years, an indicator for being married or living with a partner and the educational level (incomplete secondary, secondary, vocational secondary and higher). To increase the number of observations, for partnership status and education I include a category for missing information. As family characteristics I consider family size, age of the youngest child, an indicator for living with grandparents in the same household as well as settlement type. Since household income is one of the mechanisms through which maternal employment can affect children's weight, I do not control for it. However, the results stay similar if I take it into consideration.

The second set of control variables is a rich set of region-specific socio-demographic and economic characteristics that may affect weight outcomes and vary over time. I include a range of regional expenditures (per capita) on different policies, including expenditure on the healthcare system, family and childhood social security policy, social security, and on labour market support. To capture regional labour market conditions, I consider male employment to account for the fact that childcare availability might affect current employment rates and children's weight outcomes. I also include GDP per capita and the average proportion of social benefits in household income to capture regional wealth.

Mechanisms

I investigate the income and time effects as the mechanisms that may explain the relationship between maternal employment and childhood obesity. To study how the mechanisms work I use physical activity, sedentary behaviour and dietary habits outcomes observed in my data.

To measure physical activity, I create an indicator variable for whether a child does physical activity before/after school such as training sessions with a coach or active games outdoor at least once a week. For sedentary behaviour, I create an indicator variable for whether a child watches TV or plays video/computer games every day (this measure is available for the 2001-2017 period). I also measure number of hours of physical activity per week and number of hours of sedentary behaviour per day.

I use two ways to investigate dietary habits. First, I investigate the habit to eat out. For this I create an indicator variable for whether any family member ate out during the last 7 days and how much was spent on it. Second, I use information on family's grocery shopping during the last 7 days. I use the information on food groups such as (1) vegetables, (2) fruit and berries, (3) sweets (chocolate, biscuits, pastry, ice-cream), (4) soft-drinks, and (5) prepared or semi-prepared meat (sausages, semi-prepared meat products, canned meat, canned fish). For each food group I create three measures: (1) an indicator whether a family buys any product from a certain food group, (2) the amount in kilograms per person they buy, and (3) expenditure per person. I apply the food consumer price index to obtain food expenditure in real prices. The data lack direct information on whether the children eat out and how much food in each selected food group is eaten at home by children. Nevertheless, I assume that these measures are comprehensive and reflect dietary patterns of children.

It is important to mention that because in Russia around half of the population[36] owns plots of land on their dachas (a seasonal or year-round second home) and is engaged in home production of vegetables and fruit, I cannot measure consumption precisely as the data do not allow to fully investigate how families use their harvest (consume, sell, give away or exchange). Also, one might be concerned that home production can be affected by maternal employment. For example, there is a higher home production of vegetables and fruit if mothers do not work which increases the total consumption of vegetables and fruit in their families. However, in the case of Russia, it seems that home production is determined by a dacha ownership rather than by mother's employment status. To test this assumption, I run descriptive analysis and compare how the amount of harvested vegetables and fruit vary by mother's employment status. Figure B1.1 shows that the share of families with working and non-working mothers that use land for home production follow the same trends over the studying time period. The same can be said about the amount of harvested vegetables (Figure B1.2) and fruit

[36] https://www.themoscowtimes.com/2019/01/03/russia-disbands-the-concept-of-dacha-a64027

(Figure B1.3) for these two groups of families (except for a few years when the differences could be related to the financial crisis).

2.3.3 Estimation Sample and Data Quality

The estimation sample is restricted to children who meet three criteria: (1) they are between 6 and 13 years old[37] and attend school[38], (2) they have at least one sibling and the youngest sibling's age is between 0 and 6, and (3) their mothers live in the same household. Initially, 6,300 observations met these criteria.

For the further construction of the estimation sample, I first consider the issues of data quality. Because weight and height are parent-reported rather than professionally measured, it leads to relatively poor data quality. There are two main issues related to this: measurement error and missing data. Measurement error is mainly caused by the fact that height and weight are often misreported. For example, 12.4% of the sample have inconsistent height measurements – child's height either does not change or decreases between t and t+1. Due to missing data on either height or weight or both, 12.0% of the sample has missing information on BMI.

Regarding the measurement error issue, my main analysis is based on the raw sample to keep a sufficient sample size. However, as a robustness check, I run the analysis based on the sample where I exclude all inconsistent observations (see section 2.5.2).

To deal with the missing data issue, I first identify a missing data mechanism. According to Rubin's classification system (Rubin, 1976), data are generally considered to be missing under one of three broad mechanisms: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). Data are MCAR when missingness probability does not depend on any observed or unobserved parameters. In a MAR setting the missingness probability depends on the observed data. Finally, when data are MNAR the missingness probability depends on unobserved data, such as some unobserved characteristics, or the value of the unobserved variable itself predict missingness. There is a

[37] I restrict the sample to children older than 6 because in Russia children can be accepted to the first year of primary school at the age between 6 and 8 but I exclude those who still attend kindergarten at this age. I also restrict the sample to children up to 14 years old because when children turn 14, they participate in the survey as adults rather than as children. It means that they switch to the adult questionnaire and have another set of questions. Also, weight and height become self-reported rather than parent-reported.

[38] I take into consideration only those children who enrolled at school to ensure that school eligibility itself does not affect children's weight.

quite clear consensus and a number of methods on how to deal with missing data if missingness occurs on an independent variable. However, it is less obvious what to do if missingness exists on an outcome measure. Under MCAR, as the missing data form a random subsample of the full data set, a complete cases analysis produces unbiased estimates. Under MAR, there are generally no benefits to improve the outcome and complete case analysis can be applied. If we know or suspect that the data are MNAR the majority of econometric discussions agree that imputation can be useful.

To assess the plausibility of the MCAR mechanism, simple comparisons between individuals with and without observed data can be made. Table B2.1 shows the comparison between children with and without information on BMI. Children with missing information on BMI are more likely to be younger and to be boys. Mothers of children with incomplete data are also more likely to be younger, be single and have lower education (incomplete or complete secondary school). Families living in rural areas are also more likely to have missing data. These systematic differences in demographic characteristics between these groups indicate a violation of the MCAR mechanism, suggesting that there are either observable or unobservable characteristics that drive the data missingness.

To evaluate the plausibility of the MAR assumption, I assess the relationship between missingness on BMI and the child's and mother's individual and family characteristics. Table B2.2 shows that the main determinants of missing information on BMI are child's age and gender, mother's education and employment status and the place where the household lives. Mothers with low level of education or without a job and households living in rural area are more likely not to provide information on height and weight which in turn does not allow to calculate children's BMI.

From the analysis it is clear that there are some observable characteristics that are associated with parents' decision not to provide information on height or weight. However, I also should consider that probably there are some unobservable characteristics that affect the missingness but there are no methods to check it. The existing literature explains why adults sometimes underestimate, overestimate or do not report their weight or height but there is no evidence on children. Thus, as there is a clear pattern that less educated parents or parents with less access to weight/height information (families from rural areas) are less likely to provide the information, I assume that in my case the missingness exists under the MAR mechanism. It means that the best solution to deal with missingness is to run complete cases analysis which means simply to exclude observations with missing information.

The original sample includes 6,300 observations. After excluding observations with missing information, the resulting sample includes 5,500 observations for 1,978 children (see Table B2.3 which shows summary statistics of the original sample of all children and the final estimation sample). Table B2.4 contains descriptive statistics for the final child-level dataset both for the full sample and separately for normal weight and overweight children. The average age among all children is 122 months (around 10 years old) and overweight children are around 5 months younger than normal weight children. Among all children, 52% are boys while there are significantly more boys among overweight children (60%) than among normal weight children (48%). The average BMI z-score is 0.17, and 18% of the children are overweight while 10% of them are obese.[39]

The average age among all mothers is 32.9. In both weight groups, mothers of around 8% of children are single. There are some significant differences in terms of mothers' education between normal weight and overweight children: among overweight children there are more mothers with low education. Fifty five percent of the mothers of normal weight children work and on average there is no significant difference between the mothers of normal weight and overweight children in this respect. Eighteen percent of children have grandparents living in the same household. Normal weight children live significantly more often in cities and towns while overweight children live in semi-urban and rural areas.

2.4 Empirical approach

In order to evaluate whether maternal employment affects childhood obesity, first I apply a basic ordinary least square model (OLS) where child's BMI z-score, overweight and obesity statuses are the outcomes of interest and maternal employment is the main explanatory variable. This approach does not consider potential unobservable differences across individuals that bias the relationship between mother's employment decision and her child's weight. Thus, I next address endogeneity of maternal employment using a two-stage least square approach and instrumenting maternal employment through childcare availability.

[39] This is in line with the estimates of the Ministry of Health of the Russian Federation for the school-age children which show that 11-18% of them are overweight and 5-8% are obese.

2.4.1 Identification strategy

As an instrumental variable for maternal employment I use plausibly exogenous variation in childcare availability for the youngest child and estimate the effect of maternal employment on the weight outcomes of older siblings. This idea relies on the fact that when a mother's youngest child attends childcare, her opportunity cost of work is substantially decreased. Thus, mothers have higher incentives to join the labour market if childcare becomes available for the youngest child, while the youngest sibling's childcare attendance should not affect weight outcomes of older siblings. I exploit geographic and temporal variation in childcare coverage across regions in Russia caused by the fact that the availability of public childcare developed at different rates in different regions. In what follows, I first briefly describe the Russian childcare system to lay out the nature of this instrumental variable (see Chapter 1 for more details) and then discuss the criteria which a reliable implementation of an instrument variable must satisfy.

After the end of the Soviet Union in 1990, the fertility rate in Russia fell dramatically (DaVanzo and Farnsworth, 1996; The Demographic Yearbook of Russia, Rosstat 2002, 2015): from 1.9 in 1990 to 1.3 in 1995 and to 1.2 in 2000. The decline in the fertility rate led to a sharp decrease in the number of preschool age children enrolled in the childcare system. Due to this reduction and the economic crisis, the number of childcare providers and the number of places in the public childcare system decreased. The total number of places in the childcare system fell from 8,109 thousand in 1991 to 5,232 thousand in 2000. After 2000 fertility rates increased while the number of childcare providers further reduced, leading to place shortages in the childcare system. The proportion of children waiting for a place increased from 2.6% in 2000 to 23.3% in 2014. As there were no national-level policies in place to increase childcare availability, Russian regions had to expand public childcare on their own. Only in 2013 the Government launched a programme called "The Modernisation of Federal Preschool Childcare System" that established the right to preschool education for all children aged 3-7, but still the regions were fully responsible for the organisational implementation of the programme, using federal subsidies. In these circumstances the intensity of generating new childcare places depended on regional budgets, financial priorities and existing childcare coverage. This caused a large variation in childcare enrolment both across regions and over time – in 2000 the childcare enrolment rate varied from 3.8% to 80.7% while in 2017 from 29.9% to 90.3% (see Appendix B3 which maps the childcare enrolment rate in 2000 and 2017 by region). In the presence of childcare place shortages, I assume that the childcare enrolment rate represents childcare availability and I use variation in the enrolment rate as an instrumental variable.[40]

The first criterion the instrumental variable must satisfy is the instrument relevance that shows that there is some association between the instrument and the variable being instrumented. To confirm this for my sample, Figure 2.1 shows the relationship between the level of childcare availability for the youngest child in the household and maternal employment. This confirms the expected positive relationship: the share of employed mothers increases with the level of childcare availability. Also, this association is tested in the first chapter of the thesis and the result confirms that there is a positive causal relationship between childcare availability and maternal employment in Russia.[41]

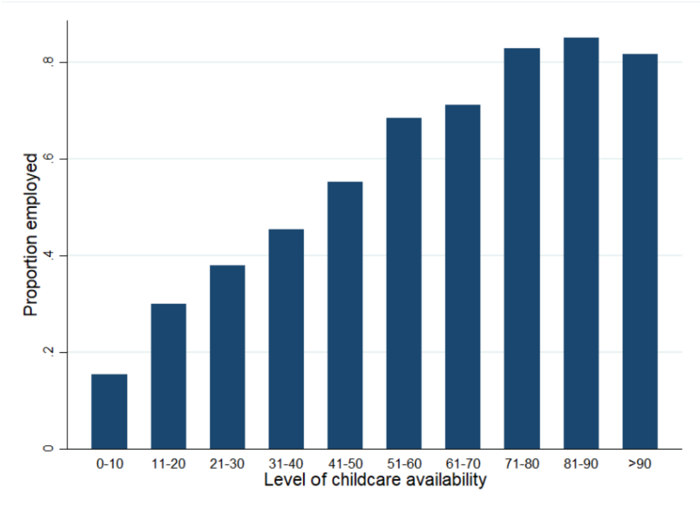

Figure 2.1 – Maternal employment by the level of childcare availability

Notes: A woman is defined as being employed if she is currently working or on paid/unpaid leave except maternity or parental leave. The level of childcare availability is defined as childcare enrolment rate which is equal to the proportion of children aged between 0 and 6 who are enrolled in public childcare system and varies from 0 to 100%.
Source: Author's calculations based on Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset, 2000-2017.

The second criterion required in order to obtain valid instrumental variable estimates is that the exclusion restriction holds which means that the instrument must be uncorrelated with the error term. In my case, it means that, conditional on the control variables, the only path through which childcare availability for the youngest child should affect the older sibling's

[40] The first chapter of the thesis comprehensively describes why the use of enrolment rates can be doubted as a measure of childcare availability in Russia and justifies why it is nevertheless a suitable measure.
[41] Even though Kazakova (2019) uses a mother-level dataset, Section 2.5 shows that the first stage results based on child-level data lead to the same conclusion.

BMI and weight status is through maternal employment. There are several potential concerns with this. One might be concerned about confounding the effect of childcare expansion with other regional policy choices taking place at the same time that could also have affected the older sibling's weight. Conditioning on a rich set of regional socio-demographic and economic time-varying characteristics, I assume that the expansion of childcare across regions and over time is independent of other regional characteristics and policies that might directly affect the older sibling's weight. To test this assumption, I use the strategy used by Havnes and Mogstad (2011) and Blanden *et al.* (2016) to compare potential treatment and comparison regions. Following their idea, I divide all regions in Russia into two equal groups depending on the percentage point increase in the enrolment rate over my observation window. The top 50% of regions with the highest increase are in the treatment group while the bottom 50% of regions with the lowest increase are in the comparison group. Figure B4.1 shows that the expansion in places between 2000 and 2017 is equal to 18.8 percentage points in the treatment group and 6.3 percentage points in the comparison group. Figure B4.2 provides a comparison of trends in some socio-demographic and economic characteristics over the observation period between the treatment and comparison groups that may affect the older sibling's weight. The figure shows that the treatment regions are quite similar to comparison ones in most regional socio-demographic and economic characteristics between 2000 and 2017. An exception is male employment and expenditure on the healthcare system in the last fewer years and expenditure on social security throughout almost the entire period of time. Overall, these cases are not an issue as the three indicators are lower in the treatment group. Also, in terms of expenditure on social security, this type of social support is aimed at protecting the most vulnerable groups of the population, including pensioners, unemployed, disabled people, Chernobyl victims, orphans, low-income people, infected with HIV, people without a permanent place of residence and families with three and more children and single mothers. A region by region analysis shows that a faster grow in social security expenditure in the control group mainly between 2004 and 2010 is determined by few regions, i.e. Moscow region and the Republic of Tatarstan, which demonstrated a higher increase in this type expenditure. Even though there were no other major changes that could affect my outcomes, I comprehensively control for the rich set of regional variables in the regression analysis. Following the same methodology, I also examine trends in one of the outcomes, i.e. child's BMI, before and after the beginning of the childcare expansion. Figure B4.3 shows mean raw BMI at age 6-9 and age 10-13. We can see that for both age groups the outcome follows nearly parallel trends before 2000 when childcare availability started expanding. The trends continue to be approximately parallel through the expansion years for the group of children aged 10-13, while for the group of children aged 6-9 the gap between outcome in the treatment and comparison group seems to increases between 2000 and 2010 and to decrease after 2010. This suggest that there is a negative effect of maternal employment at age 6-9.

One might be concerned about a possible confounding effect operating through younger siblings. Younger siblings who attend childcare directly benefit from childcare as they have more physical activities and more balanced nutrition in childcare. Potentially, these children can bring home these healthier patterns and their older siblings can benefit from following them through interaction with younger siblings. In this case, healthier habits should decrease children's weight and the IV estimates would be underestimated, which means that my findings are conservative estimates of the true effect.

Another potential concern is related to overall free time that mothers could have if their youngest child attends childcare due to the expansion of childcare. Free time can be invested not only into work but also into other activities related to children and children's health (especially if the mother takes a decision not to enter labour market). For example, they could invest time to improve children's health through physical activities with children, organizing sport training sessions, cooking healthy food. Theoretically these actions positively affect children's weight and consequently decrease their BMI and risk of obesity. In this case, the IV estimates again would be underestimated, and my findings are conservative estimates of the true effect.

Following Courtemanche et al. (2017), an additional concern relates to parenting attitudes towards healthy lifestyle that may change with childcare expansion. Potentially, if the youngest child starts attending childcare due to increased childcare availability, the parents can relax their supervision of the child's health behaviour as this child requires less direct care. The effect of less supervision can affect other children as well. This can lead to an increase in child BMI even if mother's employment status does not change and this would suggest a violation of the exclusion restriction that the instrument affect my outcomes only through maternal employment. In this case, the IV estimates would be overestimated. I test this identification assumption by implementing several falsification tests (see section 2.5.2).

One more potential concern is that childcare expansion could affect family income through the cost of childcare beyond maternal employment. However, given the low cost of childcare (see Section 1.3.4 for more details on childcare in Russia), it is unlikely that the family income will be reduced.

2.4.2 Econometric specification

The main regression model, estimated by a two-stage least square (2SLS) estimator, is defined at the child-level and presented as follows:

$$Work_{irt} = \alpha_0 + \alpha_1 Availability_{tr(age)} + \alpha_3 X_{it} + \alpha_4 Z_{rt} + \mu_r + \eta_t + \zeta_{it} \; (1)$$

$$ChildWeight_{irt} = \beta_0 + \beta_1 \widehat{Work}_{irt} + \beta_2 X_{it} + \beta_3 Z_{rt} + \mu_r + \eta_t + \xi_{it} \; (2)$$

where the first equation is the first-stage regression for the effect of childcare availability on maternal employment and the second is the second-stage regression for the effect of maternal employment on children's weight outcomes. The coefficient of interest β_1 is the local average treatment effect of maternal employment on older children's weight outcomes. The equation variables are defined as:

- $Work_{irt}$ is one of the labour market measures for the mother of child *i* in region *r* in year *t.* The first measure is maternal employment which is a dummy variable equal to 1 if the mother of child *i* is currently working or on paid/unpaid leave (except maternity or parental leave) and 0 otherwise. The second measure is hours of work with zero assigned to non-working mothers.
- $Availability_{tr(age)}$ is an indicator of childcare availability in year *t* and region *r* for the youngest child in the family that is defined as an age-specific enrolment rate which varies from 0 to 100%. $Availability_{tr(age)}$ is an instrument which predicts $Work_{irt.}$
- $ChildWeight_{irt}$ is one of the weight outcomes of child *i* in region *r* in year *t:* BMI z-score, probability to become overweight, and probability to become obese.
- $\boldsymbol{X}_{it}$ is a vector of child's and mother's individual and family characteristics: child's age in months and gender, mother's age, education, marital status, age of the youngest child, presence of grandparents in the household, household size and settlement type.
- $\boldsymbol{Z}_{tr}$ is a vector of region-specific characteristics that may affect the older sibling's weight outcomes and vary over the time. It includes information on regional expenditures on different policies including expenditure on healthcare system, family and childhood security policy, social security, and on labour market support, male employment, female unemployment in year *t-1*, the GDP per capita in period *t-1*, and an average proportion of social benefits in household income. $\boldsymbol{Z}_{tr}$ also includes the interaction between year dummies and levels of childcare availability (enrolment rate) in the year 2000, the first year in the observation period. Adding this term allows to control for the fact that

generating new childcare places across regions could be systematically related to the levels of childcare availability at the start of the observation period. Data shows that regions that experienced a more rapid increase in enrolment rates had lower starting levels of enrolment rate, and, if, for example, these regions also show a faster spread of childhood obesity, this would lead to an upward bias of the estimate.

- μ_r are the region fixed effects.
- η_t are the year fixed effects.
- ξ_{it} and ζ_{it} are error terms.

2.5 Results

2.5.1 Main results

Table 2.1 reports the main results on the relationship between maternal employment and child's weight outcomes at the extensive margin. Panels A, B and C display results for BMI z-score and the overweight and obese status indicators, respectively. Column (1) presents means of the outcomes to put the magnitude of the estimates into context. Column (2) displays the OLS results while column (3) reports the coefficients from the reduced form (RF) regressions, where the coefficient of interest is the direct effect of the instrument on the child's weight outcomes. Column (4) shows the first stage (FS) results of the relationship between maternal employment and the instrument. Columns (5) through (8) report the second-stage coefficient estimates of interest from the 2SLS model with gradual inclusion of additional control variables: column (5) presents results of a model that controls for year and region fixed effects, in column (6) I add regional time trends, in column (7) I add individual and family characteristics and in column (8) I additionally control for regional socio-demographic and economic conditions. In all specifications, I cluster standard errors at the regional level. The model in column (8) that includes all listed covariates is used as a baseline specification. For my instrumental variable I report two diagnostic tests: the F-statistic for the significance of the instrumental variable in the first stage and the test for endogeneity.

The OLS results in column (2) show that there is no statistically significant association between the child's BMI z-score, probability to become overweight or obese and maternal employment. The reduced-form (RF) estimates in column (3) are positive and statistically significant, indicating that childcare availability for the youngest child increases the older siblings' BMI z-score and probability to become overweight or obese and these results go in the expected direction. The first-stage (FS) estimates in column (4) show that maternal employment is strongly related to childcare availability: a 10 percentage points increase in childcare availability leads to an increase in the probability of maternal employment by 8 percentage points. The estimates are significant at the 1% level. Moreover, the first-stage F-statistic for the significance of the instrumental variable for the final model is equal to 1345.2. This is highly above the rule of thumb of 10 and indicates that the model does not suffer from a weak instrument problem. The endogeneity test rejects the consistency of the OLS estimates in all BMI z-score and probability to become overweight regressions and in the final two probability to become obese regressions, confirming that the 2SLS regression is more efficient.

As expected, the second-stage point estimates are higher in magnitude relative to the OLS coefficients but the differences are not statistically significant. Controlling only for region and year fixed effects (column 5), maternal employment significantly increases child's BMI z-score by 0.13 units and this effect is significant at the 5% level. Adding regional time trends (column 6) does not change the points of estimates. Further adding individual and family characteristics (column 7) increases the magnitude of the effect to 0.21 units but the difference is not statistically significant. Finally, adding in region-level controls (column 8) does not change the result and, thus, the baseline specification shows that maternal employment increases child's BMI z-score by 0.22 units at the 1% level of significance. The baseline specification also shows that maternal employment significantly increases the probability to become overweight by 5.0 percentage points and the probability to become obese by 3.2 percentage points at the 10% and 5% level of significance, respectively. The point estimates represent 14.9%, 10.5% and 10.9% of the sample standard deviations for BMI z-score, overweight and obesity, respectively.[42]

[42] The calculations are based on dividing the coefficients estimates by the standard deviations reported in column (1) of Table 2.1 and then multiplying by 100%.

Table 2.1 – The effect of maternal employment on child's weight outcomes

	Mean	OLS	RF	FS	2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: BMI z-score								
Maternal employment status	0.174	0.068	0.002**	0.008***	0.133**	0.134**	0.211***	0.216***
	(1.452)	(0.054)	(0.001)	(0.000)	(0.067)	(0.065)	(0.067)	(0.066)
First stage F-statistic					1316.9	1264.4	1306.8	1345.2
Endogeneity test p-value					0.028	0.044	0.018	0.016
Panel B: Overweight								
Maternal employment status	0.275	0.006	0.0004*	0.008***	0.024	0.024	0.050**	0.050*
	(0.447)	(0.017)	(0.000)	(0.000)	(0.025)	(0.024)	(0.025)	(0.026)
First stage F-statistic					1316.9	1264.4	1306.8	1345.2
Endogeneity test p-value					0.075	0.077	0.036	0.039
Panel C: Obese								
Maternal employment status	0.095	0.007	0.0002*	0.008***	0.013	0.014	0.033**	0.032**
	(0.293)	(0.010)	(0.000)	(0.000)	(0.016)	(0.015)	(0.015)	(0.015)
First stage F-statistic					1316.9	1264.4	1306.8	1345.2
Endogeneity test p-value					0.167	0.153	0.070	0.067
Controls								
Regional FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional time trends		Yes	Yes	Yes	No	Yes	Yes	Yes
Individual and family characteristics		Yes	Yes	Yes	No	No	Yes	Yes
Regional characteristics		Yes	Yes	Yes	No	No	No	Yes
N		5,500	5,500	5,500	5,500	5,500	5,500	5,500

Notes: The sample includes children aged 6-13 who attend school, with the youngest pre-school age sibling (0-6 years old), and mothers living at the same household. Each coefficient belongs to a separate regression. Column (1) reports means calculated for each outcome. Standard deviations of the means are reported in parentheses. Column (2) reports the OLS regression results. Column (3) presents the reduced form (RF) results. Column (4) presents the first stage (FS) results. Columns (5)-(8) show the second stage estimations (2SLS). Column (5) regressions include regional and year fixed effects. Column (6) also controls for regional time trends. Column (7) additionally includes a vector of child's characteristics such as age in months and gender, mother's characteristics such as age, marital status and education, and family's characteristics such as age of the youngest child, household size, presence of grandparents in household and settlement type. Column (8) presents regressions with all previous controls plus regional characteristics such as regional expenditures on different policies including expenditure on healthcare system, family and childhood security policy, social security, and on labour market support, male employment, the GDP per capita in period t-1, the average proportion of social benefits in household income, and the interaction between year dummies and levels of childcare availability in the year 2000. The specification that includes all covariates is used as a baseline specification (Column 8). Robust standard errors in parenthesis. Standard errors are clustered at the regional level. *p<0.10, **p<0.05, ***p<0.01.
Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

In Table 2.2, I run the same regressions for the alternative measure of maternal employment, weekly working hours, to assess the effect of maternal employment at the intensive margin. Again, the OLS estimates in column (2) show that there is no statistically significant association between the child's weight outcomes and maternal hours of work and the reduced-form estimates in column (3) go in the expected direction. The first-stage estimates from column (4) indicate that the childcare availability instrument is highly relevant and does not suffer from weak instrument problems (the first-stage F-statistic is 870.0 for the final model). As before, the endogeneity test rejects the consistency of the OLS estimates in all BMI z-score regressions, in the final probability to become overweight regression and in the final two probability to become obese regressions. The second-stage estimates show that ten additional maternal work hours per week increase a child's BMI z-score by 0.05 units and the probability to become overweight or obese by 0.1 percentage points (Column 8). The effects are statistically significant at the 1 and 5% level, respectively. In terms of magnitude, the estimates represent 13.8%, 8.9% and 13.7% of the sample standard deviations for BMI z-score, the probability to become overweight and the probability to become obese which is close to the magnitude of the previous results in Table 2.1.[43] Thus, the 2SLS estimates yield univocally positive effects of maternal employment on child's weight outcomes.

The results are not directly comparable with results for other countries as different studies focus on different child's age groups and the majority of studies investigate only the probability to become overweight. In terms of BMI z-score, my results at the extensive and intensive margins are similar to those found in the US by Lui et al. (2009) and Courtemanche et al. (2017), which are the only studies that focus on a similar age group and investigate the effect of maternal employment on BMI at either margin. The results on the probability to become overweight are similar to those found in Ireland (McDonnell and Doyle, 2019) at the extensive margin and much smaller than in other counties at the intensive margin, overall showing the smallest impact compared to countries like the US (Anderson, 2003; Ruhm, 2008; Lui et al., 2009; Courtemanche et al.,2017), the UK (Fitzsimons and Pongiglione, 2019), Germany (Meyer, 2009) and Canada (Chia, 2008). However, again, the majority of estimates cannot be directly compared.

[43] I follow the same calculations as before and then multiple the effect sizes by 10 to interpret the results in terms of "10 additional hours per week" and by 4 to get monthly rather than weekly effects.

Table 2.2 – The effect of maternal hours of work on child's weight outcomes

	Mean	OLS	RF	FS	2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: BMI z-score								
Hours of work	0.174	0.002	0.002**	0.305***	0.004**	0.003**	0.005***	0.005***
	(1.453)	(0.001)	(0.001)	(0.010)	(0.002)	(0.002)	(0.002)	(0.002)
First stage F-statistic					866.4	939.5	846.0	870.0
Endogeneity test p-value					0.034	0.061	0.024	0.022
Panel B: Overweight								
Hours of work	0.275	0.0003	0.0004*	0.305***	0.0007	0.0006	0.001**	0.001**
	(0.447)	(0.000)	(0.000)	(0.010)	(0.001)	(0.001)	(0.001)	(0.001)
First stage F-statistic					866.4	939.5	846.0	870.0
Endogeneity test p-value					0.214	0.241	0.111	0.082
Panel C: Obese								
Hours of work	0.095	0.0003	0.0002*	0.305***	0.0004	0.0004	0.001**	0.001**
	(0.293)	(0.000)	(0.000)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)
First stage F-statistic					866.4	939.5	846.0	870.0
Endogeneity test p-value					0.203	0.220	0.088	0.086
Controls								
Regional FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional time trends		Yes	Yes	Yes	No	Yes	Yes	Yes
Individual and family characteristics		Yes	Yes	Yes	No	No	Yes	Yes
Regional characteristics		Yes	Yes	Yes	No	No	No	Yes
N		5,432	5,432	5,432	5,432	5,432	5,432	5,432

Notes: The sample includes children aged 6-13 who attend school, with the youngest pre-school age sibling (0-6 years old), and mothers living at the same household. Each coefficient belongs to a separate regression. Column (1) reports means calculated for each outcome. Standard deviation of the means are reported in parentheses. Column (2) reports OLS regression results. Column (3) presents the reduced form (RF) results. Column (4) presents the first stage (FS) results. Columns (5)-(8) show the second stage estimations (2SLS). Column (5) regressions include regional and year fixed effects. Column (6) also controls for regional time trends. Column (7) additionally includes a vector of child's characteristics such as age in months and gender, mother's characteristics such as age, marital status and education, and family's characteristics such as household size, presence of grandparents in household and settlement type. Column (8) presents regressions with all previous controls plus regional characteristics such as regional expenditures on different policies including expenditure on healthcare system, family and childhood security policy, social security, and on labour market support, male employment, female unemployment in year t-1, the GDP per capita in period t-1, the average proportion of social benefits in household income, and the interaction between year dummies and levels of childcare availability in the year 2000. The specification that includes all covariates is used as a baseline specification (Column 8). Robust standard errors in parenthesis. Standard errors are clustered at the regional level. *p<0.10, **p<0.05, ***p<0.01.
Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

2.5.2 Robustness analysis

Before proceeding further with the heterogeneity analysis and investigating potential mechanisms, I test the robustness of the main findings, presented in Table 2.3. The first row repeats the main results (Table 2.1 Column (8)) for reference. The second row explores the data quality issue discussed in Section 2.3.3 and presents results based on the same analysis for a sample where I exclude all observations with inconsistent height measurements which substantially decreases the sample by around 22%. I do this check only for height because height cannot fluctuate as the child grows while weight may. The results based only on observations with consistent height are very similar to baseline results in terms of magnitude and statistical significance.

Next, I take into account mother's and child's health. First, I restrict the sample to children with mothers who are in very good or excellent health. It may be the case that mothers with serious health issues stay out of the labour force even when their youngest child is enrolled into childcare. In this case the effect of maternal employment is different for mothers with different health status and they differently respond to the instrument. Row (3) shows that restricting the sample in this way does not change the qualitative results, but the estimated effects are larger. Second, I restrict the sample to children without any chronic diseases. One might be concerned that if a child has any chronic disease their mother can either stop working or reduce working hours even if the youngest child has attends childcare. Also, the presence of chronic diseases itself can affect the child's weight. Excluding children with chronic disease should give us an idea whether the main findings might be driven by child health problems. Based on the data I consider chronic diseases related to heart, lung, liver, kidney, stomach and spinal diseases. Row (4) shows that the results are again very similar to the main results except that the probability to become overweight becomes not statistically significant. To a certain extent, these findings show that the main results are not driven by reverse causality.

Finally, I run a set of falsification tests that provide evidence to support the model's identifying assumptions. First, I test that childcare availability is not related to anything else that predicts the older sibling's weight outcomes conditional on the covariates included in the model. For this I assign to the youngest child in the household childcare availability five years into the future expecting that weight-related outcomes of older siblings should not be related to the future childcare availability. I use childcare enrolment rates in 2005-2017 for the time period 2000-2012. Row (5) of Table 2.3 displays results for this falsification test. Future childcare for the youngest child has no statistically significant effect on weight-related outcomes of older siblings and point estimates are much smaller.

Second, as discussed in section 2.4.1, maternal attitudes towards healthy lifestyles may change with the childcare expansion. To test this assumption, I investigate alternative outcomes that should not be affected by maternal employment but could be affected by overall changes in maternal healthy lifestyle attitudes that might be correlated with the instrumental variable. As alternative outcomes I choose health-related outcomes such as measures that families undertake to strengthen child's health – keeping a day regime and obliging the child to walk in fresh air. Results of this falsification test are presented in Table 2.4. None of the estimated effects are statistically significant, and thus the exclusion restriction is not rejected.

Table 2.3 – Robustness checks

	N	BMI z-score	Overweight/Obese	Obese
(1) Baseline results	5,500	0.216***	0.050*	0.032**
		(0.066)	(0.026)	(0.015)
(2) Exclude all inconsistency	4,266	0.186**	0.061**	0.026**
		(0.078)	(0.027)	(0.014)
(3) Only mothers in very good and excellent health	2,739	0.322***	0.082**	0.049**
		(0.114)	(0.037)	(0.021)
(4) Only children without chronic diseases	4,576	0.260***	0.045	0.034**
		(0.074)	(0.029)	(0.017)
(5) Falsification test (1)	3,023	0.287	0.028	0.020
		(0.334)	(0.033)	(0.021)

Notes: The sample includes children aged 6-13 who attend school, with the youngest pre-school age sibling (0-6 years old), and mothers living at the same household. Each coefficient belongs to a separate regression. All models include a full range of child, mother, family and regional controls, year and region fixed effects as well as regional time trends. Results in Row (1) are baseline model. Results in Row (2) are based on the sample where I exclude all observations with inconsistent height measurements. In Row (3) I restrict the sample to children with mothers who are in very good or excellent health. In Row (4) I restrict the sample to children without any chronic diseases. Row (5) is a falsification test when I assign to the youngest child in household childcare availability five years into the future. Robust standard errors in parenthesis. Standard errors are clustered at the regional level. *p<0.10, **p<0.05, ***p<0.01.
Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

Table 2.4 – Falsification tests (2)

	Mean	2SLS	N
(1) Keeping day regime	0.830	0.008	3,970
	(0.376)	(0.023)	
(2) Walking in fresh air	0.930	-0.004	3,974
	(0.256)	(0.014)	

Notes: The sample includes children aged 6-13 who attend school, with the youngest pre-school age sibling (0-6 years old), and mothers living at the same household. Each coefficient belongs to a separate regression. All models include a full range of child, mother, family and regional controls, year and region fixed effects as well as regional time trends. Robust standard errors in parenthesis. Standard errors are clustered at the regional level. *p<0.10, **p<0.05, ***p<0.01.
Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

2.5.3 Heterogeneity

As the effect of maternal employment on child's weight may vary with characteristics of the child, mother and her family, in this section I present subsample analyses to determine whether the effect is different for different groups of the population. The data allows me to estimate the effect by child's gender and age, mother's education, marital status and employment (part-time vs. full-time) status, family income, and settlement type. In the first row of Table 2.5, I reproduce my main results from column (8) in Table 2.1 for reference while in the subsequent panels I disaggregate the sample based on different demographic criteria. In the following analysis I focus only on the effect of maternal employment.

Panels A and B of Table 2.5 show differences in the effect of maternal employment on child's BMI z-score and body weight status by child's gender and age. Looking first at the differences by gender (Panel A), I find that the effect is statistically significant only for BMI z-score among girls and for the probability to become obese among boys. The effects are statistically significant at 1% and 10% level, respectively. These estimates are relatively large in magnitude: maternal employment causes 0.308 units increase in girls' BMI z-score and 4.6 percentage points increase in boys' probability to become obese. However, the differences between girls and boys are not statistically significant. In terms of probability to become overweight, the difference again is not statistically significant. Splitting the sample by child's age (Panel B) shows that in terms of BMI z-score the effect of maternal employment is stronger and statistically significant for younger children (6-9 years old). For this group, it is estimated that maternal employment increases BMI z-score by 0.378 units and the difference between two groups is statistically significant. In terms of the probability to become overweight or obese, the differences between two groups are not statistically significant.

The next set of panels of Table 2.5 presents effects by mothers' individual characteristics. The first dimension along which there may be heterogeneity is marital status (Panel C). I find that the effect of maternal employment is statistically significant for all outcomes among children of married or cohabiting mothers. This result is in line with the differences in the first stage (heterogeneity results of the first chapter), which show that the effect of childcare availability on employment of married/cohabiting mothers is significantly higher than on employment of single mothers. Thus, the differences are not statistically significant, it is important to take into account that the sample of single mothers is extremely small and probably there is not enough power to detect any statistically significant effect. Next, I examine the effect of maternal employment by maternal education level which is one of the proxies for socio-economic status of the family (Panel D). As mentioned earlier, some of the literature finds that the adverse effects of maternal employment are stronger for mothers of higher socio-economic status (Liu et al., 2009; Courtemanche et al., 2017). I distinguish two levels of education: low-educated mothers are those who at most have vocational education and high-educated mothers who have at least a degree of higher education. I find that only the effect of maternal employment on BMI z-score is statistically significant for both groups of children – maternal employment increases child's BMI z-score by 0.246 units among children of low-educated mothers and by 0.213 units among children of high-educated mothers. But, again, none of the differences are statistically significant.

Panel E of Table 2.5 presents the effect of maternal employment by family income, measured in quartile groups. The effect of maternal employment is mainly concentrated among children from families in the third income band. For this group of children, maternal employment increases child's BMI z-score and the probability to become overweight by 0.271 units and 9.2 percentage points at the 10% and 5% level of significance, respectively. Overall, it seems that the adverse effect of maternal employment on child's weight appears in the group of upper middle-class families, although the differences are not statistically significant.

In panel F of Table 2.5 I investigate whether there are any differences between part- and full-time employed mothers. For this I compare part-time and full-time working mothers to non-working mothers. A mother is defined as working full-time if she currently works 31 or more hours per week and as working part-time if she works 30 or less hours per week. The findings show that the effects for all outcomes are statistically significant only for children of mothers who work full-time. Maternal full-time employment increases child's BMI z-score by 0.209 units, the probability to become overweight by 5.3 percentage points and the probability to become obese by 3.6 percentage points.

Finally, panel G of Table 2.5 presents effects by settlement type. The results indicate that the adverse effect of maternal employment appears among children who live in urban areas. For this group of children maternal employment increases child's BMI z-score by 0.316 units, the probability to become overweight by 8.6 percentage points and the probability to become obese by 5.1 percentage points. The results are highly statistically significant and the differences between the groups are statistically significant for BMI z-score and the probability to become overweight.

Overall, I find that the effect of maternal employment on child's weight seems to be concentrated among children aged 6-9 years old whose mothers are upper-middle socio-economic status (high-educated mothers or from the third income quartile), have partners, work full-time, or their families live in urban area, although the differences are statistically significant only for some outcomes in terms of child's age and settlement type.

Table 2.5 – Heterogeneity analysis

			BMI z-score		Overweight/Obese		Obese	
	N	FS F-statistic	Mean	2SLS	Mean	2SLS	Mean	2SLS
Baseline results	5,500	1345.2	0.174	0.216***	0.275	0.050*	0.095	0.032**
			(1.452)	(0.066)	(0.447)	(0.026)	(0.293)	(0.015)
Panel A: By child's gender								
Girls	2,662	952.3	0.035	0.308***	0.228	0.045	0.069	0.010
			(1.369)	(0.099)	(0.420)	(0.033)	(0.254)	(0.018)
Boys	2,838	528.7	0.304	0.067	0.323	0.033	0.120	0.046*
			(1.515)	(0.125)	(0.468)	(0.038)	(0.325)	(0.026)
Equality test			*p* = 0.306		*p* = 0.892		*p* = 0.453	
Panel B: By child's age								
6-9 years old	2,645	932.7	0.260	0.376***	0.312	0.064	0.127	0.022
			(1.566)	(0.110)	(0.463)	(0.045)	(0.333)	(0.026)
10-13 years old	2,855	831.0	0.094	0.022	0.244	0.012	0.066	0.025
			(1.332)	(0.099)	(0.430)	(0.032)	(0.249)	(0.020)
Equality test			*p* = 0.013		*p* = 0.206		*p* = 0.689	
Panel C: By mother's marital status								
Single	418	42.9	0.038	0.527	0.242	-0.046	0.098	-0.021
			(1.484)	(0.421)	(0.429)	(0.103)	(0.298)	(0.056)
Married/Cohabiting	5,077	1276.7	0.185	0.190***	0.280	0.045*	0.095	0.028*
			(1.449)	(0.215)	(0.449)	(0.027)	(0.294)	(0.016)
Equality test			*p* = 0.210		*p* = 0.688		*p* = 0.718	
Panel D: By mother's education								
Low	3,655	992.8	0.205	0.246***	0.288	0.042	0.106	0.025
			(1.502)	(0.090)	(0.453)	(0.035)	(0.308)	(0.022)
High	1,842	522.4	0.114	0.213*	0.255	0.066	0.075	0.037
			(1.346)	(0.119)	(0.436)	(0.041)	(0.263)	(0.025)
Equality test			*p* = 0.777		*p* = 0.691		*p* = 0.848	
Panel E: By family income								
Lowest income band	1,153	246.6	0.157	0.198	0.269	-0.051	0.108	-0.035
			(1.557)	(0.166)	(0.444)	(0.067)	(0.310)	(0.033)
Second income band	1,269	204.5	0.112	0.212	0.264	0.076	0.090	0.037
			(1.468)	(0.183)	(0.441)	(0.051)	(0.286)	(0.034)
Third income band	1,381	361.7	0.253	0.271*	0.289	0.092**	0.091	0.015
			(1.378)	(0.147)	(0.453)	(0.041)	(0.287)	(0.032)
Highest income band	1,697	318.7	0.166	0.105	0.282	0.027	0.095	0.042
			(1.424)	(0.122)	(0.450)	(0.045)	(0.294)	(0.026)
Equality test			*p* = 1.000		*p* = 0.996		*p* = 0.999	

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Table 2.5 - Continued from previous page								
Panel F: By mother's employment status								
Part-time	3,039	160.6	0.204	0.159	0.264	-0.018	0.089	-0.012
			(1.431)	(0.209)	(0.441)	(0.072)	(0.285)	(0.042)
Full-time	4,844	1195.6	0.160	0.209***	0.271	0.053**	0.091	0.036**
			(1.413)	(0.065)	(0.445)	(0.027)	(0.288)	(0.015)
Panel G: By settlement type								
Rural	2,283	451.3	0.329	0.035	0.317	-0.018	0.130	-0.002
			(1.497)	(0.092)	(0.465)	(0.045)	(0.336)	(0.023)
Urban	3,217	770.5	0.063	0.316***	0.248	0.086**	0.071	0.051***
			(1.410)	(0.098)	(0.432)	(0.034)	(0.257)	(0.019)
Equality test			p = 0.055		p = 0.072		p = 0.148	

Notes: The sample includes children aged 6-13 who attend school, with the youngest pre-school age sibling (0-6 years old), and mothers living at the same household. Each coefficient belongs to a separate regression. All models include a full range of child, mother, family and regional controls as well as year and region fixed effects. Standard deviation of the means are reported in parentheses. Mother is defined as single if she is not married and does not have a partner. Mother is defined as having low education if at most she has vocational education and high education if has higher education or more. Income is measured in quartile groups. Mother works full-time if she is currently working more than 30 hours per week and part-time if she is currently working up to 30 hours per week. Robust standard errors in parenthesis. Standard errors are clustered at the regional level. *p<0.10, **p<0.05, ***p<0.01.
Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

2.5.4 Mechanisms

In this section I explore the income and time effects as the mechanisms underlying the adverse effect of maternal employment on child weight. I use three groups of outcomes, i.e. physical activity, sedentary behaviour and dietary habits outcomes, to investigate which effect, or both, is at play. Based on my data, not for all outcomes it is possible to disentangle whether effects indicate income and/or time effects. Effects on physical activity can be caused by both income and time. Theoretically, the time effect is negative while the income effect is positive. For example, due to time constraints that working mothers face, organizing children's physical activity and sports can be more difficult which leads to a negative effect on children's physical activity or mothers may use the additional income on children's physical activities such as sports clubs, which instead leads to a positive effect. If I find that children decrease their physical activity due to maternal employment, this potentially indicates that the time effect is bigger than the income effect or that only the time effect appears. In the case of sedentary behaviour, which I measure by watching TV, theoretically, only the time effect is at play and I would expect that the time effect on weight is negative. Dietary habits outcomes include the habit to eat out and food expenditure. In terms of eating out again effects can be caused by both income and time as families can eat out more often due to time constraints and/or due to higher income but both of them are expected to affect child's weight negatively. Estimates on food expenditure outcomes also can be driven by income and/or time effects. For example, if families buy more fruit and vegetables, this potentially indicates the income effect and I would expect it to be positive. If families buy more sweets and soft drinks, this again potentially indicates the income effect but in this case I would expect that the income effect on weight is negative. However, if families buy more processed food, this potentially indicates both the time and income effects. Both effects positively affect expenditure on processed food which in tern negatively affects children's health and weight. Overall, I suggest that the sedentary behaviour outcomes indicate just the time mechanism, the outcomes on vegetables, fruit, sweets and soft drinks expenditure indicate just the income mechanism while the outcomes on physical activity, eating out and processed food show both the income and time mechanisms.

Table 2.6 displays the 2SLS estimates of the effect of maternal employment on physical activity and sedentary behavior. In terms of physical activity, maternal employment leads to a 5.2 percentage points decrease in the probability of being physically active (training sessions with a coach/active games outdoors) at least once a week and to a 0.70 hour decrease in physical activity per week (around 42 minutes). The estimates are statistically significant at 5 and 10% levels, respectively. These results mean that even if there is an income effect that increases the child's physical activity, the time effect is bigger, and this leads to a decrease in physical activity. Regarding sedentary behavior, the 2SLS estimates suggest a 1.9 percentage points increase in the probability to watch TV/play video games every day but the effect is not statistically significant. At the intensive margin the effect is also not statistically significant.

Table 2.6 – The effect of maternal employment on physical activity and sedentary behaviour

	Mean	FS F-statistic	2SLS	N
PA before/after school at least once a week	0.624 (0.484)	1463.4	-0.052** (0.025)	5,488
Hours of PA before/after school per week	4.395 (6.247)	1445.4	-0.698* (0.364)	5,507
Watching TV/playing video games daily	0.974 (0.159)	1350.7	0.019 (0.015)	5,359
Hours of watching TV/playing video games per day	1.788 (1.069)	1638.9	0.090 (0.077)	5,217

Notes: The sample includes children aged 6-13 who attend school, with the youngest pre-school age sibling (0-6 years old), and mothers living at the same household. Each coefficient belongs to a separate regression with the corresponding mechanism variable as dependent. All models include a full range of child, mother, family and regional controls, year and region fixed effects as well as regional time trends. Standard deviation of the means are reported in parentheses. Data on watching TV for the 2001-2017 time period. Robust standard errors in parenthesis. Standard errors are clustered at the regional level. *p<0.10, **p<0.05, ***p<0.01.
Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

With respect to the child's dietary habits, Table 2.7 shows that there is a precisely estimated effect of maternal employment on eating out both at the extensive and intensive margins: maternal employment leads to a 13.3 percentage points increase in the probability to eat out at least once a week and to an increase in spending on eating out by 57.9 rubles, which is equal to a 40.2% increase. Also, I find that maternal employment significantly increases the probability to buy prepared/semi-prepared meat at least once a week by 8.9 percentage points. This result is respectively reflected in the families' food expenditure as there is a significant increase in the amount of money spent on prepared/semi-prepared meat. Moreover, the results show a significant increase in spending on sweets. Except the result on sweets, which I suggest indicates the income effect, the findings on eating out and prepared/semi-prepared meat do not allow me to separate out which mechanism leads the effects.

Overall, the findings suggest that the time and income effects on weight are negative. The time effect is driven by less energy expenditure which appears through less physical activity and more sedentary behavior. This supports the idea that working mothers, who are more time constrained, may have a more difficult time ensuring their children do regular exercise and spend an adequate amount of time watching television and playing computer games. The income effect, which is theoretically indeterminate, shows up in expenditure on sweets and leads to an increase in energy intake. The time and/or income effect are also driven by spending more on prepared/semi-prepared meat and eat out more. Even though I cannot disentangle two of them in these cases, both increase energy intake and the child's weight in turn.

Table 2.7 - The effect of maternal employment on dietary habits

	Mean	FS F-statistic	2SLS	N
Eat out at least once per week	0.657 (0.475)	1264.9	0.133*** (0.035)	5,511
Spending on eating out (ruble/person/week)	136.309 (257.05)	1001.4	57.91*** (15.68)	4,888
Probability to buy:				
Vegetables	0.465 (0.499)	1321.4	0.013 (0.028)	5,466
Fruit	0.732 (0.443)	1352.5	-0.006 (0.027)	5,439
Sweets	0.859 (0.348)	1484.5	0.028 (0.024)	5,283
Soft drinks	0.424 (0.494)	1310.6	0.022 (0.031)	5,537
Prepared/semi-prepared meat	0.769 (0.422)	1318.2	0.089*** (0.023)	5,387

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Table 2.7 - Continued from previous page

Amount:				
Vegetables (kg/person/week)	1.220 (6.242)	1321.4	-1.008 (0.646)	5,466
Fruit (kg/person/week)	0.743 (2.628)	1352.5	-0.123 (0.137)	5,439
Sweets (kg/person/week)	0.348 (0.301)	1484.5	0.033 (0.021)	5,283
Soft drinks (l/person/week)	0.282 (0.573)	1295.5	0.044* (0.025)	5,506
Prepared/semi-prepared meat (kg/person/week)	0.318 (3.283)	1318.2	0.122 (0.086)	5,387
Expenditure:				
Vegetables (ruble/person/week)	36.13 (115.81)	930.9	-6.719 (12.040)	4,910
Fruit (ruble/person/week)	53.22 (79.02)	945.0	-0.318 (4.508)	4,922
Sweets (ruble/person/week)	72.15 (72.39)	990.3	17.22*** (4.657)	4,836
Soft drinks (ruble/person/week)	17.35 (33.92)	918.9	2.320 (1.964)	4,961
Prepared/semi-prepared meat (ruble/person/week)	81.62 (87.17)	1047.4	16.07** (7.402)	4,910

Notes: The sample includes children aged 6-13 who attend school, with the youngest pre-school age sibling (0-6 years old), and mothers living at the same household. Each coefficient belongs to a separate regression with the corresponding mechanism variable as dependent. All models include a full range of child, mother, family and regional controls, year and region fixed effects as well as regional time trends. Standard deviation of the means are reported in parentheses. Data on healthy diet for the 2010-2017 time period. Robust standard errors in parenthesis. Standard errors are clustered at the regional level. *p<0.10, **p<0.05, ***p<0.01.
Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

2.6 Conclusion

In Russia like in many other countries the level and rate of change in childhood obesity are a great cause for concern. Most previous studies show that maternal employment is one of the contributors to this issue as the mother's decision to work leads to several changes in the household which may affect the child's weight. This paper provides the first evidence on the relationship between maternal employment and children's weight in Russia.

To estimate the causal effect of maternal employment on child's weight-related outcomes, I use an instrumental variable estimation approach. I use plausibly exogenous variation in childcare availability for the youngest child in the household as an instrument for maternal employment to estimate the effect of maternal employment on the weight-related outcomes of older siblings. The 2SLS estimates suggest that maternal employment has a significant adverse effect on child's weight. In particular, the main results show that maternal employment increases child's BMI z-score by 0.216 units, the probabilities to become overweight by 5.0 percentage points and the probability to become obese by 3.2 percentage points. Considering that both childhood obesity and maternal employment increased by 6 percentage points[44] over the period between 2000 and 2017, my results suggest that around 5% of the total increase in childhood obesity can be explained by the increase in maternal employment. Several robustness checks confirm the validity of the results. The effects seem to be driven by mothers of upper-middle socio-economic status, mothers with partners, mothers working full-time, and mothers whose families live in urban areas.

I also apply the 2SLS instrumental variable approach to investigate potential mechanisms underlying the effect of maternal employment, covering physical activity, sedentary behavior and dietary habits. In terms of dietary habits, the results suggest that a mother's decision to enter the labour market leads to a higher probability to buy prepared/semi-prepared meat and a higher probability to eat out. At the same time, maternal employment significantly contributes to a decrease in children's physical activity. Therefore, I suggest that the adverse effect of maternal employment on child's weight-related outcomes is driven by increased energy intake and reduced energy expenditure.

The analysis has some limitations. Because child's weight and height are parent-reported rather than professionally measured, there are measurement errors and missing data that lead to relatively poor data quality and consequently a reduction of the estimation sample. This contributes to lower statistical power, so I interpret my findings carefully. Also, there is a potential concern on external validity of the results as the main sample selection criteria is children that must have a younger sibling aged between 0 and 6. Based on the dataset I use, among all children aged 6 to 13 only 26.5% have a sibling between 0 and 6.

The results from this study have several policy implications but again they should be interpreted cautiously. It is very important to highlight that maternal employment is beneficial for mothers as well as for children, for example, in terms of having careers themselves, having better, higher paying jobs and having "more egalitarian" views on gender roles, so the conclusion should not be to deter mothers from coming back to the labour market. Instead, understanding the mechanisms through which maternal employment might affect children's weight can shed light on policies to promote children's health. Based on my findings, beneficial policies might be those that increase physical activity in schools, increase quality of school meals, include curriculum on nutrition, help to form healthy habits, or promote health education among parents. Another possible approach to reduce the adverse effect of maternal

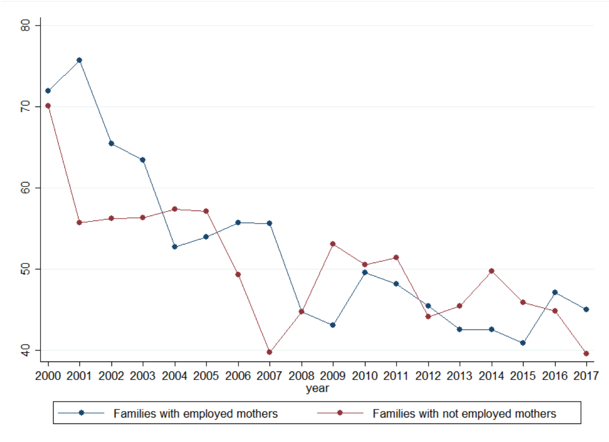
[44] This is according to the survey data as there are no official statistics at the country-level for the entire period between 2000 and 2017.

employment is to motivate fathers to contribute more time to parenting and household chores in Russia where traditionally mothers are more involved in raising children and household work.

Appendices

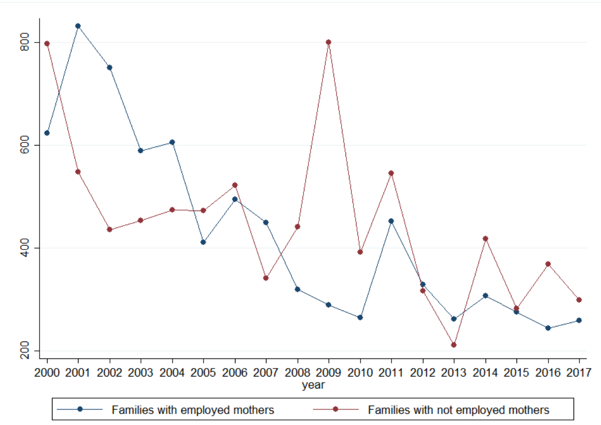
Appendix B1– Descriptive statistics on the amount of harvested vegetables and fruit by mother's employment status

Figure B1.1 – Share of families growing vegetables and fruit on their own land



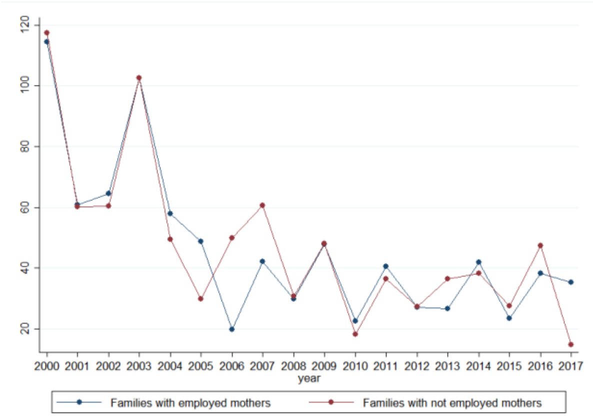
Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

Figure B1.2 – Amount of vegetables in kilograms harvested by families with employed and not employed mothers, in the past 12 months



Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

Figure B1.3 – Amount of fruit in kilograms harvested by families with employed and not employed mothers, in the past 12 months



Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

Appendix B2 – Data quality testing and sampling

Table B2.1– Plausibility of the MCAR

	Without missing data on BMI	With missing data on BMI	Δ	p-value
Child characteristics				
Male	0.52	0.55	-0.03	0.09
Age in months	121.89	118.35	3.54	0.00
Bad health	0.01	0.01	0.00	0.82
Satisfactory health	0.26	0.27	-0.01	0.61
Good health	0.73	0.72	0.01	0.62
Mother characteristics				
Age	32.85	31.56	1.29	0.00
Married/cohabiting	0.92	0.89	0.03	0.01
Incomplete secondary school education	0.13	0.24	-0.11	0.00
Secondary school education	0.30	0.35	-0.05	0.00
Vocational secondary education	0.24	0.26	-0.02	0.18
Higher education or more	0.33	0.14	0.19	0.00
In work or on leave	0.54	0.55	-0.01	0.72
Has informal job	0.06	0.06	-0.00	0.89
Household characteristics				
HH size	5.01	4.96	0.05	0.41
Settlement type				
City	0.33	0.18	0.14	0.00
Town	0.26	0.25	0.01	0.62
Semi-urban	0.05	0.06	-0.01	0.12
Rural	0.37	0.50	-0.14	0.00
N	5,545	755		

Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

Table B2.2 – Plausibility of the MAR (dependent variable "Missing on BMI")

	Coef.	SE
Child is male	0.019**	(0.008)
Child's age in months	-0.0004**	(0.0002)
Child's health: Satisfactory	-0.0003	(0.037)
Child's health: Good	-0.012	(0.037)
Child's health: Missing	-0.041	(0.090)
Mother's age in years	-0.004***	(0.001)
Marital status: Married/cohabiting	-0.020	(0.015)
Marital status: Missing	0.049	(0.131)
Mother's education: Incomplete secondary school	0.063***	(0.013)
Mother's education: Vocational secondary education	-0.006	(0.011)
Mother's education: Higher education or more	-0.068***	(0.011)
Mother's education: Missing	0.053	(0.131)
Employment status: In work or on leave	-0.016*	(0.010)
Employment status: Missing	-0.112	(0.226)
Informal job: Yes	-0.012	(0.018)
Informal job: Missing	0.027	(0.113)
HH size	-0.009***	(0.003)
Settlement type: City	-0.032***	(0.011)
Settlement type: RGT	0.044**	(0.020)
Settlement type: Rural	0.025**	(0.011)
Constant	0.366***	(0.054)
N	6,300	
R-squared	0.037	

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

Table B2.3 – Descriptive statistics of the original sample of all children (panel A) and the final estimation sample for the complete cases analysis (panel B).

	Panel A			Panel B		
	Mean	SD	N	Mean	SD	N
Child characteristics						
Age in months	121.47	24.31	6,300	121.96	24.41	5,500
Male	0.52	0.50	6,300	0.52	0.50	5,500
BMI z-score	0.17	1.45	5,502	0.17	1.45	5,500
Overweight	0.18	0.39	5,502	0.18	0.39	5,500
Obese	0.10	0.29	5,502	0.10	0.29	5,500
Mother characteristics						
Age	32.70	4.09	6,300	32.87	4.06	5,500
Married/cohabiting	0.92	0.27	6,300	0.92	0.27	5,500
Incomplete sec. education	0.14	0.35	6,300	0.13	0.33	5,500
Secondary school education	0.31	0.46	6,300	0.30	0.46	5,500
Vocational sec. education	0.24	0.43	6,300	0.24	0.43	5,500
Higher education or more	0.31	0.46	6,300	0.33	0.47	5,500
In work or on leave	0.54	0.50	6,298	0.54	0.50	5,500
Household characteristics						
Grandmother in HH	0.18	0.38	6,300	0.18	0.39	5,500
HH size	5.00	1.53	6,300	5.00	1.53	5,500
Youngest child age	2.85	1.94	6,300	2.81	1.93	5,500
Settlement type						
City	0.31	0.46	6,300	0.32	0.47	5,500
Town	0.26	0.44	6,300	0.26	0.44	5,500
Semi-urban	0.05	0.22	6,300	0.05	0.22	5,500
Rural area	0.38	0.49	6,300	0.37	0.48	5,500

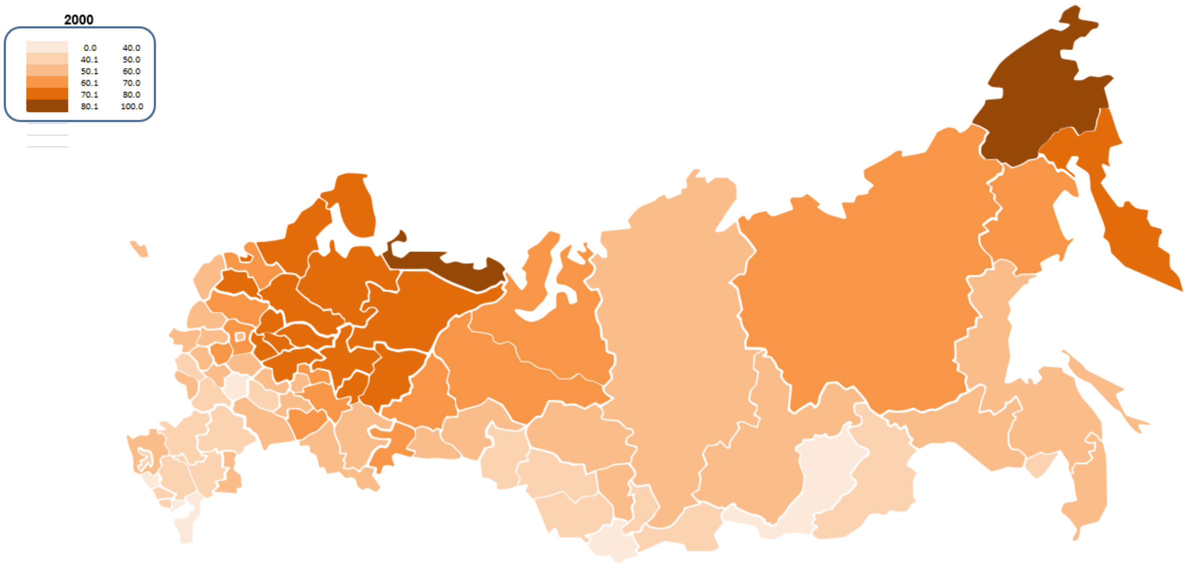
Notes: The sample includes children aged 6-13 who attend school, with the youngest pre-school age sibling (0-6 years old), and mothers living at the same household.
Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

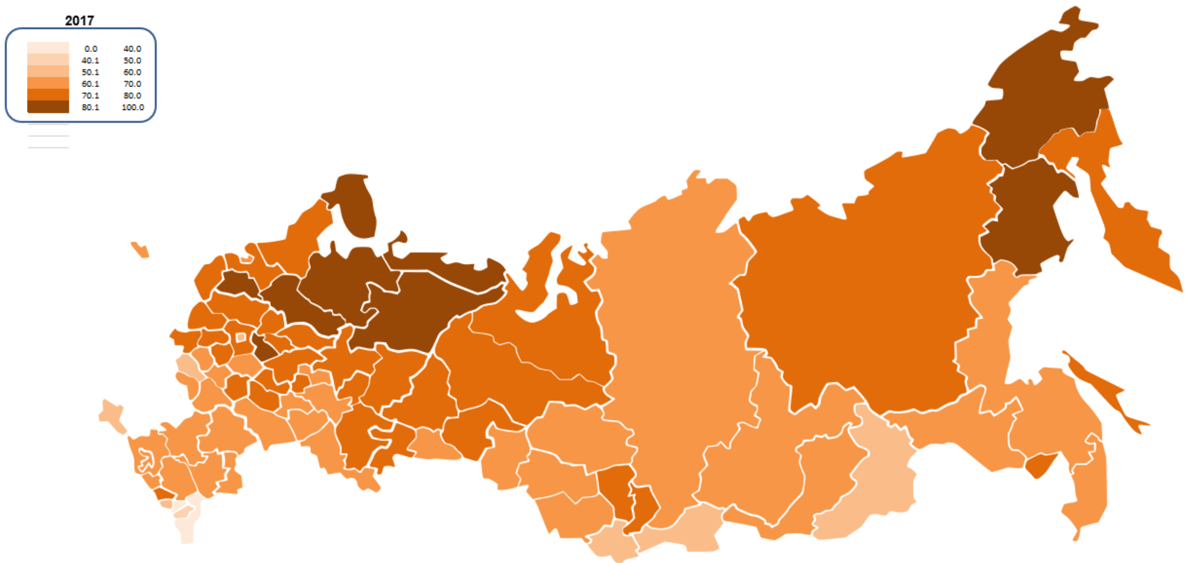
Table B2.4 – Descriptive statistics of the final sample

	Full sample (1)	Normal weight (2)	Overweight (3)	Difference (2)-(3) (4)	p-value (5)
Child characteristics					
Age in months	121.96	123.41	118.19	5.22	0.00
Male	0.52	0.48	0.60	-0.12	0.00
BMI z-score	0.17	-0.47	1.87	-2.34	0.00
Overweight	0.18	-	0.66	-	-
Obese	0.10	-	0.34	-	-
Mother characteristics					
Age	32.87	32.99	32.53	0.47	0.00
Single	0.08	0.08	0.07	0.01	0.10
Married/cohabiting	0.92	0.92	0.93	-0.01	0.07
Missing	0.00	0.00	0.00	0.00	0.17
Incomplete sec. educ.	0.13	0.12	0.14	-0.02	0.17
Secondary school educ.	0.30	0.29	0.33	-0.04	0.01
Vocational sec. educ.	0.24	0.24	0.22	0.02	0.22
Higher educ. or more	0.33	0.34	0.31	0.03	0.01
Missing	0.00	0.00	0.00	0.00	0.70
In work or on leave	0.54	0.55	0.53	0.02	0.21
Household characteristics					
HH size	5.00	4.99	5.04	-0.05	0.27
Grandparents in HH	0.18	0.18	0.20	-0.02	0.18
Age of youngest child	2.81	2.80	2.85	-0.06	0.33
Settlement type					
City	0.33	0.34	0.29	0.05	0.00
Town	0.26	0.27	0.24	0.03	0.02
Semi-urban	0.05	0.04	0.07	-0.03	0.00
Rural	0.37	0.35	0.40	-0.05	0.00
N	5,500	3,978	1,522		

Notes: The sample includes children aged 6-13 who attend school, with the youngest pre-school age sibling (0-6 years old), and mothers living at the same household.
Source: Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

Appendix B3 – Childcare enrolment rate among Russian regions in 2000 and 2017

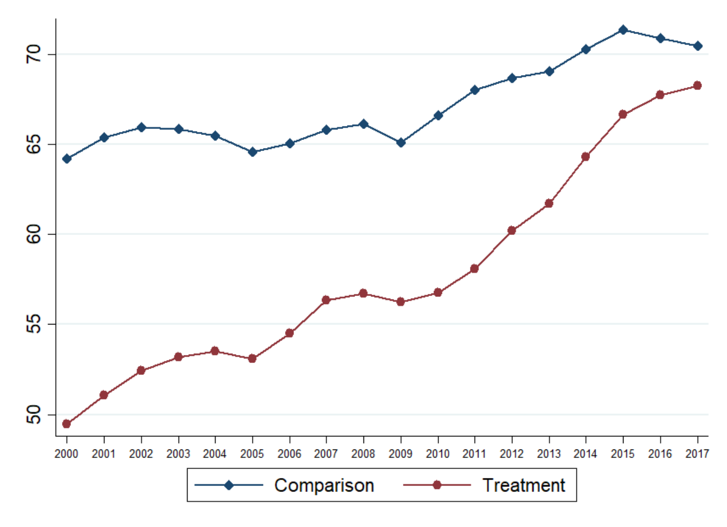




Notes: Childcare enrolment rate varies from 0 to 100%. Darker colour means a higher level of enrolment rate.
Source: Country-level data from the Federal State Statistic Service of Russian Federation.

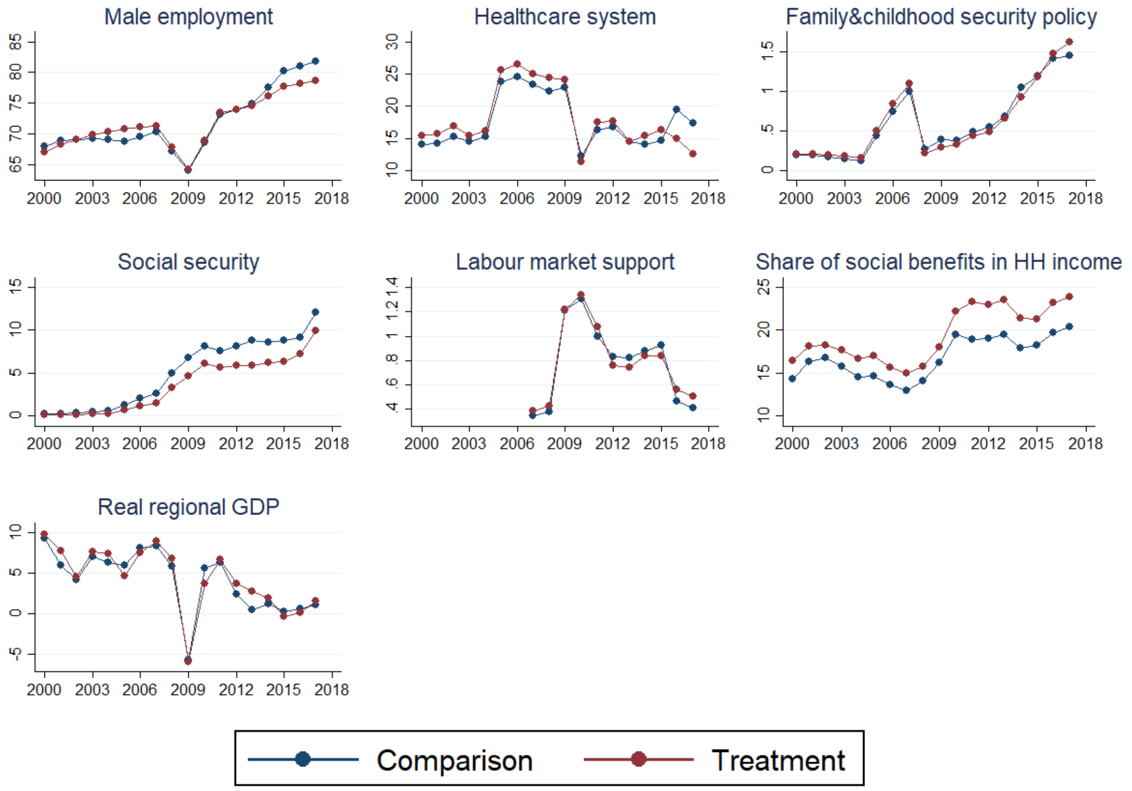
Appendix B4 – Comparison of potential treatment and comparison regions

Figure B4.1 – Expansion of childcare places across Russia, 2000-2017



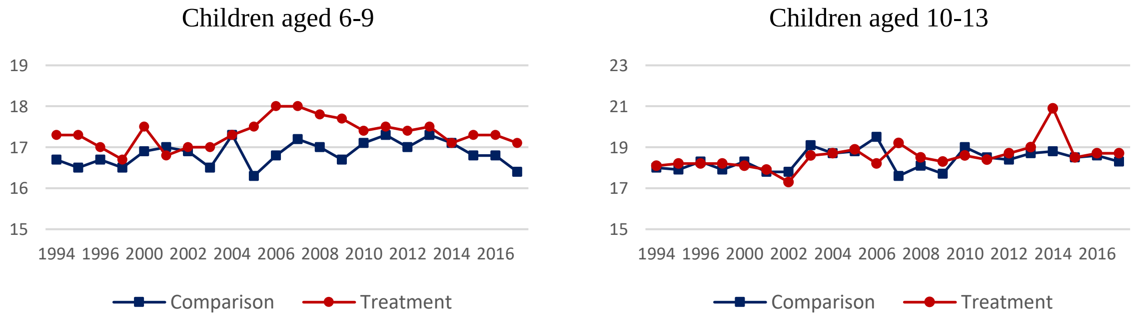
Notes: The graph shows expansion of childcare places in treatment and comparison groups. The treatment group is the top 50% regions with the highest increase in enrolment rate while the comparison group is the bottom 50% between 2000 and 2017. Enrolment rate is a proportion of children aged 0-6 in total number of children at this age group. Enrolment rate varies from 0 to 100%.
Source: Regional-level data from the Federal State Statistic Service of Russian Federation.

Figure B4.2 – Trends of regional socio-demographic and economic characteristics in treatment and comparison groups, 2000-2017



Notes: The treatment group is the top 50% regions with the highest increase in enrolment rate while the comparison group is the bottom 50% between 2000 and 2017. Family and childhood security is the measures aimed at ensuring the health of mothers and children, strengthening families, promoting motherhood, creating the most favourable conditions for the children upbringing, their physical, intellectual and moral development.
Source: Regional-level data from the Federal State Statistic Service of Russian Federation.

Figure B4.3 – Trends of children's BMI in the treatment and comparison group before and after childcare expansion, 1994-2017



Notes: The treatment group is the top 50% regions with the highest increase in enrolment rate while the comparison group is the bottom 50% between 2000 and 2017.
Source: Author's calculations based on Russian Longitudinal Monitoring Survey – Higher School of Economics Dataset.

Chapter 3

Weight report letters: help or harm in preventing childhood obesity? Evidence from England

3.1 Introduction

Childhood overweight and obesity is one of the most serious worldwide public health problems that affect both physical and psychosocial health to an important extent (Lobstein et al., 2004; Singh et al., 2008; EUFIC Childhood obesity review, 2017). Preventing childhood obesity and addressing its underlying determinants is at the top of the policy agenda of many governments. However, identifying policies that may be successful in tackling this pressing issue is not an easy task. A wide range of interventions has been trialled both in developing and developed countries, including programmes to remove vending machines from schools, increase physical activity in schools, tax soda and sugar, provide free healthy snacks, include extra curriculum on nutrition and exercise in schools, and others. Despite these policies, overweight and obesity in children have starkly increased over the past decades. According to the World Health Organization (WHO) global estimates, over 41 million children under the age of 5 and over

340 million children and adolescents aged 5-19 were overweight and obese in 2016 (WHO, 2018). The prevalence of overweight and obesity among children and adolescents aged 5-19 has risen tenfold in the past four decades (Ezzati et al. 2017).

The setting of this study is England, where in the 2018/19 school year, almost one in four children was overweight (12.9%) or obese (9.7%) when they started school at age 4-5, and this figure increases to more than one in three children by the time they left primary school at age 11 (14.1% and 20.2% of overweight and obese children, respectively) (NHS Digital, 2019). Estimates for the UK show that by 2050 approximately 25% of people in the under-20 age group will be obese and 40% overweight (McPherson et al., 2007). The economic costs related to obesity are enormous. In England, the National Health System (NHS) spent £6.1 billion on the health problems associated with being overweight and obese in 2014/15 while the overall cost of obesity to wider society is estimated at £27 billion (Public Health England, 2016).

The National Child Measurement Programme (NCMP) is an important element of the Government's strategy to tackle the rise in childhood obesity in England.[45] Established in 2005 as a child-level health surveillance programme, the NCMP annually weighs and measures children in Reception Year (aged 4-5 years) and Year 6 (aged 10-11 years). From 2008, in order to raise awareness of unhealthy body weight, the organisations responsible for data collection (Prime Care Trusts before 2013 and Local Authorities since 2013) were strongly encouraged to provide routine feedback letters to all parents/carers. This includes information on child's height, weight, body weight status (underweight/healthy weight/overweight/very overweight), information on potential health risks of being overweight, and a wide range of additional information (a leaflet, a phone number to contact back school nurses, information about local weight management services and links to websites providing further information and advice). Even though the programme is aimed at positive health-related changes, media reports have highlighted that these letters, sometimes described as 'fat letters', can have negative consequences, weighing on children's confidence and eating habits ("Girl, 11, stops eating for two days", 2016; Ardehali, 2018; Ford, 2018).

In this paper we investigate whether providing parents information about the weight status of their children modifies children's health and health-related behaviour or has any adverse effects. In our main analysis, based on the Millennium Cohort Study (MCS), we provide comprehensive evidence on the impact of sending feedback letters on adiposity-related outcomes, behavioural outcomes related to energy balance (physical activity, sedentary

[45] https://www.gov.uk/government/collections/national-child-measurement-programme

behaviour and fruit intake), and adverse effects (psychological outcomes and unhealthy eating behaviours) of the intervention.

We apply a difference-in-difference approach that takes advantage of the fact that one of the data collection years of the MCS took place when children were weighed and measured for the NCMP in their last year in primary school (Year 6). Our research design relies on a comparison of the dates of the MCS interview and the dates at which children were measured in their schools through the NCMP. We assign every child either into a treatment or control group by comparing the date of interview and the date of the NCMP measurement: children who were weighed and measured through the NCMP in the time before the day of their MCS interview are in the treatment group because their parents will have received the weight information by the time of the interview, while children who are still to be weighed and measured at the point of the MCS interview are in the control group as their parents are yet to receive the letters.

Our main results show that in the short run the intended positive effects of the feedback letters do not show up in the outcome measures available to us: adiposity-related outcomes such as BMI, body fat percentage and overweight probability as well as behavioural outcomes related to energy balance such as physical activity, sedentary behaviour and fruit intake remain unaffected. However, we find that parents' feedback letter receipt leads overweight children to skip breakfast – they are 2.3 times more likely to skip breakfast at least once a week than overweight children whose parents have not received the letters. Investigating this effect by family background, we find that sending feedback letters causes skipping breakfast to rise even more among overweight children from families of low income and children of single mothers. These groups of children are around 3 times more likely to skip breakfast than children from high income families and children from nuclear families. We also find that sending feedback letters leads some groups of overweight children to report unhappiness and tiredness at school. The effects are particularly high among children in low socio-economic background families. Overweight children of less educated mothers are about 20% more likely to feel unhappy and tired at school while this is not the case for children of highly educated mothers. The effect is even larger among overweight children of single mothers – receiving feedback letters increases the risk that these children feel unhappy at school by 30%. As not all local authorities consistently choose to share the measurement results with parents and not all children participate in the programme, we underestimate the real effects and our results present the intention-to-treat effects. A back-of-the envelope calculations on the treatment effect on the threated are presented in Section 3.6

Previous studies show that breakfast skipping impacts school test performance by affecting cognitive functioning such as focused attention and memory recall (Garg et al., 2014; Smith et al., 2014). Using a similar research design as before, we estimate whether feedback letter receipt impacts children's cognitive skills such as verbal ability and school test performance in Reading and Mathematics and do not find that this is the case.

This paper adds to the existing literature in the following ways. First, to our knowledge, this is the first comprehensive assessment of the National Child Measurement Programme feedback which costs around £1 million each year for sending letters alone.[46] We take into account both potential intended and unintended consequences of the programme, i.e. adiposity-related outcomes, outcomes related to behavioural lifestyle changes as well as potential adverse effects of the programme. This wide range of outcomes allows us to get a full picture of how the NCMP works. Second, our particular research design and unique data on the dates of the NCMP school visits in combination with a large sample size allows us to draw causal conclusions. Third, our findings contribute into the literature on tailored information interventions. Over the past decade, this type of intervention has become increasingly popular as it has been shown to lead to improved persuasive outcomes in terms of attitude, behavioural intention and behaviour change. Finally, as we find some adverse effects of sending feedback letters, we also contribute to the broader behavioural, economic, public policy and political literature and debates on unintended consequences of policies on consumers/voters when an action or policy meant to bring one set of reaction but inadvertently creates incentives that lead to another set of unexpected costs and adverse effects.[47]

The remainder of this paper is organised as follows. Section 3.2 summarises the existing literature. Section 3.3 provides information about the National Child Measurement Programme. Section 3.4 describes the data we use. Section 3.5 outlines our research design and identifying assumption. Section 3.6 presents our main results on children's response to

[46] Approximate authors' calculations based on (1) every year for around one million pupils in Reception and Year 6 valid NCMP measures are recorded; (2) around 75-80% of local authorities, which are responsible for the programme delivery, consistently choose to send feedback letters to parents; (3) the cost of letter feedback was estimated at £1.24 per child (NCMP operational guidance for the 2013/14 school year). These calculations take into account only sending feedback letters and do not include providing pro-active feedback which was estimated at £9.50 per child for a telephone call and £41 per child for a face-to-face appointment.

[47] For instance, the Sure Start programme which promotes a view of mothers as principally responsible for children's development and well-being which in turn results in blaming mothers for poor outcomes (Clarke, 2006). Another example is an unintended consequence of the Three Strikes rules in the Los Angeles area which considerably increased arrest rates, resisting and assaulting officers, and two and three-strikes crimes with a police officer victim (Johnson and Saint-Germain, 2005).

feedback letters, heterogeneity analysis, robustness checks as well as results on cognitive skills and school test performance. Section 3.7 concludes.

3.2 Literature review

Overweight and obese children and adolescents are likely to suffer from both short-term and long-term physical and mental health consequences. Immediate effects of being overweight or obese are emotional and psychological risks that include bullying and discrimination by peers, low self-esteem, anxiety and depression (Daniels, 2006; Forste and Moore, 2012). The most vital consequence of childhood obesity is a higher probability of obesity in adulthood, leading to a higher risk of morbidity, disability and premature mortality in adult life. In addition to increased future risks, obese children experience breathing difficulties, increased risk of fractures, hypertension, early markers of cardiovascular disease and insulin resistance (WHO, 2018).

Tailored information interventions, for example sending feedback letters, are aimed at achieving positive changes by increasing parental awareness and knowledge which can consequently change parents' behaviour related to their children's healthy lifestyle and diet. This type of interventions can be particularly successful for several reasons. First, information interventions have been effective in changing behaviours in many different areas. For instance, in education when information on the measured returns to education encouraged students to finish high school (Jensen, 2010) and information on children's academic performance caused parents to update their beliefs and adjust their educational investments (Dizon-Ross, 2019) or in health when information on the relative risk of HIV infection decreased teen pregnancy (Dupas, 2011). Second, health campaigns that are tailored to recipients are generally more effective than non-personalized interventions (Hawkins et al., 2008). Third, many studies find a low initial awareness among parents with overweight children as to their child's actual weight status (Chomitz et al., 2003, Grimmett et al., 2008, Prina and Royer, 2014; Black et al., 2015). The failure of parents to correctly classify their children as overweight or obese has recently been described as "promoting the silent rise" of obesity (Hochdorn et al., 2018). It is possible that helping parents to recognise and understand that their children are overweight and vulnerable to obesity-related diseases can induce them to change their and their children's behaviour.

The causal empirical evidence on the effect of tailored information on obesity-related behaviour is scant. Chomitz et al. (2003) first evaluated the risks and benefits associated with sharing routine school-based BMI surveillance data (health report cards) with families. Based on a quasi-experimental field trial, the results show that, although parents who received a health report card were more aware of their child's weight status, no changes in parents' behaviour were found. Moreover, a typical response of parents to try to control their children's weight is through dieting even though this is not recommended by paediatricians.

These findings were confirmed by later field experiments showing that parents believe that it is important for schools to assess student's height and weight yearly and they want to receive health report letters to increase their knowledge of their child's weight. However, this knowledge does not change parental concerns about obesity and only a minority of parents report that weight concerns about their children prompt them to consider further actions (Kubik et al., 2006; Prina and Royer, 2014). Based on a large randomized field experiment in 33 primary and lower secondary state schools in Denmark, Greve and Heinesen (2015) find that sharing information about the health status of the students with students and their parents through a personal webpage does not have any consistent effects on adiposity-related outcomes. The medical literature also shows that BMI screening and reporting have not demonstrated a positive impact on children's weight status (Gee, 2015; Thompson and Madesn, 2017).

The results of other multicomponent health promotion programmes aimed at the prevention of obesity in children in the UK similarly show that parents and children learn about health and nutrition, but this new knowledge has little impact on attitudes, behaviour and dietary habits. For instance, a one-year school-based health promotion intervention APPLES (Active Programme Promoting Lifestyle Education in Schools) that included components like teacher training, modification of school meals, and the development of school action plans targeting the curriculum, physical education, and tuck shops, evaluated in a randomised controlled trial, only led to a modest increase in vegetable consumption (Sahota et al., 2001). Another one-year intervention aimed at reducing consumption of carbonated drinks through educational programme on nutrition and evaluated in a randomised controlled trial induced a modest reduction of drinks, but this effect was not sustained 3 years after the programme (James et al., 2004, James et al., 2007).

Researchers propose several possible explanations as to why there are no significant effects of these programmes on real changes in behaviour. One of the most important reasons is the difficulty in changing health-related behaviour. The economic literature on dietary habit formation shows that new healthy habits are difficult to grow, and to influence dietary choices in the long run is a big challenge (Belot et al., 2016, Belot et al., 2018). Another reason is altered community perceptions of what is a healthy weight and that children who would be clinically classified as overweight may be seen by parents and the community as “normal” (Lampard et al., 2008). For instance, report cards did not have effects on parental beliefs about the child’s weight in classes where parents of overweight and obese children were told that more than a third of students were overweight or obese (Prina and Royer, 2014).

Although tailored information interventions are aimed at positive health-related changes, there is a controversy surrounding these programmes. Media, experts and some descriptive studies report potential untoward psychosocial consequences that include weight-based stigmatization, discrimination, low self-esteem and mental health problems (Ikeda et al., 2006; Kaczmarsko, 2011; Hayes, 2013; Moyer at el., 2014). Also, Almond et al. (2016) find that overweight categorization generated a small but significant increase in BMI and weight among teenage girls in New York City public schools.[48]

Unintended psychosocial consequences may transform into more serious issues. If children or adolescents have body image issues or low self-esteem, they might be at risk of engaging in unhealthy eating behaviours. For instance, skipping meals could lead to eating disorders and can cause a variety of other problems. Many medical observational studies show that breakfast skipping – an outcome we are able to observe in our data – is correlated with higher consumption of unhealthy snacks, lower overall diet quality, and irregular eating patterns which lead to higher BMI, higher levels of blood glucose and overall contributes to the epidemic rise in childhood obesity (MacFarlane et al., 2009; Szajewska and Ruszczynski, 2010; Freitas Junior et al., 2012; Wijtzes et al., 2016; Kesztyus et al., 2017).

The descriptive public health and medical literature on the NCMP shows that most parents support the programme and are generally comfortable with receiving body weight feedback letters (Grimmett et al., 2008; Shucksmith et al., 2008; Mooney et al., 2010). Grimmett et al. (2008) investigate behavioural and psychological effects of the NCMP in London schools. The descriptive results show some changes in dietary and physical activity among overweight children and a reduction in restrained eating among healthy weight children. The authors find no evidence of an increase in teasing after weight feedback, however a minority of participants found the programme distressing. Overall, they argue that this type of

[48] Based on a regression discontinuity design, this paper exploits the discrete categorization as overweight for girls with BMIs near the overweight cutoff.

intervention can be implemented without causing substantial adverse effects but due to a number of limitations the results of this study seem to have low external validity.[49] A study by Falconer et al. (2014) based on the NCMP within the 2010/11 academic year shows that body weight feedback improves parents' ability to recognise the weight problem of their children: the share of parents who could correctly identify unhealthy weight in their children after getting weight feedback rose from 21.9% to 37.7%. However, the lifestyle behavioural consequences of this improvement were minimal.

Qualitative research investigating parents who received the NCMP feedback letters informing them that their child is overweight or obese shows that parents think that BMI is an inappropriate measure of weight status as it does not consider the individual child's lifestyle, genetics or puppy fat. Moreover, parents of overweight and obese children believe that one of the biggest concerns of the NCMP programme is that it can make children aware that they are overweight and potentially can harm their self-esteem and wellbeing (Gillison et al., 2014; Syrad et al., 2015).

3.3 Background: National Child Measurement Programme

3.3.1 Programme overview

The National Child Measurement Programme is a nationally mandated public health monitoring programme which every year collects data on the height and weight of children in schools at the beginning and end of primary school, at ages 4-5 (Reception year) and 10-11 (Year 6). Data on height and weight are transformed into a body mass index (BMI) that provides an indicator for levels of body fat and shows whether a child is underweight, overweight, obese, or has a healthy weight.[50]

The NCMP includes all state schools in England (except schools that refuse to participate). Some schools such as independent and special schools as well as home-educated

[49] Authors emphasize that they cannot draw causal conclusions based on their findings in the absence of a possibility to randomize participating schools. Another issue is a selection bias. Parents of lower socio-economic status and from ethnic minority background as well as parents of overweight children were more likely to opt out of the weighing and feedback process.

[50] To identify which weight group a child falls in, the NCMP uses the British 1990 growth reference charts (UK90) which is recommended for population monitoring and clinical assessment of children in England (Cole et. al., 1995). The UK90 BMI reference provides age-gender centile curves for weight status for British children and the following standard cut-off points are used: underweight – less or equal to the 2nd BMI centile; overweight – more or equal to the 85th centile but less than the 95th centile; obese – more or equal to the 95th centile; healthy weight – more than the 2nd but less than the 85th centile (Cole et al., 2000).

children are not formally required to participate. Also, parents/carers can choose to withdraw their children from the program.[51] During the first year of the programme, 2005/06, the percentage of eligible pupils who were measured (participation rate) was 48 percent.[52] However, between the 2006/07 and 2018/19 academic years, the overall national participation rate has significantly increased from 80% to 95% (from 83% to 96% for Reception and from 78% to 94% for Year 6).[53,54]

The NCMP was launched in 2005 and initially established to track population trends in childhood overweight and obesity and to investigate heterogeneity by age, sex, ethnicity and deprivation. Since the 2008/09 academic year, the NCMP also provides local areas an opportunity to raise public awareness of child obesity and to assist families to make healthy lifestyle changes through provision of a child's results to their parents (routine feedback). Routine feedback is presented in the form of a letter with results on the child's body measurements, body weight status, and a wide range of additional information, described in the next section. According to the NCMP operational guidance for the 2011/12 school year – the year we use for our main analysis – all Prime Care Trusts (PCT), the organisations responsible for data collection[55], were strongly encouraged to provide routine feedback letters to all parents/carers on their child's weight status. Unfortunately, there are no official statistics on the number of PCTs which chose not to provide feedback letters but there are approximate numbers. For example, the Cross-Government Obesity Unit report (2010) mentions that in 2009/10 around 80% of PCTs were looking to share the measurement results with parents. In 2011, an online survey with over 200 local NCMP leads showed that 74% survey respondents mentioned that feedback was provided to all parents of children taking part in the NCMP in their area (Statham et al., 2011).

Since the 2009/10 academic year, one more element has been added to the programme – a proactive follow-up of parents whose children have been identified as overweight or very overweight. Proactive follow-up was introduced in response to studies that show that parents rarely contact back school nurses if their child is outside the healthy weight range, and,

[51] Local authorities must inform parents at least 2 weeks in advance of the measurements so that parents have the option to withdraw their children if they wish so. The pre-measurement letter includes information on exact measurement day.

[52] NHS Digital: National Child Measurement Programme, Results from the 2006-2007 school year: Report.

[53] HM Government. Childhood obesity: a plan for action. August 2016.

[54] NHS Digital: National Child Measurement Programme - England, 2018-19: Report.

[55] Until 2013, NCMP was delivered by the Department of Health and a network of regional Obesity Leads within Prime Care Trusts. From 2013 the responsibility for NCMP commissioning and delivery was transferred to a new body, Public Health England, an executive agency of the Department of Health and Social Care in the United Kingdom. Also, responsibility for programme delivery was relocated from Prime Care Trusts to local authorities.

moreover, some parents expect school nurses to contact them in case of need (Mooney et al., 2010, Counterpoint Research, 2009). Proactive follow-up is usually presented in the form of a phone call offering a meeting that gives support and referral to a weight management service or a phone call offering a brief intervention on behaviour change (Mooney et al., 2010).

3.3.2 Feedback letter

Feedback letters should be sent to parents/carers as soon as possible, and at most within 6 weeks after measurement. They are sent by post to parents and carers to mitigate the risk of the letters getting into the hands of children and their peers which could lead to comparison of results and potential bullying. It is at parents' discretion as to whether they share the results with their child.

Public Health England provides template letters which local organisations delivering the NCMP are free to adjust.[56] The content of the recommended feedback letters varies by the weight status of the child. For parents of *underweight* children the letter includes information on body measurements, weight status, a link to an on-line tool for checking BMI as well as a phone number if parents would like to speak about their child's results. Also, the letter states that underweight children are mainly perfectly healthy, but sometimes they have a health problem. The letters for parents of *healthy weight* children include the same information plus additional information with basic tips on how to help the child remain healthy. The letters for parents of *overweight* children include the same information on body measurements and weight status and also point out that if the child is overweight now, he/she is more likely to grow up as an overweight adult and this can lead to health problems. A range of additional information includes a phone number to call back for consultation and the same tips and advice as for healthy weight children. The letters for parents of *very overweight* children are identical to the letters for parents of overweight children plus they include information on potential health risks that can be caused by obesity (see Figure C1.1 for templates of all letters).

The most commonly included additional information is the Department of Health Change4Life leaflet (see Figure C1.2) and also information about local weight management services and links to national websites with information and advice on healthy eating, including

[56] An online survey showed that almost all of the 200 interviewed local NCMP leads made at least some changes to the letter, however, these were relatively minor corrections such as removing the imperial conversion, adding local branding, using simpler language, removing the term "obese", adding details of relevant local services and others (Statham et al., 2011).

Change4Life, 5ADAY and NHS. Moreover, a phone number to contact back is included in the letter template and calling back is recommended as a first step for parents to find out how they can benefit from local support if their child has unhealthy weight. School nurses usually deal with calls from parents, but sometimes it is professional staff such as a nutritionist or the NCMP coordinator, nursery nurses, Family Change4Life advisors, Health Team leaders, or public health consultant leads (Statham et al., 2011).

3.4 Data

3.4.1 Datasets and estimation sample

To estimate the impact of providing parents information about the weight status of their child, our analysis is based on two sets of survey data: the main analysis is based on the Millennium Cohort Study (MCS) and the supplementary analysis is on the UK Household Longitudinal Study (UKHLS). Survey data are linked to data on the dates of school visits for the NCMP measurement. We further link administrative data on individual child test scores to data on the dates of school visits. Test scores are from the National Pupil Datasets (NPD) which we briefly describe in section 3.6.5.

Millennium Cohort Study

The Millennium Cohort Study is a UK longitudinal birth cohort study run by the Centre for Longitudinal Studies. The MCS tracks the lives of around 19,000 children born around the Millennium from birth into adulthood.[57] The MCS represents all four UK countries, oversampling deprived areas and areas with high concentration of Black and Asian families. The study gathers information on the cohort children's siblings and parents and covers a wide range of topics such as parenting, childcare, child cognitive development, child and parental health, parents' employment and education, income and poverty, social capital and ethnicity.

The focus of this paper is on England where the first MCS survey (MCS1) took place between June 2001 and September 2002 when the cohort babies were as close as possible to 9.5 months of age. The second survey (MCS2) was carried out in the same months of the year, when the children were around 3 years old (2003/2005). The next sweeps took place at age 5 (MCS3), age 7 (MCS4), age 11 (MCS5) and age 14 (MCS6) during the child's first, third, sixth

[57] There were drop-offs in sample size over time with an achieved sample at age 3 of around 15,000 children and just under 12,000 children at age 14. Weighs are used to adjust for inter-sweep attrition/non-response.

and ninth year of compulsory schooling. To cover the academic year, which in England runs from September of one year to August of the next, fieldwork was scheduled to take place between the months of January and July of each of the academic years 2005/06, 2007/08, 2011/12 and 2014/15. When the MCS cohort children were in their 6th school year in the academic year 2011/12 and were interviewed for the MCS fifth sweep, they were also weighed and measured in schools through the NCMP and their parents subsequently received feedback letters. Importantly, these children were weighed and measured through the NCMP in their reception year in 2005/06, but feedback letters had not been implemented then so that parents received no information about the weight outcome.

The number of productive interviews in the MCS5 in England was 8,792, of which 8,720 were with children in Year 6.[58] Of these, 7,208 children were merged to the date of NCMP school visit (non-merged cases occur for children who are home schooled or in independent schools, or as a result of incorrect school codes on either of the two data sets). As we apply a difference-in-difference design, which is described in detail in the next section, we only consider those children who also participated in the fourth sweep of the MCS when children were in Year 2. This reduces the sample to 6,524 children. We also exclude those children who were interviewed within 42 days after the school visit as it might take up to 6 weeks to deliver letters (964 children), giving a final sample of 5,560 children (63.2% of the original sample) or 11,120 observations in total across the two time periods. Table C2.1 shows summary statistics of the original sample of all children in the MCS5 in England and of the final estimation sample. As we can see, the estimation sample is very similar to the original one in terms of child, mother, and household characteristics as well as region of residence, settlement type (urban/rural) and decile of overall neighborhood deprivation.

UK Household Longitudinal Study

The UKHLS originally included approximately 40,000 households or 100,000 individuals, covering people of all ages on a wide range of topics such as family life, education, employment, finance, health and wellbeing. We are particularly interested in a special questionnaire, the youth self-completion questionnaire, developed for children aged 10-15 that includes questions on family and the relationship with parents, time allocation, school, health,

[58] 91% of interviews were collected within the timetable fieldwork between January 2012 and July 2012 while 9% was delayed and interviewed either in the same or next school year.

nutrition, how children see themselves as a person and how they feel about different aspects of their life.

Despite the great variety of questions that are relevant for our study, we do not use the UKHLS for the main analysis because the majority of questions for youth that are related to our research are asked once every two years. This prevents us from applying a difference-in-difference approach as the majority of the questions that are asked at age 11 (when children are in Year 6 and participate in the NCMP) are not asked at age 10 when children first join the youth panel. Nevertheless, we use the UKHLS to produce some descriptive evidence.

For the descriptive analysis we choose those variables that complement the outcomes available in the MCS. We use a group of questions on how children feel about different aspects of their life such as school, school work, appearance, family, friends, and life as a whole. Children are asked to respond on each question on a likert scale of 1 to 7, where 1 is “not at all happy” and 7 is “completely happy”. For every life aspect we create a dummy variable that combines negative answers (values 1, 2, 3) and neutral answer (value 4) into value 0 and positive answers (values 5, 6, and 7) into value 1. We also create a dummy variable on dieting based on the question whether the child ever tried a diet, where 1 indicates that the child has been on a diet and 0 indicates that the child has never been on a diet.

Based on the UKHLS waves 1-8, there are 3,829 children in England in Year 6 with information on the youth questionnaire. After merging these observations with the school visit data and excluding those children who were interviewed within 6 weeks after the NCMP measurement, the number of observations reduces to 2,435 (63.6% of the initial sample). Table C2.2 shows that based on observable characteristics the final estimation sample is very similar to the original one.

The National Child Measurement Programme Data

Once every academic year, every primary school in England is visited by the bodies implementing the NCMP visits, and we have data on the timing of each school visit. The data was obtained from the Health and Social Care Information centre (NHS Digital), which is the national provide of information, data and IT systems in health and social care in England. Our NCMP data extract covers the 2011/12 academic year. PCTs had flexibility during the school year over when they delivered the NCMP measurements, but had to follow some time frames, including informing parents at least 2 weeks in advance of the measurements and submitting all results by August following the end of the school year. Our survey and NCMP date were merged for us by the Centre for Longitudinal Studies team, using school identifiers.

3.4.2 Normal weight and overweight children sub-sample identification

We expect that treatment effects might differ by child's weight status as the letters include different type of information according to the weight status. In order to investigate this, we split the sample into two sub-samples. We group together underweight and normal weight children into a group of normal weight children as there are very few underweight children for a separate analysis (1.6% of the sample) and overweight and very overweight children into a group of overweight children as we expect that parents of these children react to the feedback letters similarly.

Ideally, to split the sample into sub-samples of normal weight and overweight children we would like to use children's weight status just before the intervention to avoid any misclassification caused by the fact that the intervention might itself affect weight status. However, based on the MCS the most recent available measure is 4 years previous (from 2008) when children were 6 and 7 years old. 17.2% of the sample changed their weight status between 2008 and 2012 and, therefore, we split the sample using the current BMI measured in 2012. Based on this method, 3,479 (64.3%) and 1,934 (35.7%) of children belong to the sub-sample of normal weight and overweight children, respectively. The main issue with this approach is that BMI is a main outcome that could be affected by the intervention leading to a potential misclassification of normal weight and overweight children. However, only those children whose BMI is around the cut-off points to determine weight status can potentially move from one weight group to another, mitigating this problem. Moreover, as we will show in the results section, there is no effect of the intervention on BMI which is not surprising, given that we measure outcomes in the short run, within the same academic year as height and weight measurement. We also show robustness checks where we split the sample using 2008 BMI; exclude those children whose BMI is around the cut-off points; and exclude groups of children that were exposed to the treatment the longest period of time assuming that these children might change their BMI due to the intervention.

3.4.3 Outcomes

We identify three main groups of outcomes that reflect the key aspects of child's weight-related health and behaviour. These groups are (1) adiposity-related measures, (2) behavioural outcomes related to energy balance and (3) adverse effects. All outcomes are parent-reported except those we mention that are child-reported.

The group of adiposity-related outcomes includes measures such as body mass index (BMI), body fat percentage and probability to become overweight or obese. BMI is defined as weight divided by height squared and is calculated directly by the MCS. To classify weight status, we apply the National BMI percentile classification – based on British 1990 growth reference charts – that is also used for the feedback letters by the NCMP. Body fat percentage is an estimation of total body fat mass that is a direct measure of body composition. The probability to become overweight is a dummy variable that is equal to 1 if a child's BMI is higher than the BMI overweight cut-off point for certain gender and age according to the growth reference charts.

To measure behavioural outcomes related to energy balance, we aggregate information across related outcomes on child's physical activity and sedentary behaviour into summary indices following Kling, Liebman, and Katz (2007). A summary index is "defined to be the equally weighted average of z-scores of its components, with the sign of each measure oriented so that more beneficial outcomes have higher scores".[59] The aggregation of a number of outcomes into a single index improves statistical power to detect effects within a domain.

The physical activity index combines in a single measure a number of questions on physical activity answered by parents including (1) frequency of sport classes/clubs (swimming, gymnastic, football, dancing etc.), (2) frequency of any other clubs, classes or group activities (asked only in 2008), (3) frequency of physical activities or physical active play with friends/siblings, (4) frequency of playing sport or physically active games inside or outside with parents, (5) frequency of taking a child to the park or to an outdoor playground (asked only in 2008), and (6) frequency of using a bicycle including travel to and from school (asked only in 2012)[60]. Because the scale of these activity variables is not continuous, we

[59] The drawback of this approach is that we put equal weights to all different components. Another approach involves assigning different weights to components within one domain using seemingly unrelated regression estimation (SURE) approach. However, Glennerster et al. (2013) highlight that "although this approach has some merits, in general the profession has tended to view SURE as non-transparent because it is not clear what weights had been given to the different outcome variables. Most evaluators prefer the simple, equal-weight version of mean effects". Kling et al. (2004) also say that "when there is no a priori reason to assign different weights to different outcomes in the decision problem, using the mean effect size provides a simple way of aggregating disparate outcomes on a common metric".

[60] Some questions on physical activity are different in MCS4 and MCS5 in order to adjust the questionnaire to the age of the respondents. For example, the question on frequency of using bike is asked when children are 10/11 but is not asked when children are 6/7 years old so the indices are based on different variables at the two time-points.

recode them into dummies, where 1 indicates that the activity is carried out at least once a week. Further, for each outcome we calculate a z-score subtracting the control group mean and dividing by the control group standard deviation. The physical activity index is the average of the z-scores, and a higher value of the index is evidence of higher physical activity.

The sedentary behaviour index is constructed by using the same methodology and combines four variables that reflect sedentary behaviour: (1) number of hours on a normal weekday during term time watching TV, (2) number of hours on a normal weekday during term time playing electronic games, (3) whether a child has TV in his/her bedroom, and (4) whether there are rules about how early or late watch TV or play electronic games. We recode both TV watching and playing electronic games into dummy variables, where 1 indicates that the activity is carried out at least one hour per day. All outcomes are converted into z-scores, which are combined into an index. A higher value of the final index indicates more sedentary behaviour.

We also measure fruit intake as an outcome related to energy balance. Due to an ordinal scale of this variable, we create a dummy variable that combines answers "none", "one fruit per day", and "two fruits per day" into value 0 and "three or more fruits per day" into value 1.

The group of adverse outcomes includes indicators of bullying by other children, breakfast intake, happiness and tiredness at school, and a measure of child mental health, which we do not summarise in a single index as these outcomes measure very distinct things. There are two outcomes related to bullying, one of which is child-reported bullying and the second one is bullying reported by parents. The dummy variable on child-reported bullying is equal to 1 if other children hurt or pick on a child on purpose with any frequency and to 0 if it never happens.[61] The dummy variable on bullying reported by parents is equal to 1 if parents think that a child picked on or bullied by other children is certainly or somewhat true and to 0 if it is not true at all.[62] We also take into consideration whether the intervention can affect the child's social behaviour such as hurting other children. The dummy variable is equal to 1 if the child sometimes hurts other children and to 0 if this never happens.[63]

[61] The question on child-reported bullying has different response categories in the MCS4 and MCS5. In the MCS4, the categories are "all of the time", "some of the time" and "never", while in the MCS5 they are "most days", "about once a week", "about once a month", "every few months", "less often" and "never". Thus, to standardize these scales, we combine all categories with any frequency into one.

[62] We combine those who answered "certainly true" and "somewhat true" in one group due to a relatively small size of the last one (less than 5% both years).

[63] The questions sound slightly different and the response categories are different in the MCS4 and MCS5. In the MCS4, the question is "How often are you horrible to other children as school?" and the response categories are "All of the time", "Some of the time" and "Never". In the MCS5, the question is "How often do you hurt or pick on other children on purpose?" and the response categories are "Most days", "About once a week", "About

To measure breakfast intake, we consider both breakfast at home and breakfast at school and define breakfast skipping and double breakfast. Breakfast skipping is equal to 1 if in total a child has breakfast less than 7 times a week, and double breakfast is equal to 1 if a child has breakfast more than 7 times a week.

We assume that if children are bullied and/or experience unhealthy behaviour such as breakfast skipping, they might feel unhappy or tired at school. To measure this, we use child-reported answers on questions such as "How often do you feel happy at school" and "How often do you get tired at school". A dummy variable on unhappiness at school is equal to 1 if a child sometimes feels unhappy and to 0 if this never happens. Similarly, a dummy variable on tiredness at school is equal to 1 if a child sometimes feels tired at school and to 0 if it never happens.[64]

Finally, to measure children's mental health, we use the results of the Strengths and Difficulties Questionnaire (SDQ) completed by parents (Goodman, 1997). The SDQ is a brief emotional and behavioural screening questionnaire used to construct a measure of child mental health and wellbeing. It comprises 25 questions that are grouped to assess children on five different dimensions: emotional symptoms, conduct problems, hyperactivity/inattention problems, peer relationship problems, and prosocial behaviour. In our main analysis we use a total difficulties score which is generated by summing scores from all the dimensions except the prosocial one. The resultant score ranges from 0 to 40, where a higher score indicates worse behavioural problems. Additionally to our main analysis, we investigate the effect of the intervention separately on all five dimensions of a child's mental health.

3.5 Identification strategy

3.5.1 Defining treatment and control groups

We define the information intervention as providing parents information about the weight status of their children which they should receive within 6 weeks after the children are measured for the NCMP. To identify treatment and control groups, we rely on variation in the

once a month", "Every few months", "Less often" and "Never". To standardize these scales, we combine all categories with any frequency into one.

[64] The response categories for both questions are slightly different in the MCS4 and MCS5. In the MCS4, there are three categories: "All of the time", "Some of the time" and "Never". In the MCS5 the questions are the same but there are four response categories: "All of the time", "Most of the time", "Some of the time" and "Never". To standardize these scales, we combine all categories with any frequency into one.

timing of the NCMP school visit with respect to the Millennium Cohort Study survey interview. For our research design, we take advantage of the fact that the fifth sweep of the MCS took place when children were in Year 6 meaning that they were also measured for the NCMP in that academic year.

The NCMP school visits take place in throughout the academic year (September to July) and MCS interviews take place in all months (see Figure C3.1 that shows the timing of the NCMP school visits and MCS interviews). Therefore, we observe some children and their parents being interviewed before the NCMP school visit, and some being interviewed after the NCMP school visit. We know the exact date of the MCS interview and the exact date of the NCMP measurement in school. To assign all children observed in the MCS into either the treatment or control group, we compare these two dates. If a child and his/her parents were interviewed before the day of the school visit, then this child is in the control group because at the day of interview the child and his/her parents have not gotten the treatment – a feedback letter. If a child and his/her parents were interviewed after the day of the school visit, then this child is assigned to the treatment group as the child and his/her parents are interviewed after they have gotten the treatment (Panel *(a)* of Figure 3.1). Thus, we compare outcomes of children whose families had received feedback letters at the time of their MCS survey interview with those whose families had not. Although we do not know the exact day when parents receive the feedback letters, we know that schools should send letters to parents within 6 weeks after measurement. To make sure all parents will have received the letters, we exclude children interviewed within 6 weeks of measurement (Panel *(b)* of Figure 3.1). 74.7% of sample children are in the treatment group and 25.3% are in the control (the same distribution occurs in the sub-samples of normal and overweight children).

Because every child is interviewed at a different time interval after the intervention, we take into account the duration of treatment exposure, i.e. the number of months between the intervention and the interview. Table 3.1 shows that among those who were interviewed after the intervention, the vast majority was interviewed within the first 4 months (77.1%) with a quarter being interviewed within first month after the intervention. Only a small group of children was interviewed more than six months after the intervention (7.5%).

As it was mentioned above parents/carers can choose to withdraw their children from the program, which suggests that there is a possible selection into treatment. For example, parents of overweight children opt out of the programme or do not send their children to school on the day of the NCMP visit. Such selective non-participation of overweight and obese children could potentially bias the results. There are three pieces of evidence that show that the

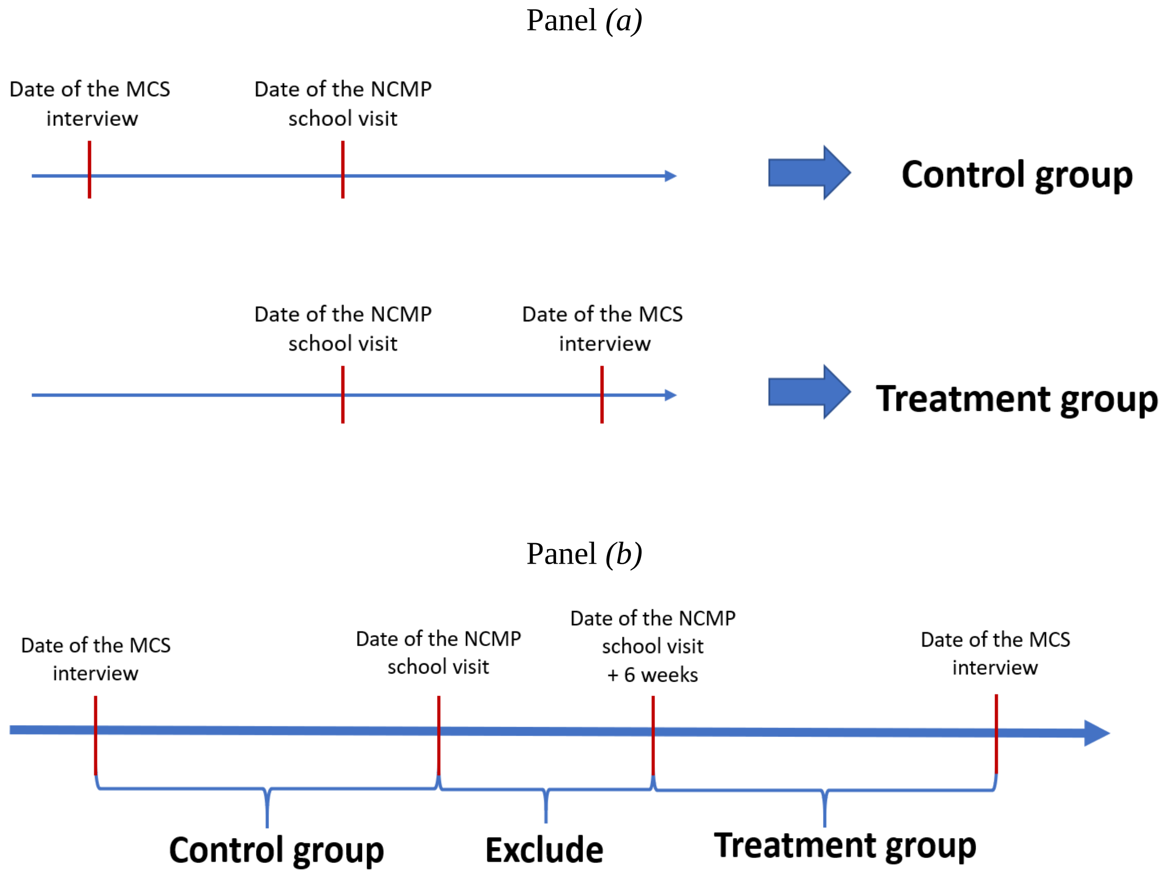


Figure 3.1 – Treatment and control groups construction

Table 3.1 – Distribution of children by the treatment exposure duration

	Share of children, %
Up to 1 month	24.5
2 months	20.1
3 months	19.0
4 months	13.7
5 months	9.2
6 months	6.2
7-10 months	7.5

Notes: Millennium Cohort Study Sweep 5. The duration of treatment exposure is the number of months between the intervention (receiving a feedback letter) and the MCS interview. Children interviewed within first 6 weeks are excluded.

selection problem might not be so big. First, based on the sample of the present study, 14.4% and 21% of children were respectively overweight and obese, which is very close to the 14.7% and 19.2% observed at the national level[65] in the 2011/12 academic year and suggests that parents of overweight and obese children were not likely to exclude their children from the weighing process. Second, according to the 2010/11 and 2011/12 NCMP data quality reports, the impact of differential opt-out among obese children was considered negligible, requiring no adjustment to either prevalence estimates or the associated 95% confidence intervals.[66] Third, because in the MCS survey parents should give their consent for physical measurement of their children, we can use it as a reasonable proxy for parental consent for physical measurement in our study even thought this is not entirely comparable as the NCMP setting is school, not home. Based on MCS5, 0.69%, 0.79% and 0.02% of parents do not give their consent for weight, body fat and height measurements of their children. These three factors indicate that the selection problem does not seem an issue for our study.

3.5.2 Research design

We implement a difference-in-difference (DID) framework with two groups, treatment and control.[67] We exploit the panel structure of the data and observe both groups in the intervention period (MCS fifth sweep, *t*) and baseline period four years earlier (MSC fourth sweep, *t-4*).

Our baseline model, estimated by OLS, is presented as follows:

$$Y_{it} = \alpha + \beta_1\, Treated_i + \beta_2\, Post_t + \gamma\,(Treated_i \times Post_t) + X'_{it}\beta_3 + Z'_{it}\beta_4 + \beta_5 Duration_i + \xi_{it} \quad (1)$$

where Y_{it} is the outcome of individual i in the period t, *Treated* is a dummy equal to 1 if the child i is in the treatment group and 0 otherwise, *Post* is a dummy variable equal to 1 for the

[65] https://files.digital.nhs.uk/publicationimport/pub09xxx/pub09283/nati-chil-meas-prog-eng-2011-2012-rep.pdf

[66] https://files.digital.nhs.uk/publicationimport/pub03xxx/pub03034/nati-chil-meas-prog-eng-2010-2011-rep1.pdf

[67] An alternative method to identify the intervention effect would be to apply a regression discontinuity design (RDD) using the fact that the allocation of the 'fat letters', letters for overweight and very overweight children, is based on observed BMI. The main idea is that children with BMI just below overweight cut-off (who did not receive the 'fat letter') are good comparison to those just above the cut-off (who did receive the 'fat letter'). We do not apply this identification strategy as we do not have sufficient number of observations in our data (400-700 observations depending on bandwidth selection).

observations from the academic year of the NCMP visit (MCS sweep 5) and 0 for baseline period (MCS sweep 4). We estimate the model with and without a set of controls for child, mother and family characteristics, X'_{it}, such as the child's age in months and gender, the mother's age, marital status, education, ethnicity, religion, employment status as well as family weekly income and the number of siblings in the household. We also include region of residence, settlement type (urban/rural) and decile of overall neighborhood deprivation in the vector Z'_{it}. Moreover, we control for the duration between the intervention and the interview in months, $Duration_i$. ξ_{it} is an error term. In all specifications we control for the month of interview.

We define treatment as receiving a feedback letter before interview irrespective of the body weight status of the child and we assume that parents of all treated children receive the letter before interview. However, we know that some parents choose to withdraw their children from the programme, not all local authorities decide to provide feedback letters and we do not know exactly whether parents get and open the letters. Thus, our parameter of interest, γ, shows the causal effect of assignment into treatment and captures the intention-to-treat (ITT) effect of sending feedback letters to parents on outcomes of their children. It shows how child's weight-related health and behaviour change in families that were eligible to get the feedback letters in comparison to other families. Based on the ITT effects and information on the overall participation rate for the NCMP and an approximate share of local authorities choosing to send feedback letters, in sections 6.1.3 and 6.2 we will perform back-of-the-envelope calculations in order to magnitude the treatment-on-the-treated (ToT) effect.

We run the analysis based on the sample of all children and then separately for the sub-sample of normal weight children and the sub-sample of overweight children. Further we analyse whether the effect of the intervention varies by the duration of treatment exposure, i.e. the number of months since the parents received the feedback letter. It is possible that the effect of sending feedback letters on behaviours can decay over time, while for body weight outcomes the effect may only appear a few months after receiving the letter. To take this into account, we interact the treatment variable with the duration between the intervention and the interview.[68]

[68] This paper is based on data that is available only through the Secure Lab service, which is part of the UK Data Service. Due to the current situation with COVID-19 and the lack of access to the University and, therefore, the Secure Lab, these results are not reported in the paper but will be added later. However, the regression analysis where we interact the treatment variable with the duration between the intervention and the interview does not show any clear patterns on how the effect of intervention develops over time.

3.5.3 Identifying assumptions

To be able to identify a causal effect of sending feedback letters, we rely on the following assumptions: (1) there is no selection of schools by month of NCMP visit so that the timing of the NCMP school visits is random across schools; (2) there is no selection of households by month of interview; (3) all outcomes in the treatment and control groups follow the same trends before the year of intervention (parallel trend assumption). We test these assumptions based on the MCS data which we use for the main analysis.

If assumption (1) on the random allocation of NCMP visits is violated and the timing of the NCMP school visits is related to, for example, observed outcomes such as children's BMI or obesity, we would be concerned that our results represent spurious correlation. For instance, if schools with the biggest concern over obesity were visited first in the school year then these children are more likely to be in the treatment group due to the timing and we would find that the intervention increases BMI.

According to the NCMP Support Team, the timing of the NCMP visits is a local decision and usually dependents on how the local authority or NCMP provider plans for the measurements to be taken. Usually, the timing of the measurements is organised around other health checks in the school, the capacity of the staff undertaking the measurements, or the school availability within the academic year.[69] This suggests that the visit dates are orthogonal to school's overall weight status.

To investigate whether there is a correlation between month of NCMP school visit and weight-related characteristics we conduct the following check. We use BMI, overweight and obesity outcome measures and regress them on month of school visit. The coefficients on the months of NCMP visits will show us whether schools with a higher mean BMI, a higher level of the overweight or obesity prevalence were more likely to be visited in particular months. Ideally, this analysis needs to be checked at the school level using school-level characteristics as outcomes, but we do not have access to school-level information. In absence of such information we check it at the individual child-level, assuming that the children in the survey data are representative of the children in schools included in the NCMP measurement. Table C3.1, Columns (1)-(3), shows that all three outcomes are not significantly predicted by any of the school visit months. We also investigate whether the timing of school visits is related to student characteristics that are known to be correlated with higher overweight and obesity rates

[69] Provided information by NCMP programme support manager (April 2019).

– gender and black ethnicity. Column 4 shows that gender also is not significantly predicted by the timing of school visits. In column 5 we see that students measured in February, April, May and June with higher probability are black, suggesting that schools with a higher proportion of black students were visited in these months. However, the effects are very small at 0.04-0.07 percentage points. We control for these characteristics in all our regression specifications.

Similarly to assumption (1), if assumption (2) on random allocation of MCS interviews is violated, our results might represent spurious correlation.[70] For example, if households in more deprived areas were interviewed first in the fifth MCS sweep then these children are more likely to be in the control group due to the timing. As we know that the level of obesity is higher in more deprived areas, it means that we would find that the intervention decreases BMI.

To examine assumption (2), we do a similar exercise as for assumption (1). We investigate whether there is a correlation between month of the fifth MCS sweep interview and children characteristics by regressing them on month of MCS interview. We use gender, black ethnicity, urban areas, and more deprived areas measures. Table C3.2 shows that some characteristics are significantly predicted by the timing of interview, but the effects are very small. For example, children interviewed in July are more likely to be boys (0.05 percentage points) and less likely to be black (0.02 percentage points) and live in urban areas (0.03 percentage points).

The timing of the school visit for the NCMP measurement and the timing of the MCS interview together assign children into the treatment and control groups. Based on assumptions (1) and (2), if the timing is random, the treatment and control groups should be balanced. Table C3.3 Panel A shows balance between the treatment and control groups on the child, mother and household's characteristics based on the sample of all children. There are a few significant differences between children of the treatment and control groups. The treatment group children are significantly older, but this difference is explained by the design we use to identify treatment and control groups – the treatment group children were interviewed for the MCS later than the control group children thus they are older. In terms of mother's characteristics,

[70] In terms of MCS fieldwork, we know that the first MCS fieldwork was organised the way that all the families were interviewed while the cohort baby was as close as possible to 9.5 months of age. The same algorithm was used for the second sweep – the children were around 3 years old at the date of interview. However, from the third sweep, the fieldwork timetable was compressed into school years so that all the children are interviewed within one academic year. The fieldwork for the fifth MCS sweep was organised the following way: those who were born between September 1, 2000, and February 28, 2001, were interviewed in January-April 2012, and those who were born between March 1, 2001, and August 31, 2001, were interviewed in April-July 2012. Nine percent of interviews were delayed and collected between July 2012 and February 2013.

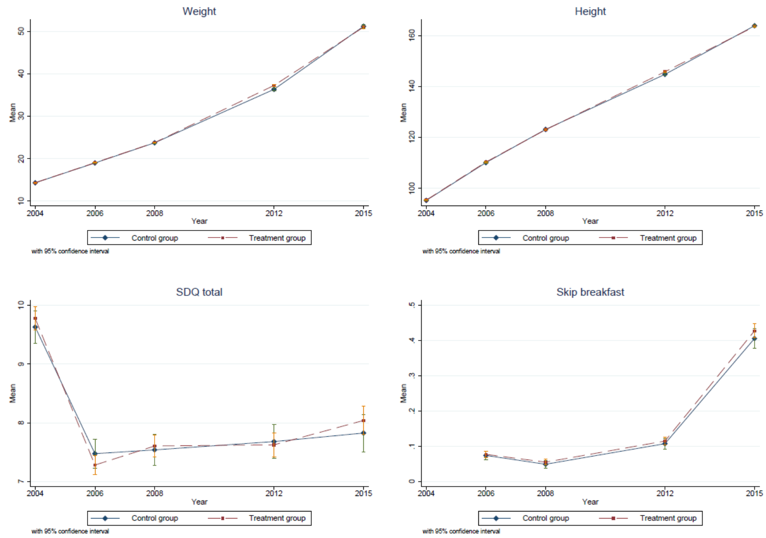
we find that the mothers of the treatment group children are significantly younger, with a higher proportion of White, a lower proportion of A-level education and a lower proportion of currently working mother. The size of the differences is relatively small in nominal values – not more than 2 percentage points. Panels B and C show balance between treatment and controls for the sub-sample of normal weight and overweight children. We find a higher degree of balance between the treatment and control groups for both sub-samples.

If assumption (3) on parallel trends is violated and the difference in outcomes between the treatment and control groups are not constant over time, our results would be biased. One reason why the assumption could be violated is that there were other policies introduced in the 2011/12 academic year that could affect the outcomes of our analysis. However, to our knowledge, there were no such policies. Ideally, to test this assumption we would perform visual inspection comparing trends in the outcome variables between the treatment and control groups over a sufficient number of years. However, we can do it for more than two sweeps only for certain outcomes because the MCS questionnaires differ over the sweeps to adjust the questions to the children's age. Also, the wording and response categories of many questions vary across the sweeps. Thus, due to these restrictions, we test the pre-treatment parallel trend assumption for four measures – weight, height, SDQ total score and breakfast skipping.[71] For the weight, height and SDQ measures we have five data points – three before the intervention (MCS2, MCS3, MCS4), one for the year of intervention (MCS5) and one after the intervention (MCS6); for the measure of breakfast skipping we have one data point less as the question on breakfast consumption was not asked in sweep 2 when children were 3 years old.

Figure 3.2 shows mean raw weight, height, SDQ and breakfast skipping in the treatment and control group separately for normal weight and overweight children. For the group of normal weight children, we can see that all outcomes follow the same trends before and after the intervention. For the group of overweight children, there are also no differences in the pre-treatment trends for all outcomes. At the same time, for this group of children we see some differences between treated and untreated children in the SDQ and breakfast skipping measures in the year of treatment. Even though, the difference are not statistically significant (and for the SDQ measure the confidence intervals are particularly wide), this is our first indicative evidence of an adverse effect of the treatment. For the rest of our outcomes, given limited number of data points, we assume that pre-treatment trends are parallel.

[71] Here we consider the measures of weight and height rather than BMI to increase the number of variables to test the assumption.

Normal weight children



Overweight children

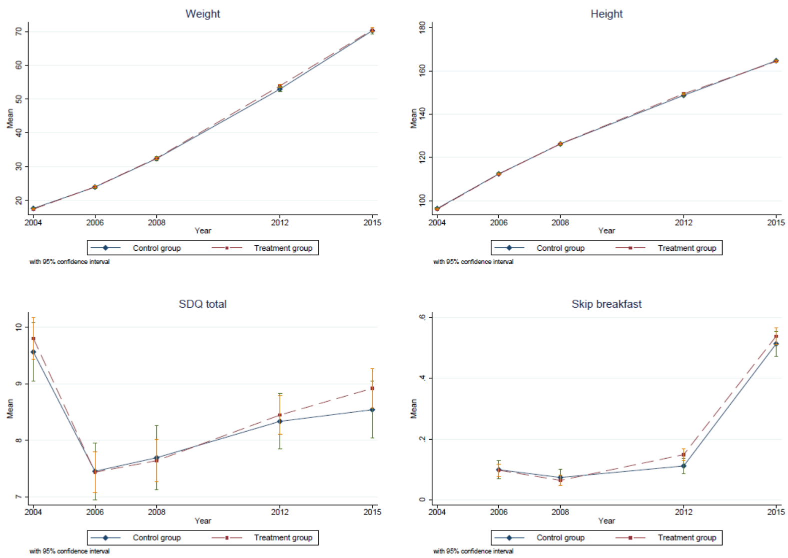


Figure 3.2 – Parallel trends assumption test

Notes: The sample includes MCS children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Treated (control) children are defined as those whose MCS Sweep 5 interview took place after (before) the date of the NCMP school visit.

3.6 Results

3.6.1 Main results

We are primarily interested in the effects among the overweight children, the main target group of this intervention. However, we also present our treatment effect estimates for all children combined and for the normal weight children. The difference-in-difference estimates for different specifications and samples are presented in Table 3.2-3.6. The sample sizes differ across three groups of children and across the outcomes due to item non-response. Each estimate comes from a separate regression. For each outcome, the tables report the results of a model that controls for the month of interview (Column 1), child's and mother's individual characteristics as well as family characteristics (Column 2), regional and neighbourhood characteristics (Column 3), and the duration in months between the intervention and interview (Column 4). The model that includes all listed covariates is used as a baseline specification. In all regressions sampling weights are used, and standard errors are clustered by individual.

Following Anderson (2008), we adjust p-values for the number of multiple hypothesis being tested by applying the method for controlling the false discovery rate (FDR) proposed by Benjamini, Krieger and Yekutieli (2006).[72] The statistical significance of the results in Tables 3.2-3.6 is assessed based on the adjusted p-values and Table C4.1 reports the comparison of unadjusted and adjusted ones.

Impact on adiposity-related outcomes

We first examine the effect of feedback letters directly on health outcomes such as BMI, body fat percentage and the probability to become overweight based on the sample of all children (Table 3.2). We find that feedback letters have no overall impact on adiposity-related outcomes – we do not observe significant changes in BMI, body fat percentage and the probability to become overweight. We expected these results because, given that BMI changes relatively slowly, it is likely that the time period between treatment and survey interview (85% of treated children were interviewed within 5 months after the intervention) may have been too short for children to adjust their behaviour and to lose weight. These results are consistent with the existing literature showing no effect of feedback letters on BMI. Given that we do not find any

[72] In the paper we present only the results based on the method proposed by Benjamini, Krieger and Yekutieli (2006), however, following Anderson (2008), we also applied the method for controlling the false discovery rate proposed by Benjamini and Hochberg (1995) and obtained identical results.

significant short-term effect of the intervention on BMI, it seems justified to use the current BMI to split the sample into sub-samples of normal weight and overweight children, and we check this later in the paper. Because we use the current BMI to split the sample, we do not test our model for the health outcomes (BMI, body fat percentage and the probability to become overweight) separately for normal weight and overweight children.

Table 3.2 – Effect of sending feedback letters on adiposity-related outcomes, all children sample

	(1)	(2)	(3)	(4)
BMI	-0.007	-0.036	-0.032	-0.038
SE	(0.103)	(0.104)	(0.103)	(0.103)
Mean=16.56				
N=10,602				
Body fat percentage	0.027	-0.019	-0.015	-0.015
SE	(0.205)	(0.207)	(0.207)	(0.207)
Mean=21.18				
N=10,420				
Probability to become overweight	0.007	0.005	0.006	0.006
SE	(0.014)	(0.016)	(0.016)	(0.016)
Mean=0.24				
N=10,602				
Controls				
Month of interview	Yes	Yes	Yes	Yes
Individual and family	No	Yes	Yes	Yes
Region/Settlement type/ IMD	No	No	Yes	Yes
Duration b/t the intervention and the interview	No	No	No	Yes

Notes: The sample includes MCS children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Treated (control) children are defined as those whose MCS Sweep 5 interview took place after (before) the date of the NCMP school visit. Results are from separate linear regressions. Robust standard errors clustered at the individual level are in parentheses. Weights are applied. The first column regressions control for month of interview. The second column additionally includes a vector of child's characteristics including age in months and gender, mother's characteristics including age, ethnicity, religion, education, marital and employment statuses and family's characteristics including income and number of siblings in household. The third column specification includes all previous controls plus settlement type, region and overall index of multiple deprivation. The fourth column presents regressions with all previous controls plus the duration in months between the intervention and the interview. The fourth specification that includes all listed covariates is used as a baseline specification. The sample sizes sometimes are slightly different from column to column due to different number of missing values for different control variables. Ns show the number of observations for the final specification. Means calculated for the treatment group at the baseline. *p<0.10, **p<0.05, ***p<0.01. Significance of the results is based on the p-values adjusted for the number of multiple hypotheses being tested following Benjamini, Krieger, and Yekutirli (2006). See Table C4.1 for the comparison of adjusted and unadjusted p-values.

Impact on health-related behavioural outcomes

In this subsection, we examine the effect of sending feedback letters on behavioural outcomes related to health and energy balance as measured in the physical activity index, sedentary behaviour index and fruit intake. Table 3.3 presents overall estimates based on the sample of all children. As shown, the direction of the estimates indicates that sending feedback letters is related to higher physical activity and a lower probability of consuming three or more fruit per day, but the results are not statistically significant. The results on sedentary behaviour are also not statistically significant and close to zero. These results are consistent across all specifications.

Table 3.3 – Effect of sending feedback letters on behavioural outcomes related to energy balance, all children sample

	(1)	(2)	(3)	(4)
Physical activity index	0.027	0.028	0.027	0.026
SE	(0.025)	(0.025)	(0.025)	(0.025)
Mean=-0.02				
N=10,958				
Sedentary behaviour index	0.006	0.007	0.007	0.009
SE	(0.023)	(0.023)	(0.023)	(0.023)
Mean=-0.02				
N=10,970				
Fruit intake	-0.036	-0.034	-0.034	-0.033
SE	(0.021)	(0.021)	(0.021)	(0.021)
Mean=0.51				
N=10,966				
Controls				
Month of interview	Yes	Yes	Yes	Yes
Individual and family	No	Yes	Yes	Yes
Region/Settlement type/ IMD	No	No	Yes	Yes
Duration b/t the intervention and the interview	No	No	No	Yes

Notes: The sample includes MCS children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Treated (control) children are defined as those whose MCS Sweep 5 interview took place after (before) the date of the NCMP school visit. Results are from separate linear regressions. Robust standard errors clustered at the individual level are in parentheses. See notes to Table 3.2 for details in specifications. The sample sizes sometimes are slightly different from column to column due to different number of missing values for different control variables. Ns show the number of observations for the final specification. Means calculated for the treatment group at the baseline. *p<0.10, **p<0.05, ***p<0.01. Significance of the results is based on the p-values adjusted for the number of multiple hypotheses being tested following Benjamini, Krieger, and Yekutirli (2006). See Table C4.1 for the comparison of adjusted and unadjusted p-values.

Table 3.4 displays our estimates on behavioural outcomes related to health and energy balance separately for normal weight and overweight children. The results do not change across the model specifications. After including all covariates, the effect of the treatment on physical activity, sedentary behaviour and fruit consumption are sizable but not statistically significant. Comparing the directions and the size of the estimates for normal weight and overweight children we see a positive effect on physical activity for both groups and of almost the same magnitude of the effects. The effect on sedentary behaviour has different directions for these groups – as a result of sending feedback letters normal weight children show less sedentary behaviour while overweight children show more (a higher value of the index indicates higher sedentary behaviour). This is surprising as we would expect overweight children to reduce their sedentary behaviour in order to reduce their weight. However, again, the effects are not statistically significant, nor are the differences between the groups of children.

Table 3.4 – Effect of sending feedback letters on behavioural outcomes related to energy balance, by weight status

	Normal weight children				Overweight children			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Physical activity index	0.023	0.025	0.024	0.025	0.035	0.031	0.031	0.030
SE	(0.031)	(0.031)	(0.031)	(0.031)	(0.044)	(0.044)	(0.044)	(0.044)
Mean	0.0007				-0.02			
N	6,850				3,820			
Sedentary behaviour index	-0.017	-0.017	-0.018	-0.018	0.039	0.041	0.041	0.045
SE	(0.028)	(0.028)	(0.028)	(0.028)	(0.040)	(0.041)	(0.041)	(0.041)
Mean	0.02				0.04			
N	6,854				3,826			
Fruit intake	-0.037	-0.037	-0.037	-0.036	-0.028	-0.024	-0.024	-0.025
SE	(0.027)	(0.027)	(0.027)	(0.027)	(0.035)	(0.035)	(0.035)	(0.035)
Mean	0.53				0.44			
N	6,846				3,830			
Month of interview	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual and family	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Region/Settlement type/ IMD	No	No	Yes	Yes	No	No	Yes	Yes
Duration b/t the intervention and the interview	No	No	No	Yes	No	No	No	Yes

Notes: The sample includes MCS children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Results are from separate linear regressions. Robust standard errors clustered at the individual level are in parentheses. See notes to Table 3.2 for details in specifications. The sample sizes sometimes are slightly different from column to column due to different number of missing values for different control variables. Ns show the number of observations for the final specification. Means calculated for the treatment group at the baseline. *p<0.10, **p<0.05, ***p<0.01. Significance of the results is based on the p-values adjusted for the number of multiple hypotheses being tested following Benjamini, Krieger, and Yekutirli (2006). See Table C4.1 for the comparison of adjusted and unadjusted p-values.

Adverse effects

In this subsection, we study the adverse effects of sending feedback letters to parents. Although children do not get information on their weight status at school after participating in the NCMP and the feedback letters are sent exclusively to parents/careers, parents can share this information with their children. Thus, we test whether sending feedback letters affects the level of bullying by other children, the child's own bullying behaviour, breakfast consumption (breakfast skipping and double breakfast), happiness and tiredness at school as well as mental health measured by the Strengths and Difficulties Questionnaire completed by parents.

Table 3.5 reports the effects of sending feedback letters for the whole sample of children. The point estimates are sizable for the outcomes that show whether the child is bullied by other children (both self- and parent-reported) and feels tired at school. However, the results are not statistically significant once we adjust p-values for multiple hypothesis testing (without adjustment the estimated coefficients are statistically significant for the bulling reported by parents and tiredness at school, see Table C4.1).

Table 3.6 shows the adverse effects of sending feedback letters to parents separately for normal weight and overweight children. None of the outcomes on bullying behaviour are significant for either groups but we can see a clear difference in the direction and the size of these effects. Based on the child-reported answers, the effect on bullying by other children is 5 times bigger for overweight children than for normal weight children once their parents have received the letter. However, the results are very similar between these two groups based on parent-reported answers on bullying. Again, none of these results are statistically significantly different from zero or from each other.

Breakfast intake results show a highly significant effect of the intervention on breakfast skipping among overweight children. The intervention increases the probability to skip breakfast at least once a week by 7.8 percentage points. This result is statistically significant at 5% level and consistent across the specifications. In contrast, among normal weight children the effect of the treatment on breakfast skipping is negative but statistically not significant. Our point estimates on the probability to have double breakfast at least once a week show very small effects that are not statistically significant for either sub-group.

Next in Table 3.6 we examine the effect of the intervention on unhappiness and tiredness at school. Although the results on unhappiness at school are not statistically significant, the size and the direction of the coefficients suggest that the intervention could substantially increase the probability to feel unhappy at school among overweight children and decrease this probably among normal weight children. The effect on tiredness at school is also not statistically significant in either group but the effect is slightly bigger among overweight children.

Lastly, we test whether the intervention has effect on child's mental health. Surprisingly, the point estimates indicate that the intervention worsens mental health and wellbeing among normal weight children and improves it among the overweight (a higher score indicates a higher risk of developing mental health disorders) but none of the effects are statistically significant. Further, when looking at the components of the total score separately, there are no statistically significant impacts except the inattention problem among normal weight children but the effect is very small and statistically significant only at the 10% level (Table C4.2).

We can use the main findings on breakfast skipping for a back-of-the envelope calculations of the treatment effects on the treated. In 2011/12, the overall participation rate for the NCMP was 92% for Year 6. Around 75% of local authorities consistently chose to send feedback letters to parents.[73] Dividing our intention-to-treat estimates on breakfast skipping for overweight children 0.078 from Table 3.6 by 0.92 and 0.75 indicates that among overweight children providing parents information about the weight status of their child increases the probability to skip breakfast at least once a week by 11.3 percentage points. This is equal to a 2.9 times higher risk of skipping breakfast at least once a week among overweight children – compared to the ITT effect indicated a 2.3 times higher risk. This result is still underestimated as we do not know the proportion of parents who actually received and read the letters.

Table 3.5 – Effect of sending feedback letters on adverse outcomes, all children sample

	(1)	(2)	(3)	(4)
Child is bullied by children (child-reported)	0.021	0.031	0.030	0.030
SE	(0.025)	(0.025)	(0.025)	(0.025)
Mean=0.49				
N=10,054				
Child is bullied by children (parent-reported)	0.032	0.034	0.033	0.032
SE	(0.020)	(0.020)	(0.020)	(0.020)
Mean=0.22				
N=9,916				
Child hurts other children (child-reported)	-0.012	-0.010	-0.010	-0.011
SE	(0.022)	(0.022)	(0.022)	(0.022)
Mean=0.16				
N=10,062				

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[73] We assume that local authorities are of average population size.

Table 3.5 – Continued from previous page

Breakfast skipping	0.013	0.012	0.012	0.012
SE	(0.013)	(0.013)	(0.014)	(0.014)
Mean=0.05				
N=10,984				
Double breakfast	0.004	0.004	0.004	0.005
SE	(0.013)	(0.013)	(0.013)	(0.013)
Mean=0.11				
N=10,984				
Unhappy at school	-0.0003	0.004	0.003	0.003
SE	(0.024)	(0.024)	(0.024)	(0.024)
Mean=0.59				
N=9,982				
Tired at school	0.041	0.041	0.040	0.041
SE	(0.022)	(0.022)	(0.022)	(0.022)
Mean=0.72				
N=9,992				
Total difficulties score	0.012	0.062	0.054	0.040
SE	(0.176)	(0.180)	(0.180)	(0.180)
Mean=7.58				
N=10,294				
Controls				
Month of interview	Yes	Yes	Yes	Yes
Individual and family	No	Yes	Yes	Yes
Region/Settlement type/ IMD	No	No	Yes	Yes
Duration b/t the intervention and the interview	No	No	No	Yes

Notes: The sample includes MCS children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Treated (control) children are defined as those whose MCS Sweep 5 interview took place after (before) the date of the NCMP school visit. Results are from separate linear regressions. Robust standard errors clustered at the individual level are in parentheses. See notes to Table 3.2 for details in specifications. The sample sizes sometimes are slightly different from column to column due to different number of missing values for different control variables. Ns show the number of observations for the final specification. Means calculated for the treatment group at the baseline. *p<0.10, **p<0.05, ***p<0.01. Significance of the results is based on the p-values adjusted for the number of multiple hypotheses being tested following Benjamini, Krieger, and Yekutirli (2006). See Table C4.1 for the comparison of adjusted and unadjusted p-values.

Table 3.6 – Effect of sending feedback letters on adverse outcomes, by weight status

	Normal weight children				Overweight children			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Child is bullied by children	0.010	0.014	0.012	0.011	0.048	0.055	0.055	0.058
(child-reported)	(0.031)	(0.031)	(0.031)	(0.031)	(0.041)	(0.041)	(0.041)	(0.042)
Mean	0.48				0.51			
N	6,338				3,504			
Child is bullied by children	0.028	0.030	0.028	0.027	0.028	0.035	0.034	0.034
(parent-reported)	(0.024)	(0.024)	(0.024)	(0.024)	(0.034)	(0.035)	(0.035)	(0.035)
Mean	0.20				0.24			
N	6,222				3,440			

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Table 3.6 – Continued from previous page

Hurt other children	-0.009	-0.006	-0.007	-0.011	-0.031	-0.033	-0.033	-0.030
(child-reported)	(0.028)	(0.028)	(0.028)	(0.028)	(0.038)	(0.039)	(0.039)	(0.039)
Mean		0.15				0.18		
N		6,348				3,504		
Breakfast skipping	-0.026	-0.027	-0.027	-0.028	0.077**	0.078**	0.079**	0.078**
SE	(0.016)	(0.016)	(0.017)	(0.017)	(0.024)	(0.024)	(0.023)	(0.024)
Mean		0.05				0.06		
N		6,862				3,832		
Double breakfast	-0.0005	0.0002	0.001	0.002	0.012	0.012	0.010	0.010
SE	(0.016)	(0.016)	(0.017)	(0.017)	(0.023)	(0.023)	(0.023)	(0.023)
Mean		0.10				0.11		
N		6,862				3,832		
Unhappy at school	-0.035	-0.032	-0.034	-0.035	0.053	0.059	0.059	0.060
(child-reported)	(0.030)	(0.031)	(0.031)	(0.031)	(0.039)	(0.039)	(0.039)	(0.039)
Mean		0.60				0.58		
N		6,292				3,474		
Tired at school	0.039	0.037	0.035	0.037	0.040	0.043	0.042	0.042
(child-reported)	(0.028)	(0.028)	(0.028)	(0.028)	(0.037)	(0.037)	(0.038)	(0.038)
Mean		0.72				0.72		
N		6,292				3,486		
Total difficulties score	0.134	0.187	0.180	0.166	-0.274	-0.219	-0.234	-0.260
SE	(0.229)	(0.231)	(0.231)	(0.230)	(0.288)	(0.299)	(0.300)	(0.300)
Mean		7.37				7.94		
N		6,452				3,578		
Controls								
Month of interview	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual and family	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Region/Settlement type/ IMD	No	No	Yes	Yes	No	No	Yes	Yes
Duration b/t the intervention and the interview	No	No	No	Yes	No	No	No	Yes

Notes: The sample includes MCS children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Treated (control) children are defined as those whose MCS Sweep 5 interview took place after (before) the date of the NCMP school visit. The group of normal weigh children includes underweight and normal weight children. The group of overweight children includes overweight and very overweight children. The number of normal weight and overweight children does not equal to the total number of children due to missing information on BMI for some of them. Results are from separate linear regressions. Robust standard errors clustered at the individual level are in parentheses. See notes to Table 3.2 for details in specifications. The sample sizes sometimes are slightly different from column to column due to different number of missing values for different control variables. Ns show the number of observations for the final specification. Means calculated for the treatment group at the baseline. *p<0.10, **p<0.05, ***p<0.01. Significance of the results is based on the p-values adjusted for the number of multiple hypotheses being tested following Benjamini, Krieger, and Yekutirli (2006). See Table C4.1 for the comparison of adjusted and unadjusted p-values.

3.6.2 Heterogeneity analysis

We show that sending feedback letters leads to breakfast skipping among overweight children in the short run. It may be that it also changes other health-related behavioural or adverse outcomes among particular groups of overweight children and that breakfast skipping is more prevalent in some groups than other. A large body of literature finds that girls and children in families of higher socio-economic status are more responsive to interventions aimed at reducing the prevalence of obesity than boys and children in families of lower socio-economic status (Plachta-Danielzik et al., 2007; Lavelle et al., 2012; Beauchamp et al., 2014). However, to our knowledge, nothing is known about heterogeneity in potential adverse effects across these groups. We run heterogeneity analysis only for the group of overweight children as it is the main target group of the intervention and we find significant changes for this group.[74] Table 3.7 demonstrates how our estimates of the effect of sending feedback letters vary across girls and boys and children of different socio-economic status. Due to many outcomes, the table focuses on the behavioural outcomes related to energy balance and adverse outcomes where we find significant results, while Table C4.4 presents the results for the rest of our outcomes. As before, the significance of the results is presented based on the adjusted p-values and Table C4.5 reports the comparison of adjusted and unadjusted ones.

We first investigate whether girls and boys respond differently to the intervention (Panel A). In terms of behavioural outcomes related to energy balance, we see that physical activity of boys is more affected than that of girls while girls are more affected in their sedentary behaviour and fruit intake. The results are sometimes in unexpected direction but they are not different from zero. Regarding adverse effects, we do not find a differential impact of the intervention by gender. The results are not statistically significant but present similar patterns among girls and boys (we do find a significant effect on probability to skip breakfast for both boys and girls before adjusting the p-values).

Next, we consider whether children from families of lower and higher socio-economic status differ in their response to the intervention. The data allow us to distinguish children by their mother's educational attainment (Panel B) and partnership status (Panel C), their family's income (Panel D) and their neighbourhood level of deprivation (Panel D).[75] We find notable

[74] We also estimated models separately based on the sample of all children and normal weight children. Results showed no significant impacts on any of outcomes. For space reason, we do not report them but they are available on request.

[75] Mother is defined as having high education if she has A level and above. Mother is defined as single if she is not married and does not have a partner. Low-income family is defined as a family with total weekly income

patterns. First, although the results on all behavioural outcomes related to energy balance are not statistically significant for either group, we see that children of lower socio-economic status are more responsive in terms of higher level of physical activity. At the same time there are no clear patterns in terms of sedentary behaviour and fruit intake.

Second, we find that several of the adverse effects of the intervention are concentrated on children in families of lower socio-economic status while they occur much less often in higher socio-economic status families. We find highly significant negative effect of the intervention on breakfast skipping. In particular, sending feedback letters increases the probability to skip breakfast by 9 percentage points among overweight children of mothers with low educational qualification, by 16.5 percentage points among overweight children of mothers without a partner, by 11.3 percentage points among overweight children from low-income families, and by 7.8 percentage points among overweight children from more deprived neighborhoods. For the children of lower socio-economic status, we also find statistically significant evidences of the negative impact of sending feedback letters on unhappiness and tiredness at school. Overweight children of single mothers experience a 15.3 percentage points increase in the probability of feeling unhappy at school. The negative effect also appears among children from more deprived neighborhoods – there is a 12.7 and 12.3 percentage points increase in the probability to feel unhappy and tired at school, respectively. For the group of children of mothers with low education and children from low-income families, the coefficients for unhappiness and tiredness at school are not statistically significant but very similar in magnitude.

In summary, our findings suggest that overweight children in low socio-economic status families are most affected by the adverse effects of providing parents information about their weight while children in families of higher socio-economic status seem largely protected from the adverse effects. There are several potential reasons why feedback letters might affect overweight children from disadvantaged families. Prior research suggests that socio-economic standing is associated with child's health – there is a link between higher socio-economic status and positive physical and psychological health (Case et al., 2002; Currie and Stabile, 2003; Currie et al., 2007; Kumar et al., 2014). Thus, in terms of breakfast skipping, the negative effect among disadvantaged families could be caused by the lack of knowledge that breakfast

equal or lower than £391.7 which is mean income for the sample of families with overweight children. Neighbourhood is defined as less deprived if an index of multiple deprivation (IMD) falls into the top 50% of IMD distribution. The sample of overweight children is characterized by a high level of low educated mothers (67.7%), a medium level of single mothers (33.8%) and a high level of low-income (57.8%) families and families from more deprived neighborhoods (57.5%).

skipping is a harmful weight loss option. Also, because low parental involvement occurs more often among families of lower socio-economic status (Conger et al., 2010), our findings could be explained by a lower level of parents' supervision which could enable children to skip breakfast unnoticed if they consider this as a way to lose weight. At the same time, parents of higher socio-economic status may be more proactive in their child's health by supervising proper nutrition. Moreover, these parents possibly do not share negative feedback results on bodyweight status as they may focus on building self-esteem of their children.

Table 3.7 – Heterogeneous effect of sending feedback letters

	Physical activity index	Sedentary behaviour index	Fruit intake	Breakfast skipping	Unhappy at school	Tired at school
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A- Child's gender						
Girls	0.015	0.086	-0.074	0.085	0.044	0.043
	(0.063)	(0.056)	(0.049)	(0.036)	(0.055)	(0.056)
Boys	0.043	0.004	0.023	0.072	0.074	0.040
	(0.059)	(0.057)	(0.049)	(0.029)	(0.053)	(0.049)
N	3,820	3,826	3,830	3,832	3,474	3,486
Panel B – Mother's education						
Low	0.049	0.014	-0.038	0.090**	0.104	0.110
	(0.056)	(0.052)	(0.043)	(0.031)	(0.048)	(0.049)
High	0.017	0.110	-0.035	0.050	-0.072	-0.073
	(0.070)	(0.065)	(0.062)	(0.032)	(0.063)	(0.058)
N	3,608	3,614	3,618	3,620	3,286	3,292
Panel C – Mother's partnership status						
Single	0.078	0.067	-0.044	0.165***	0.153*	0.096
	(0.076)	(0.071)	(0.053)	(0.046)	(0.063)	(0.063)
Partnered	-0.016	0.033	-0.007	0.012	-0.026	-0.003
	(0.051)	(0.047)	(0.045)	(0.023)	(0.046)	(0.046)
N	3,736	3,742	3,746	3,748	3,398	3,408
Panel D – HH Income						
Low	0.071	0.045	-0.085	0.113**	0.089	0.074
	(0.066)	(0.059)	(0.046)	(0.037)	(0.057)	(0.055)
High	-0.018	0.049	0.038	0.035	0.024	0.007
	(0.053)	(0.053)	(0.050)	(0.026)	(0.050)	(0.050)
N	3,820	3,826	3,830	3,832	3,474	3,486
Panel E – Index of multiple deprivation						
More deprived	0.101	-0.031	-0.020	0.078*	0.127*	0.123*
	(0.060)	(0.055)	(0.045)	(0.033)	(0.051)	(0.052)
Less deprived	-0.055	0.142*	-0.026	0.081*	-0.025	-0.060
	(0.061)	(0.059)	(0.053)	(0.032)	(0.056)	(0.051)
N	3,820	3,826	3,830	3,832	3,474	3,486

Notes: The sample includes MCS children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Results are from separate linear regressions. Robust standard errors clustered at the individual level are in parentheses. See notes to Table 3.2 for details in baseline specifications. Mother is defined as having high education if she has A level and above. Mother is defined as single if she is not married and does not have a partner. Low-income family is defined as a family with total weekly income equal or lower than £391.7 which is the mean income for the sample of families with overweight children. Neighbourhood is defined as less deprived if index of multiple deprivation falls into the top 50% of IMD distribution. *p<0.10, **p<0.05, ***p<0.01. Significance of the results is based on the p-values adjusted for the number of multiple hypotheses being tested following Benjamini, Krieger, and Yekutirli (2006). See Table C4.5 for the comparison of adjusted and unadjusted p-values.

We again can use these results for a back-of-the envelope calculations of the treatment effects on the treated by dividing our intention-to-treat estimates from Table 3.7 by 0.92 and 0.75. These calculations indicate that providing parents information about the weight status of their child increases the probability to skip breakfast at least once a week by 13.0 percentage points among overweight children of low-educated mothers, by 23.9 percentage points among overweight children of single mothers, by 16.4 percentage points among overweight children from low-income families, and by 11.3 percentage points among overweight children from more deprived neighborhoods. It also shows that providing feedback letters increases the probability of feeling unhappy at school by 22.2 percentage points among overweight children of single mothers and by 18.4 percentage points among children from more deprived neighborhoods. Moreover, children from more deprived neighborhoods experience an increase in the probability to feel tired at school by 17.8 percentage points.

3.6.3 Robustness checks

We conduct a variety of robustness checks on our estimates of the effect of sending feedback letters and report the results in Table 3.8 both for normal weight and overweight children. Columns (1) and (8) present baseline results for the normal weight and overweight children.

For the first check we exclude children with extreme BMIs. Even though height and weight are measured by interviewers using professional stadiometers and scales, there are observations that might be considered outliers.[76] We exclude children with BMI lower than 10 and higher than 30. Columns (2) and (9) report that excluding outliers does not affect our results for either group of children.

Next, we run a set of tests investigating our strategy on how we split the sample into normal weight and overweight children. Although we show that the intervention has no overall impact on BMI, one might be concerned that using the current BMI to split the sample can lead to misclassification of normal weight and overweight children. We use several approaches to test this. First, we split the sample based on a lagged measure of the children’s weight using BMI in 2008 (Columns (3) and (10) for normal weight and overweight children, respectively). Second, we use the current BMI but we exclude from the analysis those children who were

[76] According to the Millennium Cohort Study dataset guide (eighth edition), all height and weight measurements are included in the dataset and it is up to individual researchers to take decisions on whether they consider any of the measurements to be outliers and what they do with such observations.

exposed to the intervention relatively longer, thus, they had higher probability to change their BMI and be misclassified. We exclude those who were interviewed 6 or more months after the intervention – 10.2% of the sample (Columns (4) and (11)), and also test the results' sensitivity excluding those who were interviewed 5 and more months after the intervention – 17.1% of the sample (Columns (5) and (12)). Third, we use the current BMI but exclude those children whose BMI was around the overweight cut-off points – within 0.5 SDs which is roughly 2 BMI units – around 10% of the initial sample (Columns (6) and (13)). As these children were close to the overweight cut-off points, they had higher probability to change their weight status and be misclassified. The results of listed checks are very similar in magnitude and statistical significance to the baseline results. Several differences occur when we use BMI in 2008 to split the sample into normal and overweight children, but the coefficients are not statistically significant.

We also investigate whether our estimated treatment effects could be driven just by participating in the programme – whether measuring children's height and weight affects their behaviour. Neither child's BMI nor weight status are reported to children after the measurement but children might be informed of their weight and height that can potentially change their health-related behaviour. To test this hypothesis, we change our approach to define the treatment group. Instead of identifying the treatment group as those who were interviewed at least 6 weeks after their participation in the NCMP[77], we define it as a group of children who were interviewed within 6 weeks after the NCMP measurement. Columns (7) and (14) report results for normal weight and overweight children, respectively. Our main finding is that a very strong treatment effect on breakfast skipping among overweight children becomes smaller and statistically not significant which suggests that the breakfast skipping effect emerges after sending the feedback letters.[78]

[77] Feedback letters should be sent to parents/carers at most within 6 weeks after measurement and for our main analysis we exclude those children who were interviewed within 6 weeks after the NCMP measurement.

[78] Again, due to the current situation with COVID-19 and the lack of access to the University and the Secure Lab, not all robustness checks are presented. Other checks that will be added to the paper are: (1) to split the sample into normal and overweight children using BMI in 2008 but excluding children at the overweight cut-off. We suggest this check as the results of the robustness check where we split the sample using BMI in 2008 show some unexpected results on tiredness at school and total difficulties score; (2) the feedback letters should be sent to all parents within 6 weeks, and we exclude the children who were interviewed within 6 weeks after the measurement when we construct the sample. As a robustness check, we use a more narrow group and exclude children who were interviewed only within 3 weeks after the measurement; (3) sensitivity checks using different methods to constructs physical activity and sedentary behaviour indices. For example, an alternative index construction that does not assign equal weights to different components (Anderson, 2008).

Table 3.8 – Robustness checks

	Normal weight children							Overweight children						
	Baseline model (1)	Exclude extreme BMI (2)	BMI 2008 (3)	Exclude 6+ months (4)	Exclude 5+ months (5)	Exclude around cut-off points (6)	Treated - interview ed within 6 weeks (7)	Baseline model (8)	Exclude extreme BMI (9)	BMI 2008 (10)	Exclude 6+ months (11)	Exclude 5+ months (12)	Exclude around cut-off points (13)	Treated- interview ed within 6 weeks (14)
Physical activity index	0.025	0.024	0.014	0.017	0.017	0.036	-0.041	0.030	0.039	0.062	0.030	0.029	0.026	0.049
	(0.031)	(0.031)	(0.030)	(0.031)	(0.032)	(0.033)	(0.042)	(0.044)	(0.045)	(0.050)	(0.045)	(0.045)	(0.046)	(0.058)
	6,850	6,840	7,694	6,136	5,652	6,140	2,980	3,820	3,690	2,886	3,432	3,190	3,454	1,574
Sedentary behaviour index	-0.018	-0.017	-0.015	-0.014	-0.016	-0.014	0.003	0.045	0.046	0.054	0.046	0.043	0.064	0.010
	(0.028)	(0.028)	(0.027)	(0.028)	(0.028)	(0.029)	(0.036)	(0.041)	(0.041)	(0.047)	(0.041)	(0.042)	(0.043)	(0.053)
	6,854	6,844	7,698	6,140	5,656	6,144	2,976	3,826	3,696	2,890	3,440	3,196	3,458	1,578
Fruit intake	-0.036	-0.036	-0.035	-0.042	-0.041	-0.020	-0.037	-0.025	-0.034	-0.028	-0.025	-0.022	-0.039	0.015
	(0.027)	(0.027)	(0.025)	(0.027)	(0.027)	(0.028)	(0.035)	(0.035)	(0.036)	(0.040)	(0.035)	(0.036)	(0.036)	(0.050)
	6,846	6,836	7,694	6,132	5,648	6,136	2,976	3,830	3,700	2,892	3,442	3,198	3,462	1,578
Child is bullied by children (self-reported)	0.011	0.012	0.025	0.024	0.026	0.011	0.084*	0.058	0.056	0.032	0.058	0.055	0.057	-0.044
	(0.031)	(0.031)	(0.029)	(0.031)	(0.032)	(0.033)	(0.040)	(0.042)	(0.043)	(0.050)	(0.042)	(0.043)	(0.044)	(0.058)
	6,338	6,332	7,150	5,674	5,218	5,676	2,766	3,504	3,382	2,660	3,152	2,932	3,178	1,456
Child is bullied by children (parent-reported)	0.027	0.027	0.028	0.025	0.022	0.032	0.015	0.034	0.038	0.036	0.026	0.026	0.040	-0.004
	(0.024)	(0.024)	(0.022)	(0.024)	(0.025)	(0.026)	(0.030)	(0.035)	(0.034)	(0.044)	(0.035)	(0.036)	(0.037)	(0.049)
	6,222	6,121	6,986	5,584	5,138	5,584	2,698	3,440	3,318	2,612	3,086	2,872	3,124	1,414
Child hurts other children	-0.011	-0.011	-0.006	-0.006	-0.015	-0.017	-0.033	-0.030	-0.023	-0.040	-0.034	-0.037	-0.026	-0.074
	(0.028)	(0.028)	(0.027)	(0.028)	(0.029)	(0.029)	(0.034)	(0.039)	(0.040)	(0.044)	(0.039)	(0.039)	(0.041)	(0.047)
	6,348	6,338	7,164	5,688	5,234	5,684	2,756	3,504	3,384	2,654	3,152	2,934	3,176	1,464
Breakfast skipping	-0.028	-0.028	-0.007	-0.032	-0.029	-0.022	-0.030	0.078**	0.075**	0.058**	0.078**	0.075**		0.039
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.020)	(0.024)	(0.025)	(0.024)	(0.024)	(0.025)		(0.032)
	6,862	6,852	7,708	6,148	5,662	6,152	2,980	3,832	3,702	2,894	3,444	3,200		1,578
Double breakfast	0.002	0.002	0.008	0.001	0.002	0.002	0.008	0.010	0.017	-0.003	0.014	0.013	0.001	0.007
	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)	(0.023)	(0.023)	(0.024)	(0.026)	(0.023)	(0.024)	(0.024)	(0.032)
	6,862	6,282	7,708	6,148	5,662	6,152	2,980	3,832	3,702	2,894	3,444	3,200	3,464	1,578
Unhappy at school	-0.035	-0.035	-0.009	-0.032	-0.029	-0.030	-0.044	0.060	0.048	0.027	0.044	0.046	0.046	0.045
	(0.031)	(0.031)	(0.029)	(0.031)	(0.032)	(0.032)	(0.042)	(0.039)	(0.040)	(0.045)	(0.039)	(0.040)	(0.040)	(0.054)
	6,292	6,282	7,102	5,632	5,188	5,634	2,712	3,474	3,354	2,630	3,130	2,914	3,150	1,460

Continued on next page

Table 3.8 – Continued from previous page

Tired at school	0.037	0.036	0.056*	0.035	0.043	0.015	0.073*	0.042	0.039	-0.014	0.029	0.039	0.032	0.019
	(0.028)	(0.028)	(0.026)	(0.028)	(0.029)	(0.030)	(0.036)	(0.038)	(0.038)	(0.043)	(0.038)	(0.039)	(0.039)	(0.053)
	6,292	6,284	7,102	5,634	5,190	5,636	2,704	3,486	3,366	2,642	3,142	2,926	3,164	1,462
Total difficulties score	0.166	0.165	-0.070	0.222	0.225	0.162	-0.089	-0.260	-0.245	0.366	-0.285	-0.256	-0.189	-0.510
	(0.230)	(0.230)	(0.210)	(0.230)	(0.234)	(0.247)	(0.290)	(0.300)	(0.302)	(0.368)	(0.303)	(0.308)	(0.317)	(0.438)
	6,452	6,442	7,246	5,778	5,314	5,788	2,814	3,578	3,366	2,710	3,212	2,988	3,242	1,482

Notes: The sample includes MCS children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Treated (control) children are defined as those whose MCS Sweep 5 interview took place after (before) the date of the NCMP school visit. The group of normal weigh children includes underweight and normal weight children. The group of overweight children includes overweight and very overweight children. The number of normal weight and overweight children does not equal to the total number of children due to missing information on BMI for some of them. Results are from separate linear regressions. Robust standard errors clustered at the individual level are in parentheses. See notes to Table 3.2 for details in baseline specifications. Results in Columns (1) and (8) are baseline model. Results in Columns (2) and (9) are without extreme BMIs. Results in Columns (3) and (10) are based on splitting the sample into normal and overweight children using their BMI in 2008. Results in Columns (4) and (11) are without children who interviewed 6 or more months after the intervention. Results in Columns (5) and (12) are without children who interviewed 5 or more months after the intervention. Results in Columns (6) and (13) are without children who BMI was around the overweight cut-off points in 2012. Results in Columns (7) and (14) are based on the identifying the treatment group as a group those who were interviewed withing 6 weeks after the NCMP measurement. *p<0.10, **p<0.05, ***p<0.01. Significance of the results is based on the p-values adjusted for the number of multiple hypotheses being tested following Benjamini, Krieger, and Yekutirli (2006).

3.6.4 Results based on UKHLS

We use the UKHLS to run a supplementary descriptive analysis for the variables that complement the outcomes available in the MCS. We construct the treatment and control groups following the same ideas as before. We compare treated and control group children in the year they participate in the NCMP (see Table C4.6 that shows no imbalances between treatment and controls). Based on the sample of all children, Table 3.9 Panel A shows the difference between the treatment and control groups in how children feel about different aspects of their lives and their experience in dieting. As we can see, there is only one significant difference between the two groups of children - those whose parents will have received feedback letters feel worse about their appearance compared to children from the treatment group.

An analysis based on sub-samples of normal weight and overweight children faces two data issues. First, the questions on weight and height are asked in every second wave, thus, this significantly reduces the number of observations. Second, weight and height are self-reported by young people and the response rates are very low – between 36 and 48% in different waves. This again significantly reduces the sample size. Thus, only 18.3% of the estimation sample has information on BMI (445 observations out of 2,435). In order to partly solve this issue and, therefore, increase the sample size of normal weight and overweight children, we apply (1) linear interpolation for the cases when BMI in [t-1] and [t+1] are known and (2) imputations BMI[t+1] = BMI[t] and BMI[t-1] = BMI[t] for the cases when both BMI in [t-1] and [t+1] are unknown. Panels B and C of Table 3.9 show the results for the groups of normal weight and overweight children. There are no significant differences between the treatment and control groups among normal weight children but there are some significant results for the overweight children. Among overweight children those who are in the treatment group feel worse about their friends and more often try dieting. The difference on dieting is substantial – 67% of children in the treatment group mentioned that they have tried diet, while in the control group only 47% mention it. In line with our main results on breakfast skipping among overweight children after their parents receive feedback letters, these findings confirm that feedback letters can cause unhealthy eating behaviour.

Table 3.9 – Descriptive results based on the UKHLS

	N (1)	Treatment (2)	Control (3)	Difference (4)	p-value (5)
Panel A – all children					
Feel about school work	2,375	0.81	0.83	-0.02	0.19
Feel about your appearance	2,368	0.80	0.84	-0.04	0.02
Feel about your family	2,375	0.96	0.97	-0.01	0.21
Feel about your friends	2,379	0.95	0.94	0.01	0.55
Feel about the school you go to	2,374	0.88	0.87	0.01	0.60
Feel about your life as a whole	2,373	0.90	0.91	-0.01	0.65
Ever tried diet	969	0.39	0.37	0.02	0.49
Panel B – normal weight children					
Feel about school work	837	0.84	0.85	-0.01	0.72
Feel about your appearance	833	0.83	0.86	-0.03	0.30
Feel about your family	836	0.96	0.98	-0.02	0.10
Feel about your friends	836	0.94	0.95	-0.01	0.68
Feel about the school you go to	836	0.89	0.87	0.02	0.31
Feel about your life as a whole	836	0.92	0.94	-0.02	0.34
Ever tried diet	419	0.23	0.27	-0.04	0.34
Panel C – overweight children					
Feel about school work	357	0.81	0.82	-0.01	0.87
Feel about your appearance	355	0.74	0.77	-0.03	0.52
Feel about your family	356	0.97	0.96	0.01	0.77
Feel about your friends	357	0.92	0.97	-0.05	0.04
Feel about the school you go to	356	0.89	0.85	0.03	0.35
Feel about your life as a whole	356	0.90	0.86	0.04	0.21
Ever tried diet	158	0.67	0.47	0.20	0.02

Notes: The sample includes UKHLS children who were successfully merged to the date of NCMP school visit. Treated (control) children are defined as those whose UKHLS interview took place after (before) the date of the NCMP school visit. The group of normal weigh children includes underweight and normal weight children. The group of overweight children includes overweight and very overweight children. The number of normal weight and overweight children does not equal to the total number of children due to missing information on BMI for some of them. Columns (2) and (3) show means for treated and control group children, respectively. Column (4) shows differences in means between treatment and control groups. Column (5) shows p-values.

3.6.5 Cognitive skills and school test performance

Our main results show that in the short run sending feedback letters leads overweight children to skip breakfast and the effect is especially pronounced among overweight children of low socio-economic status. The existing literature shows that skipping breakfast leads to mid-morning fatigue, affects cognitive skills such as focused attention and memory recall and may affect children's school test performance (WHO, 2004a; Garg et al., 2014; Smith et al., 2014). Similarly, there is considerable evidence that eating breakfast is associated with better motor functional skills, better learning in children in terms of behaviour, cognitive, and school test performance, suggesting that skipping breakfast could negatively affect children's skills and school attainment (Wyatt et al., 2002; Baldinger et al., 2012; Wesnes et al., 2012; Adolphus et al., 2013; de la Hunty et al, 2013; Barr et al., 2014).

In this section we investigate whether sending feedback letters affect children's cognitive skills and school test performance. To estimate the effect of sending feedback letters on cognitive skills, we use the Millennium Cohort Study data. The MCS administrates several cognitive assessments from age 3 onwards. We use verbal ability, which is the only skill assessed both in the fourth and fifth MCS sweeps. We estimate a version of equation (1), where the outcome is a percentile rank that shows where a child's verbal ability score lies in relation to children of his/her same age.

To evaluate the effect of sending feedback letters on children's school test performance, we use data from the National Pupil Database (NPD) linked to the MCS and NCMP school visit dates. The NPD is a longitudinal register dataset for all children in state schools in England. We are particularly interested in Key Stage 2 exam results which are National Curriculum assessments pupils take at age 11, in the year they are also weighed and measured for the NCMP. We use results in Reading and Mathematics for which equivalent measures are available from Key Stage 1 assessments, taken when the pupils are age 7. As outcomes we use the standardised point scores in Reading and Mathematics, which are standardised separately by academic year and subject.

The analysis is based on a sample of 4,573 children who were in Year 6 in 2012 and took part in Key Stage 2 exams. To evaluate the effect of sending feedback letters, we apply the same empirical approach as before but a slightly different way to identify treatment and control groups. The difference is that for the previous outcomes the measures were taken at interview, i.e. on different days, whereas for the school test performance outcomes we use data from exams taken by the treatment and control group at the same time. In the 2011/12 academic year, the Key Stage 2 exams were held in the week starting May 14, 2012, and the NCMP measurements were taken between September 2011 and July 2012. It means that some children were measured for the programme before the exam week and some after. Thus, we compare end of academic year test results between children of parents who received the feedback letters prior to the exam period (treatment group), to those whose parents receive the letters later in the academic year after the exam period (control group). This assigns 87.0% of the sample (3,980 children) to the treatment group and 13.0% (593 children) to the control group. As we do not know the exact dates for every exam within the exam week, we use the 14th of May as a single date for all of them. We use Key Stage 1 exam results as outcomes in the baseline period.

Table 3.10 presents the results and indicates no adverse effect of sending feedback letters on children's verbal ability or school test performance. We also run a specification where we interact treatment with the duration of treatment exposure, i.e. the duration between the intervention and the week of exams, and we do not find any clear effect (Table C4.7). There are several limitations of this exercise. First, the measures of the verbal ability outcome are not entirely comparable across the sweeps as each sweep measures different aspects of verbal ability – the word reading assessments were used in MCS4 and verbal similarities in MCS5. Second, for the school test performance outcomes, the control group is relatively small which significantly limits the statistical power of the analysis. Thus, our results should be interpreted with caution.

Table 3.10 – Effect of sending feedback letters on verbal ability and school test performance

	All children (1)	Normal weight children (2)	Overweight children (3)
Verbal ability	1.899*	2.609*	0.939
	(1.148)	(1.470)	(1.875)
N	10,702	6,734	3,756
Reading	-0.043	-0.061	-0.014
	(0.038)	(0.046)	(0.067)
N	9,038	5,662	3,148
Mathematics	-0.044	-0.047	-0.038
	(0.034)	(0.043)	(0.058)
N	9,044	5,666	3,150

Notes: For verbal ability, the sample includes MCS children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Treated (control) children are defined as those whose MCS Sweep 5 interview took place after (before) the date of the NCMP school visit. For school test performance outcomes, the sample includes MCS children linked to the NPD dataset who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Treated (control) children are defined as those whose end of academic years exams took place after (before) the date of the NCMP school visit. The group of normal weigh children includes underweight and normal weight children. The group of overweight children includes overweight and very overweight children. The number of normal weight and overweight children does not equal to the total number of children due to missing information on BMI for some of them. *p<0.10, **p<0.05, ***p<0.01.

3.7 Conclusion

In this paper we study how a health information intervention can change children's behaviour. Based on the National Child Measurement Programme in England, which is a weight-screening intervention to assess the prevalence of overweight and obesity in children, we investigate the effect of providing parents feedback letters containing the body weight status of their children, a set of recommendations and pro-active feedback by school nurses on children's behaviour related to energy balance, unhealthy eating, psychological qualities, cognitive skills and school test performance.

We find that in the short-run children's BMI, body fat percentage, the probability to become overweight as well as physical activity, sedentary behaviour and fruit intake remain unaffected by the program. On the other hand, we find evidence that due to the intervention overweight children experience adverse effects of the programme. Overweight children whose parents have received the feedback letters have a 2.3 times higher risk of skipping breakfast at least once a week than overweight children whose parents have not yet received the letters. Heterogeneity analysis suggests that the breakfast skipping effect is concentrated among overweight children from families of lower socio-economic status. For example, overweight children of single mothers and overweight children from low-income families have 3 times higher risk of skipping breakfast after receiving feedback letters. We also find that overweight children from families of lower socio-economic status whose parents have received feedback letters are more likely to feel unhappy and tired at school. For example, we find that receiving feedback letters increases the risk that children from more deprived neighborhoods feel unhappy and tired at school by around 30%. Additionally, we find that overweight children whose parents have received the feedback letters much more often report that they have tried dieting that overweight children not in receipt of the letters.

Most of the literature on tailored information interventions shows positive changes in people's attitudes and behavioural intentions. However, the overall patten from our results show that in the short-run the effects of the programme are related to unhealthy dietary habits, including breakfast skipping. This behaviour is contrary to a weight loss strategy as the existing literature shows that skipping breakfast is associated with overweight and obesity (see Monzani et al. (2019) for a systematic review). Moreover, our findings on the concentration of adverse effect among children from lower socio-economic status families shed more light on how socio-economic inequalities relating to childhood overweight and obesity might be exacerbated.

Our results suggest three main insights for policy. First, the information provided in the letters itself may not be enough to lead to changes in parent and child behaviour. In this case, further work is needed to identify what can encourage parents to change their children's lifestyle. Second, changes to the way information on the weight status of children is relayed to parents are needed to stop negative psychosocial consequences and motivate the intended outcomes. Some aspect of the programme have already changed since 2011/12. For example, more recent feedback letter templates are more explicit in informing parents that it is not intended that parents discuss the letters and its content with their children unless they choose to do so. Third, the focus of health interventions to tackle obesity should also take into account socio-economic health inequalities, including social-environmental conditions that form health-related decisions and behaviours.

This study has some limitations. First, almost 80% of the children were interviewed within four months after their parents were expected to receive feedback letters, with a quarter being interviewed within the first month. This means we are able to observe only short-run effects of the intervention and it is possible that our estimates of a null impact on adiposity-related outcomes could be due to not enough time for children to change behaviours. Second, in our survey data we do not observe the child's NCMP participation and therefore our baseline results are intention-to-treat which do not take into account that not all PCTs decided to send feedback letters, not all children participated in the measurement and that some parents probably did not open the letters they received. However, since we assume that there is more compliance than there actually is, if anything our baseline results underestimate the treatment effect and we provide back-of-the-envelope calculations that come closer to a treatment-on-the-treated effect. Third, in order to classify children into normal and overweight, we use their current BMI that could be affected by the intervention. In this case, there is a possibility of misclassification. However, a set of robustness checks suggests this is not likely to affect our results. Finally, children gain weight and become overweight and obese when energy intake (food consumption) exceeds energy expenditure (physical activity). The data available to us measure a number of behaviours related to physical activity and sedentary behaviour but in terms of food consumption we observe only fruit intake in both of the MCS sweep used for the analysis.[79] Further research that takes into account food intake such as fast food, unhealthy snacks and fizzy drinks could improve the understanding of behavioural changes related to the feedback letters.

[79] The MCS does provide information on unhealthy snacks and sweetened drinks but only either in sweep 4 or 5.

Appendices

Appendix C1 – NCMP Feedback Letters

Figure C1.1 – Specimen result letters to parents/carers in 2011/2012 for different weight statuses

«PCTName»
«Address_Line1»
«Address_Line2»
«Address_Line3»
«Address_Line4»
«Address_Line5»
«PCT_Postcode»

Telephone: «PCT_Telephone»
Email Address: «PCTEmail»

Private and confidential
Parent / Carer of «Child_Firstname» «Child_Surname»
«Child_Address1»
«Child_Address2»
«Child_Address3»
«Child_Address4»
«Child_Postcode»

[Date]

NHS Number [Optional]

Dear Parent/Carer,

We recently measured your child's height and weight at school as part of the National Child Measurement Programme. A letter about this was sent to you before the measurements were taken. Your child's results are shown below.

Your child's results:

Date measured	Date of Birth	Height	Weight	Body-mass index centile
«DateofMeasurement»	«DateofBirth»	«Height2»	«Weight2»	«BMIPercentile2» (see table overleaf)

(Child summary paragraph goes here [see page 3])

Yours sincerely,

«PCTLeadContact» («PCTLeadContactTitle»)

1

If you want this leaflet in other formats, please contact your local NHS on the number above.

What is Body-mass index (BMI) centile?

BMI centile is a good way of finding out whether a child is a healthy weight and is used by health care professionals.

By comparing your child's weight with their height, age and sex, we can tell whether they're growing as expected. This is something you may have done when your child was a baby, using the growth charts in the Personal Child Health Record.

Once your child's BMI centile has been calculated, they will be in one of four categories:

	BMI centile range
Underweight	below 2nd BMI centile
Healthy weight	between 2nd and 90th BMI centile
Overweight	Between 91st up to 97th BMI centile
Very Overweight (doctors call this clinically obese)	At or above 98th BMI centile

Most children should fall in the healthy weight range, with fewer than one in ten in the overweight or very overweight range.

Research shows that children who are overweight or very overweight have higher risk of ill health during childhood and in later life.

Some medical conditions or treatment that your child is receiving may mean that BMI centile is not the best way to measure for your child. Your GP or other health professional caring for your child will be able to discuss this with you.

For more information about BMI centiles, visit www.nhs.uk/tools/pages/healthyweightcalculator.aspx.

[Underweight]

Your child's result is in the underweight range.

We wanted to let you know your child's result because it is an important way of checking how your child is growing.

Many underweight children are perfectly healthy, but sometimes it can mean they have a health problem.

Some parents find it helpful to re-check their child's BMI after a few months, to see if they have moved into the healthy range as they grow. You can do this using the Healthy Weight tool at www.nhs.uk/tools/pages/healthyweightcalculator.aspx

If you would like to speak to us about your child's result, please phone the number at the top of this letter.

[Healthy]

Your child's result is in the healthy range.

We wanted to let you know your child's result because it is an important way of checking how your child is growing.

Children of a healthy weight are more likely to grow into healthy adults. To keep growing healthily, it is important that your child eats well and is active.

Some parents find it helpful to re-check their child's BMI after a few months, to see if they remain in the healthy range as they grow. You can do this using the Healthy Weight tool at www.nhs.uk/tools/pages/healthyweightcalculator.aspx

Many parents have found the tips in the enclosed leaflet and at www.nhs.uk/change4life useful in helping them make changes to help their child grow healthily. If you would like more advice about your child's eating or activity, visit www.nhs.uk/change4life, or phone the number at the top of this letter.

[Overweight]

You may be surprised that your child's result is in the overweight range.

It can sometimes be difficult to tell if your child is overweight as they may look similar to other children of their age, but more children are overweight than ever before.

Research shows that if your child is overweight now, they are more likely to grow up to be overweight as an adult. This can lead to health problems. So this measurement is an important way of checking how your child is growing.

Many parents have found the tips in the enclosed leaflet and at www.nhs.uk/change4life useful in helping them make small lifestyle changes to keep their child in the healthy weight range.

Some parents also find it helpful to re-check their child's BMI after a few months, to see if they have moved into the healthy range as they grow. You can do this using the Healthy Weight tool at www.nhs.uk/tools/pages/healthyweightcalculator.aspx

If you are concerned about the result and would like further information and to find about local activities, please phone us on the number at the top of this letter. **[If PCT is proactively following up overweight children:** We will also contact you soon to offer you further information**]**.

[Very overweight]

Your child’s result is in the very overweight range. Doctors call this clinically obese. We wanted to let you know your child’s result because it is an important way of checking how your child is growing.

Children who are very overweight are more likely to have health problems at a young age, such as high blood pressure, early signs of type 2 diabetes and low self-confidence. Later in life, they are more likely to have illnesses like heart disease and some types of cancer.

Small lifestyle changes started now can help your child to grow healthily. Many parents have found the tips in the enclosed leaflet and at www.nhs.uk/change4life useful in helping them make changes to help their child grow healthily.

Some parents also find it helpful to re-check their child’s BMI after a few months, to see if they have moved towards the healthy range as they grow. You can do this using the Healthy Weight tool at www.nhs.uk/tools/pages/healthyweightcalculator.aspx.

If you are concerned about the result and would like further information, please phone us on the number at the top of this letter. **[If PCT is proactively following up overweight children:** We will also contact you soon to offer you further information**]**.

Figure C1.2 - Change4Life leaflet

Appendix C2 – Sample Selection of Children

Table C2.1 – Descriptive statistics of the original and estimation samples – Millennium Cohort Study

	Panel A – All children (England)			Panel B – Estimation sample after sampling decisions		
	Mean	SD	N	Mean	SD	N
Child characteristics						
Child is male	0.51	0.50	8,792	0.50	0.50	5,560
Age in months	133.82	4.10	8,792	133.63	3.92	5,560
White	0.75	0.43	8,789	0.78	0.42	5,560
Speak (mainly) English	0.90	0.30	8,792	0.91	0.29	5,560
Excellent or very good health	0.85	0.35	8,716	0.86	0.35	5,558
BMI	19.16	3.66	8,512	19.23	3.67	5,362
Mother characteristics						
Age	40.00	5.70	8,792	40.10	5.63	5,560
White	0.73	0.44	8,792	0.75	0.43	5,560
Mixed	0.01	0.11	8,792	0.01	0.10	5,560
Indian	0.04	0.19	8,792	0.03	0.17	5,560
Pakistani and Bangladeshi	0.10	0.30	8,792	0.09	0.28	5,560
Black	0.04	0.21	8,792	0.04	0.20	5,560
Other groups	0.02	0.15	8,792	0.02	0.13	5,560
Ethnicity missing	0.06	0.23	8,792	0.06	0.23	5,560
No education	0.16	0.37	8,792	0.15	0.36	5,560
Below O Level	0.14	0.34	8,792	0.13	0.34	5,560
O Level	0.31	0.46	8,792	0.33	0.47	5,560
A Level	0.08	0.28	8,792	0.09	0.28	5,560
Diploma in HE	0.08	0.28	8,792	0.09	0.28	5,560
Degree or higher	0.17	0.37	8,792	0.16	0.36	5,560
Education missing	0.06	0.23	8,792	0.05	0.23	5,560
Married/cohabiting	0.65	0.48	8,792	0.66	0.47	5,560
Single or other	0.31	0.46	8,792	0.31	0.46	5,560
Partnership missing	0.04	0.18	8,792	0.02	0.15	5,560
In work or on leave	0.62	0.48	8,792	0.66	0.47	5,560
Not in work	0.35	0.48	8,792	0.32	0.47	5,560
Missing	0.03	0.16	8,792	0.02	0.15	5,560
Household characteristics						
Weekly income	406.08	185.26	8,792	410.66	181.30	5,560
Number of siblings in HH	1.62	1.17	8,792	1.60	1.14	5,560
Settlement type						
Urban > 10K	0.83	0.38	8,792	0.84	0.37	5,560
Town and Fringe	0.09	0.28	8,792	0.08	0.28	5,560
Village, Hamlet and Isolated Dwelling	0.08	0.28	8,792	0.08	0.27	5,560
Region						
North East	0.04	0.21	8,792	0.05	0.22	5,560
North West	0.13	0.33	8,792	0.13	0.34	5,560
Yorkshire and the Humber	0.12	0.32	8,792	0.12	0.33	5,560
East Midlands	0.08	0.28	8,792	0.08	0.28	5,560
West Midlands	0.12	0.32	8,792	0.12	0.33	5,560
East of England	0.11	0.31	8,792	0.11	0.31	5,560
London	0.15	0.36	8,792	0.13	0.34	5,560

Continued on next page

Table C2.1 – Continued from previous page

South East	0.16	0.36	8,792	0.15	0.36	5,560
South West	0.09	0.29	8,792	0.10	0.30	5,560
Not app in IoM Ch Is	0.00	0.02	8,792	-	-	-
Overall Index of multiple deprivation						
Most deprived decile	0.14	0.35	8,786	0.15	0.35	5,559
10 - <20%	0.12	0.32	8,786	0.11	0.31	5,559
20 - <30%	0.10	0.30	8,786	0.10	0.31	5,559
30 - <40%	0.09	0.29	8,786	0.09	0.28	5,559
40 - <50%	0.09	0.29	8,786	0.09	0.29	5,559
50 - <60%	0.09	0.29	8,786	0.09	0.29	5,559
60 - <70%	0.09	0.28	8,786	0.09	0.28	5,559
70 - <80%	0.09	0.28	8,786	0.09	0.28	5,559
80 - <90%	0.09	0.28	8,786	0.09	0.29	5,559
Least deprived decile	0.10	0.30	8,786	0.09	0.29	5,559

Notes: Panel A is based on the initial sample of MCS children interviewed for the fifth sweep in England. Panel B shows our final sample after our sampling decisions: (1) children were in Year 6, (2) children were successfully merged to the date of NCMP school visit, (3) children were also interviewed for the fourth sweep of the MCS, (4) children were not interviewed within 6 weeks after the school visit.

Table C2.2 – Descriptive statistics of the original and estimation samples – UK Household Longitudinal Study

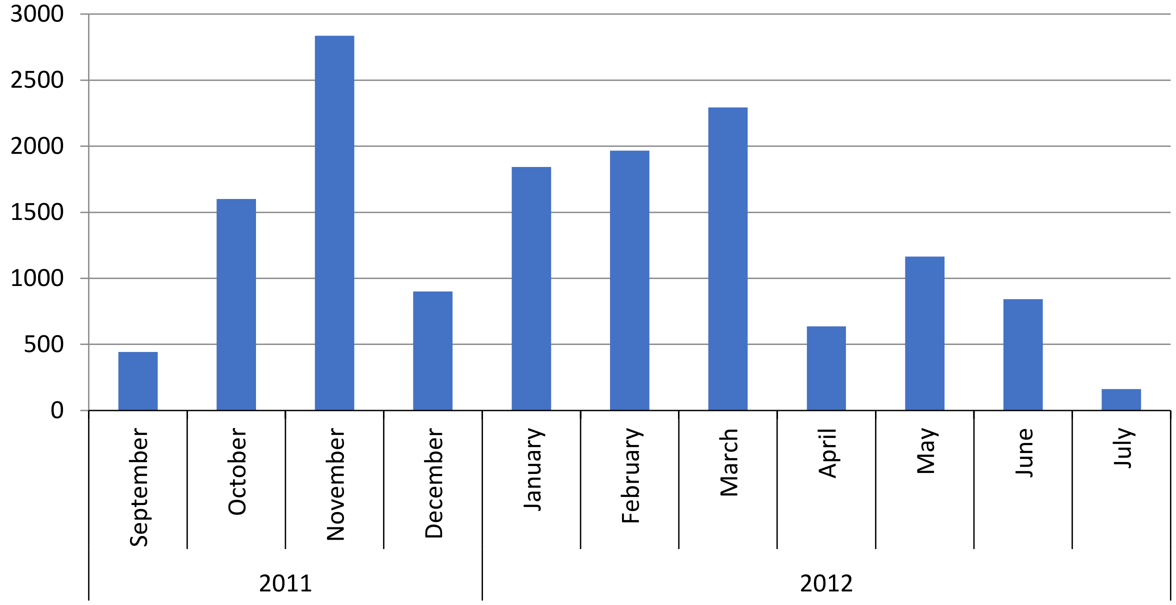
	Panel A – All children in Year 6 with youth information			Panel B – Estimation sample after sampling decisions		
	Mean	SD	N	Mean	SD	N
Child characteristics						
Child is male	0.50	0.50	3,829	0.49	0.50	2,435
Age in months	132.0	4.93	3,827	132.10	5.03	2,433
Mother characteristics						
Age	40.03	5.69	3,829	39.90	5.67	2,435
Single or other	0.30	0.46	3,829	0.32	0.47	2,435
Married or cohabiting	0.64	0.48	3,829	0.65	0.48	2,435
Partnership missing	0.06	0.24	3,829	0.03	0.18	2,435
GCSE or below	0.45	0.50	3,829	0.46	0.50	2,435
Further education	0.09	0.28	3,829	0.09	0.28	2,435
Foundation degree	0.13	0.34	3,829	0.14	0.35	2,435
Degree or above	0.23	0.42	3,829	0.23	0.42	2,435
Education missing	0.10	0.31	3,829	0.08	0.27	2,435
White	0.69	0.46	3,829	0.73	0.45	2,435
Not white	0.27	0.44	3,829	0.25	0.44	2,435
Ethnicity missing	0.05	0.21	3,829	0.03	0.16	2,435
In work or on leave	0.62	0.48	3,829	0.64	0.48	2,435
Not in work	0.33	0.47	3,829	0.34	0.47	2,435
Missing	0.05	0.21	3,829	0.03	0.16	2,435
HH characteristics						
Income (total hh net)	3,291.0	2,014.2	3,829	3,202.3	1,911.3	2,435
HH size	4.50	1.37	3,829	4.47	1.35	2,435
Number of children in HH	2.34	1.06	3,829	2.35	1.04	2,435
Own accommodation	0.63	0.48	3,829	0.63	0.48	2,435
Settlement type						
Urban	0.84	0.37	3,829	0.83	0.38	2,435
Region						
North East	0.05	0.21	3,829	0.05	0.22	2,435
North West	0.13	0.33	3,829	0.13	0.34	2,435
Yorkshire and the Humber	0.10	0.30	3,829	0.11	0.31	2,435
East Midlands	0.09	0.28	3,829	0.08	0.28	2,435
West Midlands	0.11	0.32	3,829	0.11	0.32	2,435
East of England	0.10	0.30	3,829	0.11	0.31	2,435
London	0.19	0.40	3,829	0.17	0.37	2,435
South East	0.14	0.34	3,829	0.14	0.35	2,435
South West	0.09	0.29	3,829	0.10	0.30	2,435

Notes: Panel A is based on the initial sample of UKHLS children in Year 6 with information of the youth questionnaire interviewed at 1-8 waves. Panel B shows our final sample after our sampling decisions: (1) children were successfully merged to the date of NCMP school visit, (2) children were not interviewed within 6 weeks after the school visit.

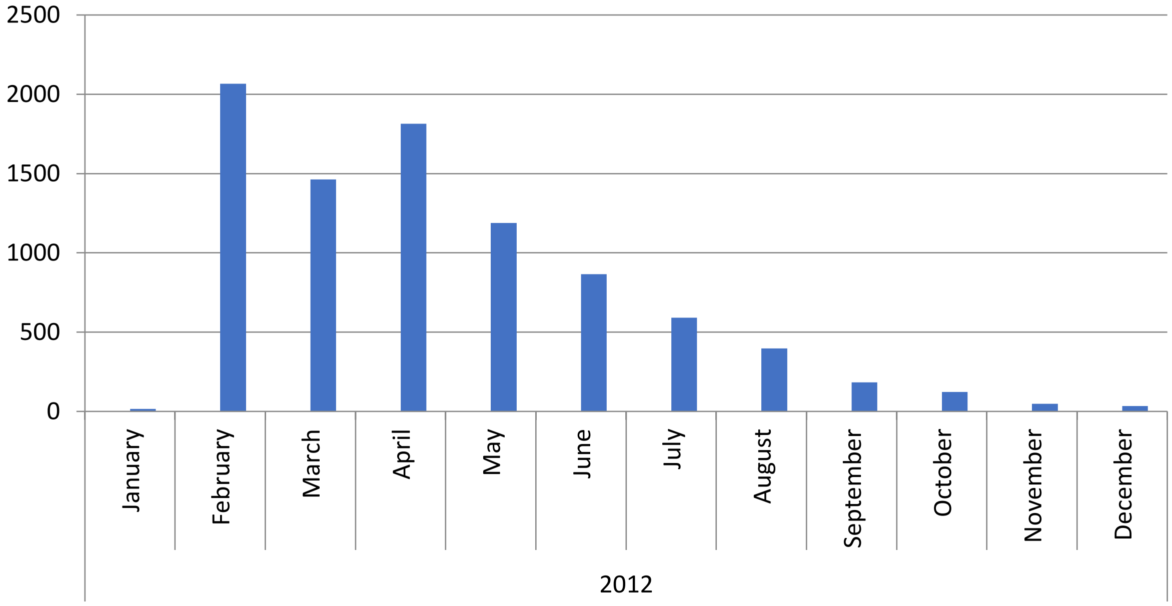
Appendix C3 – **Identifying Assumptions Tests**

Figure C3.1 – Timing of NCMP school visits and MCS interviews

(a) Timing of NCMP school visits



(b) Timing of MCS sweep 5 interviews



Notes: Panels A shows the distribution of school visits throughout the 2011/12 academic year. Panel B shows the distribution of MCS interviews for the fifth sweep throughout 2012.

Table C3.1 – Children characteristics by timing of NCMP visit

	BMI (1)	Overweight (2)	Obese (3)	Male (4)	Black (5)
September	Base	Base	Base	Base	Base
October	0.126	0.002	0.0002	0.034	-0.002
	(0.322)	(0.042)	(0.036)	(0.043)	(0.018)
November	-0.067	-0.004	-0.005	-0.008	0.019
	(0.315)	(0.041)	(0.035)	(0.042)	(0.018)
December	0.146	0.010	0.021	0.018	0.016
	(0.342)	(0.045)	(0.038)	(0.046)	(0.019)
January	-0.337	-0.049	-0.051	-0.007	0.015
	(0.323)	(0.042)	(0.036)	(0.043)	(0.018)
February	-0.090	-0.018	-0.029	0.001	0.036**
	(0.322)	(0.042)	(0.036)	(0.043)	(0.018)
March	-0.315	-0.034	-0.025	0.016	0.010
	(0.315)	(0.041)	(0.035)	(0.042)	(0.018)
April	-0.452	-0.032	-0.030	0.007	0.041**
	(0.356)	(0.047)	(0.040)	(0.048)	(0.020)
May	-0.157	-0.036	0.0003	0.051	0.074***
	(0.338)	(0.044)	(0.038)	(0.045)	(0.019)
June	0.0270	0.011	-0.018	0.028	0.045***
	(0.346)	(0.045)	(0.039)	(0.046)	(0.020)
July	0.796	0.003	-0.014	0.043	0.002
	(0.519)	(0.068)	(0.058)	(0.070)	(0.017)
N	7,008	7,008	7,008	7,208	7,207

Notes: The sample includes MCS Sweep 5 children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Columns present results from separate linear regressions of children characteristics on month of NCMP school visit. Robust standard errors clustered at the individual level are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table C3.2 – Children characteristics by timing of MCS interview

	Male (1)	Black (2)	More deprived areas (3)	Urban area (4)
February	Base	Base	Base	Base
March	0.019	0.003	-0.019	-0.031**
	(0.019)	(0.008)	(0.019)	(0.014)
April	0.002	0.003	-0.020	-0.015
	(0.018)	(0.008)	(0.017)	(0.013)
May	0.024	-0.016*	-0.050**	-0.021
	(0.020)	(0.009)	(0.020)	(0.015)
June	0.001	-0.014	-0.045**	0.009
	(0.022)	(0.009)	(0.022)	(0.016)
July	0.054**	-0.024**	-0.005	-0.034*
	(0.026)	(0.011)	(0.026)	(0.019)
August	0.034	-0.021	-0.037	-0.012
	(0.031)	(0.013)	(0.031)	(0.023)
September	0.008	0.147**	0.225	-0.048
	(0.159)	(0.068)	(0.158)	(0.118)
October	0.508	-0.053	0.425	0.152
	(0.500)	(0.214)	(0.497)	(0.372)
N	7,008	7,007	7,007	7,008

Notes: The sample includes MCS Sweep 5 children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Columns present results from separate linear regressions of children characteristics on month of MCS interview. Neighbourhood is defined as more deprived if index of multiple deprivation falls into the bottom 50% of IMD distribution. Robust standard errors clustered at the individual level are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table C3.3 – Balance between treatment and control groups on characteristics of the child, mother and household

	Panel A – All children				Panel B – Normal weight children				Panel C – Overweight children			
	Control group (1)	Treatment group (2)	Difference (3)	p-value (4)	Control group (1)	Treatment group (2)	Difference (3)	p-value (4)	Control group (1)	Treatment group (2)	Difference (3)	p-value (4)
Child characteristics												
Age in months	132.72	134.03	-1.30	0.00	132.79	134.05	-1.26	0.00	132.64	133.95	-1.31	0.00
Male	0.50	0.49	0.01	0.47	0.49	0.49	0.00	0.98	0.51	0.50	0.01	0.64
Mother characteristics												
Age	40.44	39.99	0.44	0.00	40.48	39.93	0.55	0.00	40.28	40.11	0.17	0.54
Single	0.33	0.31	0.02	0.19	0.33	0.29	0.04	0.02	0.34	0.35	-0.01	0.59
Married/cohabiting	0.67	0.69	-0.02	0.21	0.67	0.71	-0.04	0.02	0.66	0.65	0.01	0.54
Partnership missing	0.00	0.00	-0.00	0.31	0.00	0.00	0.00	-	0.00	0.00	-0.00	0.31
White ethnicity	0.74	0.76	-0.02	0.07	0.76	0.78	-0.02	0.27	0.71	0.74	-0.03	0.16
Not White	0.21	0.18	0.03	0.02	0.19	0.17	0.02	0.26	0.25	0.20	0.04	0.02
Ethnicity missing	0.05	0.05	-0.00	0.52	0.05	0.05	0.00	0.89	0.05	0.06	-0.01	0.20
No education	0.14	0.15	-0.01	0.24	0.13	0.15	-0.02	0.16	0.17	0.17	0.00	1.00
Below A level	0.45	0.47	-0.02	0.23	0.44	0.45	-0.01	0.70	0.46	0.49	-0.03	0.25
A level	0.10	0.08	0.02	0.04	0.11	0.09	0.02	0.27	0.09	0.07	0.02	0.09
Above A level	0.26	0.24	0.02	0.19	0.27	0.26	0.01	0.47	0.23	0.21	0.02	0.33
Education missing	0.05	0.05	-0.00	0.55	0.05	0.05	0.00	0.86	0.05	0.06	-0.01	0.22
FT resident in hh	0.99	0.99	0.00	0.64	0.99	0.99	0.00	0.25	0.99	1.00	-0.00	0.24
In work or on leave	0.69	0.66	0.02	0.06	0.69	0.67	0.02	0.33	0.68	0.64	0.04	0.08
Household Characteristics												
Number of siblings in household	1.59	1.60	-0.01	0.66	1.62	1.64	-0.02	0.66	1.54	1.56	-0.02	0.68
Number of other people in household	4.48	4.49	-0.02	0.62	4.51	4.55	-0.04	0.43	4.42	4.42	-0.00	0.98
N	1,376	4,047			897	2,582			479	1,455		

Notes: The sample includes MCS Sweep 5 children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Treated (control) children are defined as those whose MCS Sweep 5 interview took place after (before) the date of the NCMP school visit. The group of normal weigh children includes underweight and normal weight children. The group of overweight children includes overweight and very overweight children. The number of normal weight and overweight children does not equal to the total number of children due to missing information on BMI for some of them. In each panel columns (1) and (2) show means for control and treatment groups, respectively, column (3) shows differences in means between control and treatment groups, column (4) shows p-values difference of means.

Appendix C4 – Results Supplementary Material

Table C4.1 - Comparison of unadjusted (naïve) and adjusted (FDR q-value) p-values that correspond to Tables 3.2-3.6

	All children		Normal weight children		Overweight children	
	Naïve p-value	FDR q-value	Naïve p-value	FDR q-value	Naïve p-value	FDR q-value
BMI	0.715	1.000	-	-	-	-
Body fat percentage	0.942	1.000	-	-	-	-
Probability of overweight	0.721	1.000	-	-	-	-
Physical activity index	0.290	1.000	0.426	1.000	0.493	1.000
Sedentary behaviour index	0.706	1.000	0.524	1.000	0.271	1.000
Fruit intake	0.113	1.000	0.179	1.000	0.479	1.000
Child is bullied by children (self-reported)	0.230	1.000	0.729	1.000	0.165	1.000
Child is bullied by children (parent-reported)	**0.100**	1.000	0.261	1.000	0.331	1.000
Child hurt other children	0.619	1.000	0.706	1.000	0.445	1.000
Breakfast skipping	0.383	1.000	**0.095**	1.000	**0.001**	**0.017**
Double breakfast	0.717	1.000	0.895	1.000	0.666	1.000
Unhappy at school	0.914	1.000	0.254	1.000	0.125	1.000
Tired at school	**0.061**	1.000	0.184	1.000	0.270	1.000
Total difficulties score	0.823	1.000	0.470	1.000	0.387	1.000

Notes: This is a table of p-values and q-values corresponding to the baseline model specification in Tables 3.2-3.6. Q-values are p-values that are adjusted for the number of multiple hypotheses being tested. First column (Naïve p-value) is unadjusted p-values. Second column (FDR q-value) is sharpened two-stage q-values introduced by Benjamini, Krieger, and Yekutirli (2006).

Table C4.2 – Effect of the NCMP on five Strengths and Difficulties dimensions

	All children (1)	Normal weight children (2)	Overweight children (3)
Emotional problems	-0.001	-0.014	0.012
SE	(0.020)	(0.025)	(0.033)
Mean	0.66	0.66	0.65
N	10,984	6,862	3,832
Conduct problems	-0.020	-0.029	-0.003
SE	(0.018)	(0.023)	(0.033)
Mean	0.65	0.63	0.67
N	10,984	6,862	3,832
Inattention problems	0.029	0.048*	-0.008
SE	(0.014)	(0.017)	(0.024)
Mean	0.88	0.87	0.89
N	10,984	6,862	3,832
Peer relationship problems	0.022	0.014	0.033
SE	(0.021)	(0.026)	(0.034)
Mean	0.59	0.57	0.61
N	10,984	6,862	3,832
Antisocial behaviour problems	-0.016	-0.008	-0.034
SE	(0.021)	(0.027)	(0.036)
Mean	0.60	0.61	0.59
N	10,414	6,512	3,832
Controls			
Month of interview	Yes	Yes	Yes
Individual and family	Yes	Yes	Yes
Region/Settlement type/ IMD	Yes	Yes	Yes
Duration b/t the intervention and the interview	Yes	Yes	Yes

Notes: The sample includes MCS children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Treated (control) children are defined as those whose MCS Sweep 5 interview took place after (before) the date of the NCMP school visit. To create outcomes, we follow Meroni et al. (2018) and recode all behavioural score variables into dummies, which take a value of 1 if the child has a score larger than 0 for the emotional symptoms, conduct, inattention and peer relationship problems dimensions and lower than 10 for the prosocial behaviour dimension. Thus, the outcomes indicate the presence of problematic/antisocial behaviour in each of five dimensions. The group of normal weigh children includes underweight and normal weight children. The group of overweight children includes overweight and very overweight children. The number of normal weight and overweight children does not equal to the total number of children due to missing information on BMI for some of them. Results are from separate linear regressions. Robust standard errors clustered at the individual level are in parentheses. See notes to Table 3.2 for details in specifications. Means calculated for the treatment group at the baseline. *p<0.10, **p<0.05, ***p<0.01. Significance of the results is based on the p-values adjusted for the number of multiple hypotheses being tested following Benjamini, Krieger, and Yekutirli (2006). See Table C4.3 for the comparison of adjusted and unadjusted p-values.

Table C4.3 - Comparison of unadjusted (naïve) and adjusted (FDR q-value) p-values that correspond to Table C4.2

	All children		Normal weight children		Overweight children	
	Naïve p-value	FDR q-value	Naïve p-value	FDR q-value	Naïve p-value	FDR q-value
Emotional problems	0.970	1.000	0.564	1.000	0.711	1.000
Conduct problems	0.268	1.000	0.195	1.000	0.923	1.000
Inattention problems	**0.035**	1.000	**0.005**	**0.087**	0.749	1.000
Peer problems	0.296	1.000	0.597	1.000	0.339	1.000
Antisocial behaviour problems	0.443	1.000	0.759	1.000	0.357	1.000

Notes: This is a table of p-values and q-values corresponding to Table C4.2. Q-values are p-values that are adjusted for the number of multiple hypotheses being tested. First column (Naïve p-value) is unadjusted p-values. Second column (FDR q-value) is sharpened two-stage q-values introduced by Benjamini, Krieger, and Yekutirli (2006).

Table C4.4 – Table 3.7 continuation

	Child is bullied by children (self-reported)	Child is bullied by children (parent-reported)	Hurt others	Double breakfast	Total difficulties score
	(1)	(2)	(3)	(4)	(5)
Panel A - Child's gender					
Girls	0.082	0.006	-0.017	-0.009	-0.438
	(0.060)	(0.054)	(0.052)	(0.034)	(0.416)
Boys	0.034	0.063	-0.043	0.028	-0.081
	(0.055)	(0.045)	(0.054)	(0.031)	(0.849)
Δ	-0.048	0.056	-0.026	0.037	0.357
	(0.080)	(0.070)	(0.074)	(0.046)	(0.589)
N	3,504	3,440	3,504	3,832	3,578
Panel B - Mother's education					
Low	0.070	0.063	-0.027	0.019	0.110
	(0.051)	(0.045)	(0.048)	(0.028)	(0.372)
High	0.045	0.002	-0.024	-0.034	-0.927
	(0.073)	(0.058)	(0.062)	(0.043)	(0.521)
Δ	-0.025	-0.061	0.003	-0.053	-1.037
	(0.088)	(0.073)	(0.077)	(0.050)	(0.621)
N	3,304	3,250	3,308	3,620	3,380
Panel C – Mother's partnership status					
Single	0.081	0.030	0.036	-0.029	-0.242
	(0.069)	(0.056)	(0.068)	(0.041)	(0.489)
Partnered	0.033	0.033	-0.077	0.033	-0.259
	(0.053)	(0.044)	(0.044)	(0.027)	(0.383)
Δ	0.048	-0.003	0.113	-0.061	0.017
	(0.085)	(0.073)	(0.080)	(0.049)	(0.616)
N	3,428	3,364	3,426	3,748	3,500
Panel D – Family income					
Low	0.036	-0.030	0.003	-0.014	-0.341
	(0.060)	(0.052)	(0.058)	(0.033)	(0.461)
High	0.084	0.101	-0.065	0.034	-0.205
	(0.055)	(0.046)	(0.048)	(0.031)	(0.364)
Δ	0.048	0.131	-0.068	0.048	0.135
	(0.080)	(0.070)	(0.074)	(0.045)	(0.581)
N	3,504	3,440	3,504	3,832	3,578
Panel E – Index of multiple deprivation					
More deprived	0.088	0.034	0.021	-0.011	-0.280
	(0.054)	(0.048)	(0.052)	(0.032)	(0.401)
Less deprived	0.013	0.032	-0.095	0.038	-0.256
	(0.062)	(0.051)	(0.056)	(0.031)	(0.448)
Δ	-0.075	-0.002	-0.117	0.049	0.024
	(0.081)	(0.070)	(0.075)	(0.045)	(0.598)
N	3,504	3,440	3,504	3,832	3,578

Notes: The sample includes MCS children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Treated (control) children are defined as those whose MCS Sweep 5 interview took place after (before) the date of the NCMP school visit. Results are from separate linear regressions. Robust standard errors clustered at the individual level are in parentheses. See notes to Table 3.2 for details in baseline specifications. Mother is defined as having high education if she has A level and above. Mother is defined as single if she is not married and does not have a partner. Low-income family is defined as a family with total weekly income equal or lower than £391.7 which is the mean income for the sample of families with overweight children. Neighbourhood is defined as less deprived if index of multiple deprivation falls into the top 50% of IMD distribution. *p<0.10, **p<0.05, ***p<0.01. Significance of the results is based on the p-values adjusted for the number of multiple hypotheses being tested following Benjamini, Krieger, and Yekutirli (2006). See Table C4.5 for the comparison of adjusted and unadjusted p-values.

Table C4.5 – Comparison of unadjusted (naïve) and adjusted (FDR q-value) p-values that correspond to Table 3.7 and Table C4.4

		Physical activity index	Sedentary behaviour index	Fruit intake	Child is bullied by children (self-reported)	Child is bullied by children (parent-reported)	Hurt others	Breakfast skipping	Double breakfast	Unhappy at school	Tired at school	Total difficulties score
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A - Child's gender												
Girls	Naïve p-value	0.809	0.124	0.123	0.173	0.910	0.751	**0.019**	0.798	0.425	0.442	0.292
	FDR q-value	1.000	0.705	0.705	0.763	1.000	1.000	0.265	1.000	0.908	0.908	0.877
Boys	Naïve p-value	0.469	0.946	0.635	0.537	0.163	0.430	**0.014**	0.361	0.162	0.415	0.849
	FDR q-value	1.000	1.000	1.000	1.000	1.000	1.000	0.183	1.000	1.000	1.000	1.000
Δ	Naïve p-value	0.742	0.297	0.147	0.549	0.423	0.722	0.779	0.421	0.687	0.964	0.544
	FDR q-value	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Panel B - Mother's education												
Low	Naïve p-value	0.377	0.794	0.370	0.167	0.160	0.580	**0.004**	0.499	**0.031**	**0.023**	0.767
	FDR q-value	0.581	0.764	0.581	0.365	0.365	0.631	**0.047**	0.599	0.116	0.116	0.764
High	Naïve p-value	0.812	**0.092**	0.564	0.538	0.978	0.694	0.115	0.429	0.255	0.213	**0.075**
	FDR q-value	1.000	0.730	1.000	1.000	1.000	1.000	0.730	1.000	0.730	0.730	0.730
Δ	Naïve p-value	0.706	0.239	0.970	0.773	0.404	0.975	0.354	0.299	**0.025**	**0.015**	0.102
	FDR q-value	1.000	0.858	1.000	1.000	0.858	1.000	0.858	0.858	0.160	0.160	0.441
Panel C – Mother's partnership status												
Single	Naïve p-value	0.303	0.349	0.410	0.241	0.609	0.597	**0.000**	0.498	**0.015**	0.129	0.621
	FDR q-value	0.898	0.898	0.898	0.898	0.898	0.898	**0.001**	0.898	**0.082**	0.632	0.898
Partnered	Naïve p-value	0.758	0.484	0.884	0.524	0.454	**0.078**	0.610	0.219	0.567	0.942	0.500
	FDR q-value	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Δ	Naïve p-value	0.293	0.692	0.586	0.575	0.967	0.155	**0.002**	0.211	**0.020**	0.199	0.978
	FDR q-value	0.785	0.867	0.867	0.867	1.000	0.613	**0.023**	0.613	0.112	0.613	1.000

Continued on next page

Table C4.5 – Continued from previous page

Panel D – Family income												
Low	Naïve p-value	0.416	0.386	**0.069**	0.382	0.877	0.917	**0.002**	0.888	0.102	0.196	0.542
	FDR q-value	0.907	0.907	0.516	0.907	1.000	1.000	**0.012**	1.000	0.516	0.645	1.000
High	Naïve p-value	0.959	0.419	0.433	0.215	**0.028**	0.154	0.299	0.691	0.706	0.883	0.497
	FDR q-value	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Δ	Naïve p-value	0.508	0.901	**0.080**	0.784	0.382	0.287	**0.045**	0.851	0.358	0.408	0.990
	FDR q-value	1.000	1.000	0.786	1.000	1.000	1.000	0.786	1.000	1.000	1.000	1.000
Panel E – Index of multiple deprivation												
More deprived	Naïve p-value	**0.095**	0.570	0.654	0.105	0.473	0.678	**0.018**	0.734	**0.013**	**0.019**	0.485
	FDR q-value	0.202	0.668	0.668	0.202	0.668	0.668	**0.075**	0.668	**0.075**	**0.075**	0.668
Less deprived	Naïve p-value	0.360	**0.015**	0.628	0.834	0.536	**0.089**	**0.011**	0.228	0.651	0.235	0.568
	FDR q-value	0.924	**0.090**	1.000	1.000	1.000	0.365	**0.090**	0.603	1.000	0.603	1.000
Δ	Naïve p-value	**0.062**	**0.029**	0.935	0.358	0.973	0.120	0.938	0.280	**0.040**	**0.011**	0.967
	FDR q-value	0.172	0.154	1.000	0.443	1.000	0.206	1.000	0.389	0.154	0.138	1.000

Notes: This is a table of p-values and q-values corresponding to Table 3.7 and Table C4.4. Q-values are p-values that are adjusted for the number of multiple hypotheses being tested. First column (Naïve p-value) is unadjusted p-values. Second column (FDR q-value) is sharpened two-stage q-values introduced by Benjamini, Krieger, and Yekutirli (2006).

Table C4.6 – Characteristics of treated and control group children based on UKHLS

	N (1)	Control (2)	Treatment (3)	Difference (4)	p-value (5)
Child characteristics					
Age	2,433	129.70	134.24	-4.54	0.00
Male	2,435	0.48	0.50	-0.03	0.20
Mother characteristics					
Age	2,435	39.82	39.98	-0.16	0.48
White	2,435	0.72	0.73	-0.01	0.75
Married/cohabiting	2,435	0.64	0.66	-0.02	0.23
GCSE or below	2,435	0.46	0.47	-0.00	0.93
Further education	2,435	0.09	0.09	0.01	0.57
Foundation degree	2,435	0.14	0.14	-0.00	0.91
Degree or above	2,435	0.22	0.23	-0.01	0.39
In work or on leave	2,435	0.63	0.64	-0.01	0.52
Household characteristics					
Household size	2,435	4.48	4.46	0.02	0.71
N of children in HH	2,435	2.37	2.32	0.05	0.25
HH owns a house	2,419	0.63	0.63	0.00	0.94

Notes: The sample includes UKHLS children who were successfully merged to the date of NCMP school visit. Treated (control) children are defined as those whose UKHLS interview took place after (before) the date of the NCMP school visit. Columns (2) and (3) show means for control and treated children, respectively. Column (4) shows differences in means between control and treatment groups. Column (5) shows p-values difference of means.

Table C4.7– Effect of sending feedback letters on verbal ability and school test performance by the treatment exposure duration

	All children (1)	Normal weight children (2)	Overweight children (3)
Verbal ability			
Treatment*1 month	-0.927	-0.993	-1.198
	(1.292)	(1.635)	(2.179)
Treatment*2 months	-2.175	-3.244*	-0.136
	(1.392)	(1.788)	(2.226)
Treatment*3 months	-3.878**	-5.855***	-1.118
	(1.590)	(2.009)	(2.384)
Treatment*4 months	-3.791**	-0.703	-9.118***
	(1.566)	(1.888)	(2.750)
Treatment*5 months	0.775	0.950	0.835
	(1.782)	(2.115)	(3.300)
Treatment*6 and more months	-2.840*	-3.906*	-1.473
	(1.616)	(2.074)	(2.650)
N	10,702	6,734	3,756
Reading			
Treatment*1 month	-0.101**	-0.115**	-0.101
	(0.041)	(0.050)	(0.074)
Treatment*2 months	-0.007	0.013	-0.042
	(0.049)	(0.061)	(0.089)
Treatment*3 months	0.059	0.057	0.094
	(0.064)	(0.074)	(0.135)
Treatment*4 months	0.012	0.006	0.015
	(0.045)	(0.056)	(0.079)
Treatment*5 months	-0.009	-0.082	0.110
	(0.067)	(0.093)	(0.081)
Treatment*6 and more months	-0.098**	-0.116**	-0.042
	(0.044)	(0.054)	(0.077)
N	9,038	5,662	3,148
Mathematics			
Treatment*1 month	-0.049	-0.064	-0.042
	(0.039)	(0.050)	(0.066)
Treatment*2 months	-0.087*	-0.085	-0.078
	(0.049)	(0.062)	(0.085)
Treatment*3 months	0.043	0.001	0.137
	(0.060)	(0.072)	(0.112)
Treatment*4 months	-0.006	0.002	-0.014
	(0.042)	(0.054)	(0.073)
Treatment*5 months	-0.020	-0.048	0.030
	(0.046)	(0.060)	(0.074)
Treatment*6 and more months	-0.085**	-0.049	-0.125*
	(0.041)	(0.051)	(0.070)
N	9,044	5,666	3,150

Notes: For verbal ability, the sample includes MCS children who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Treated (control) children are defined as those whose MCS Sweep 5 interview took place after (before) the date of the NCMP school visit. For school test performance outcomes, the sample includes MCS children linked to the NPD dataset who were successfully merged to the date of NCMP school visit in the 2011/12 academic year. Treated (control) children are defined as those whose end of academic years exams took place after (before) the date of the NCMP school visit. The duration of treatment exposure is the number of months between the intervention (receiving a feedback letter) and the MCS interview. The group of normal weigh children includes underweight and normal weight children. The group of overweight children includes overweight and very overweight children. The number of normal weight and overweight children does not equal to the total number of children due to missing information on BMI for some of them. *p<0.10, **p<0.05, ***p<0.01.

Conclusion

This thesis analyses from different angles highly policy-relevant topics of maternal employment and children's health.

The first chapter provides evidence of the effects of public childcare expansion on maternal labour market outcomes in Russia. Between 2000 and 2015, Russia experienced an increase in childcare enrolment from 55% to 66.2%, reflecting an increase in childcare availability that was rolled out unequally across the Russian regions - the enrolment rate has increased from less than 1% in some regions to almost 35% in other regions. I exploit this variation across regions over time, conditioning on a rich set of economic time-varying regional characteristics, to establish causality between childcare availability and maternal employment. Using a wide range of labour market outcomes, the estimates reveal that there is a significant positive effect of childcare expansion on maternal employment both at the extensive and intensive margins. The effects are significantly smaller for single mothers which is in line with high level of employment among single mothers in Russia. A set of robustness checks confirm the validity of the identification strategy and the results.

Overall, the results show that an expansion of public childcare is an effective policy to increase employment of mothers of young children. The Russian labour market and social system are currently exposed to high risks as the share of pensioners is increasing while the share of working people is decreasing. Under these circumstances, the creation of appropriate conditions for maternal employment is one of the potential mechanisms in mitigating these problems. However, it is crucial to keep in mind that mothers' labour market behaviour is a complex phenomenon and that to help mothers to join the labour market a complex of measures is required. This could include creating flexible and part-time job opportunities or increasing the quality and flexibility (such as more flexible hours) of childcare.

In the second chapter, I further investigate the increase in maternal employment in Russia and study the effect of maternal employment on childhood obesity. In Russia, as in many other countries, the level and rate of change in childhood obesity over the last 20 years are a serious cause for concern. Most previous studies show that maternal employment is one of the contributors to this issue as the mother's decision to work leads to several changes in the household which may affect the child's weight. This chapter provides the first evidence on the relationship between maternal employment and children's weight in Russia. To estimate the causal effect of maternal employment on child's weight-related outcomes, I use an instrumental variable estimation approach. I use a plausibly exogenous variation in childcare availability for the youngest child in the household as an instrument for maternal employment to estimate the effect of maternal employment on the weight-related outcomes of older sibling. The results show that maternal employment leads to an increase in children's BMI z-score and probabilities to become overweight and obese. Exploring potential underlying mechanisms, I find that the adverse effect of maternal employment on child's weight-related outcomes can be explained through unhealthy diet and a reduction in physical activity.

It is very important to highlight that maternal employment is beneficial for mothers as well as children, for example, in terms of having "more egalitarian" views on gender roles, so the conclusion should not be to deter mothers from coming back to the labour market. Instead, understanding the mechanisms through which maternal employment might affect children's weight can shed light on policies to promote children's health. Based on my findings, beneficial policies might be those that increase physical activity in schools, increase quality of school meals, include curriculum on nutrition, help to form healthy habits, or promote health education among parents.

In the third chapter, we study the childhood overweight and obesity problem in England and evaluate the impact of sending parents information about the weight status of their child. Based on the National Child Measurement Programme, which is a school-based weight-screening programme to assess overweight and obesity levels in children in England, parents receive weight feedback letters that comprise information on child's body measurements, supporting materials, and a list of resources for further assistance. Based on the Millennium Cohort Study, we use variation in the timing of the NCMP school visits with respect to the timing of survey interview. We evaluate the effect of the information intervention on children's behaviour related to energy balance, unhealthy eating, psychological qualities, cognitive skills and school test performance. We find that in the short-run children's BMI, body fat percentage, the probability to become overweight as well as sedentary behaviour, physical activity, and fruit intake remain unaffected by the programme while it leads overweight children to skip breakfast. The heterogeneity analysis suggests that the breakfast skipping effect is concentrated among overweight children from families of lower socio-economic status. We also find that overweight children from families of lower socio-economic status whose parents have received feedback letters are more likely to feel unhappy and tired at school.

Our results suggest three main insights for policy. First, the information provided in the letters itself may not be enough to lead to changes in parent and child behaviour. In this case, further work is needed to identify what can encourage parents to change their children's lifestyle. Second, changes to the way information on the weight status of children is relayed to parents are needed to stop negative psychosocial consequences and motivate the intended outcomes. Third, the focus of health interventions to tackle obesity should also take into account socio-economic health inequalities, including social-environmental conditions that inform health-related decisions and behaviours.

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