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Spillovers of Health Education at School on Parents' Physical Activity

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Abstract

To prevent modern health conditions like obesity, cancer, cardiovascular illness, and diabetes, which have reached epidemic-like proportions in recent decades, many health experts argue students should receive Health Education (HED) at school. Although this type of education aims mainly to improve children's health profiles, it might affect other family members as well. This paper exploits state HED reforms as quasi-natural experiments to estimate the causal impact of HED received by children on their parents' physical activity. We use data from the Panel Study of Income Dynamics (PSID) for the period 1999-2005 merged with data on state HED reforms from the National Association of State Boards of Education (NASBE) Health Policy Database, and the 2000 and 2006 School Health Policies and Programs Study (SHPPS). To identify the spillover effects of HED requirements on parents' behavior we use a "differences-in-differences-in-differences" (DDD) methodology in which we allow for different types of treatments. We find a positive effect of HED reforms at the elementary school on the probability of parents doing light physical activity. Introducing major changes in HED increases the probability of fathers engaging in physical activity by 20 percentage points, although the probability of mothers being physically active did not seem to be affected. We find evidence of two channels that may drive these spillovers. We conclude that the gender specialization of parents in childcare activities, as well as information sharing between children and parents, may play a role in generating these indirect effects and in turn, in shaping healthy lifestyles within the household.

JEL Classification: I12, I18, I28, C21.
Keywords: physical activity; healthy lifestyles; indirect treatment effects; health education; triple differences.

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1 Introduction

Non-communicable diseases such as obesity, cancer, cardiovascular conditions, and diabetes have reached epidemic-like proportions in recent decades. Physical inactivity is one of the most important risk factors for these diseases (WHO, 2003). As a result, prevention increasingly involves changes in lifestyles, such as introducing the practice of regular physical activity in order to reduce risk factors (Kenkel, 2000). In the US, physically active individuals save an estimated US$ 500 per year in health care costs according to 1998 data (WHO, 2003).

Interactions within the family may crucially affect the "production" of healthy lifestyles. As Kenkel (2000) points out, the family is often identified as the unit of production of preventive practices. Previous literature on intra-household health decisions has focused on the interactions between spouses.[1] As well, the literature on intergenerational transmission of characteristics such as health, ability, education or income, has focused on the effects that parents' decisions can have on children's behaviors and outcomes.[2] However, little research has been done to evaluate the impact of children on parents' decisions, in particular on healthy lifestyle choices.

Schools can play a fundamental role in providing children with information about healthy lifestyles and health decisions, which may complement what they learn at home. At school, the knowledge about health is transferred to children through the implementation of specific curricular modules, often known as Health Education (HED).[3] Although HED is likely to affect children's health behaviors, it may be the case that parents are also affected by the education about preventive health care that their children acquire at school.[4] Moreover, the indirect effect of HED on parents may in turn enhance the effectiveness of HED delivered in the school setting in changing children's health behaviors.

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[1] For instance, see Clark and Etile (2006) on spousal correlation of smoking behavior.

[2] There are numerous studies quantifying the role of intergenerational transmission of parents' characteristics and behaviors on children's outcomes (Currie, 2009).

[3] According to the Centers for Disease Control and Prevention (CDC) "*Health Education is a planned, sequential, and developmentally appropriate instruction about Health Education designed to protect, promote, and enhance health literacy, attitudes, skills, and well-being*" (Kann et al., 2007).

[4] As stated by WHO (1999), there are several reasons for promoting healthy behaviors through schools. Schools are an efficient way to reach school-age children and their families in an organized way and students spend a great portion of their time in schools, where education and health programs can reach them at influential stages in their lives.

The first goal of this paper is to assess the existence of spillover effects of Health Education received by children at school on their parents.[5] We exploit the quasi-experiment provided by the changes in the state-level HED requirements in elementary schools implemented between the school years 1999/2000 and 2005/2006 in the US to quantify the effects of these programs on parents' physical activity.[6] Thus, the focus is on a policy that does not imply any transfer of resources to children -the targeted individuals- but instead provides them with new information. A second goal of this paper is to discuss the plausible channels through which children receiving HED at schools may affect the probability that their parents engage in physical activity.

To identify the spillover effects of HED policies, we use a "differences-in-differences-in-differences" (DDD) strategy, exploiting not only the time series and cross-state variation, but also within-state variation. The time dimension allows us to include year effects in order to capture national trends in physical activity. The variation across states allows for controlling for systematic differences in physical activity between people living in states that change their HED policies and people living in states that do not change their HED policies. The variation within states makes possible controlling for state-specific time trends that can be correlated with the change in HED policies. We are able to exploit the third difference because within each state there are individuals who were exposed to the treatment and others who were not. We show in Section 3 that there are remarkable differences in the pre-treatment trends in the outcomes of experimental versus non-experimental states, indicating that the implementation of HED policies is correlated with the behavior of the outcome of interest, which makes the use of a DDD estimator crucial here. The data we use is from the Panel Study of Income Dynamics (PSID) for the period 1999-2005, merged with data on state HED reforms from the State School Healthy Policy Database of the National Association of State Boards of Education (NASBE), and the 2000 and 2006 surveys of the School Health Policies and Programs Study (SHPPS).

Our results show evidence of a positive effect of HED received by children in elementary

[5] For instance, providing physical education at school has proven to be an effective way to improve healthy habits in children (Cawley et al., 2007).

[6] Further details on these policy reforms can be found in Section 2.

schools on their fathers' probability of engaging in physical activity. Introducing major reforms in HED in elementary schools makes a father exposed to this policy 20 percentage points more likely to be physically active than a comparable father not affected by the policy. We do not find evidence that the policy under analysis affects the decision of mothers to engage in physical activity.

We explore the channels behind these results, and find two non-exclusive explanations. First, we argue that a "role model" channel may explain the differential impact according to parent gender. In effect, the roles that mothers and fathers play for their children in the activities they usually do together are important for this result. Parents usually spend more time with their children doing gendered activities, such as physical activity in the case of fathers. Therefore, the promotion of healthy behaviors at school is more likely to have an effect on the behavior of fathers than that of mothers. Second, we find evidence consistent with an "information sharing" channel. We analyze the differential impact of HED reforms on individuals with low and high education and income levels and find greater effect on individuals with lower education and income levels. The existence of spillovers of HED on parents' lifestyles indicates that the interaction between children and parents plays a role in the formation of healthy lifestyles within the household, which must be taken into account to properly design policy interventions aimed at increasing the adoption of healthy lifestyles in a given community.

We perform a number of robustness checks that support the causality of the link between HED received by children in elementary schools and the probability of their fathers engaging in physical activity. First, we show that HED reforms do not affect outcomes that are not related to health behaviors, such as labor force participation. Second, we perform a "placebo" test on adults that were not exposed to the potential indirect effect of HED. The test shows that the placebo treatment group is not affected by the HED reforms, indicating that our results are not driven by other shocks contemporaneous to HED changes that systematically affected parents in the treatment group. Finally, we show that our results are also robust to alternative definitions of the control group.

This work is related to two strands of literature. First, it is related to the literature on policy evaluation that focuses on measuring the spillover effects of policy interventions on non-targeted individuals, also known as Indirect Treatment Effects (ITE). We focus on spillovers of a program targeting children on parents' behavior. We know of two interventions explicitly designed to have school-age children affecting their families and other community members health behaviors. Harre and Coveney (2000) evaluate two pilot studies implemented in a New Zeland school that taught children aged 7-11 years about burns and scalds hazards, and encouraged changes to the home environment and family practices through a take-home exercise. The intervention was designed to have an impact on the safety knowledge and behavior of primary school children and their parents. Nandha and Krishnamoorthy (2007) describe the role and effectiveness of school-based HED for social mobilization to promote the use of a fortified salt in an Indian district where lymphatic filariasis is endemic. HED through classroom sessions was the main motivational strategy used in this intervention that targeted community members to receive the message through children. Regrettably, both case studies lack the ability to state causality since the interventions were not randomly assigned and affected few individuals. There are a small number of works in the economic literature assessing the existence of spillovers on non-targeted individuals within the household that present reliable results by using neat identification methodologies. One exception is Bhattacharya et al. (2006), who analyze the effects of the School Breakfast Program (SBP) in the US on not only targeted children but also on adult (non-targeted) family members. They find that the SBP improves the quality of diets even for family members who were not directly exposed to the program.[7] The explanation for family spillover effects in this work is that the particular program reduces family budgetary constraints, freeing resources that may be redirected towards other household members. In contrast, we explore family spillovers occurring for non-budgetary reasons. There are also some works in this literature evaluating external effects at the community level instead of the family level. Some examples are

[7] Jacoby (2002) and Shi (2008) also analyze the effects of policies directed at children on non-eligible members of the household. They do not find evidence of family spillover effects. Jacoby (2002) analyzes the impact of a school meals program in the Philippines on caloric intake of targeted and non-targeted individuals in the family, whereas Shi (2008) studies resource reallocation in the household after a child receives a subsidy to cover school fees in rural China. These two papers find evidence of intra-household flypaper effects, that is no sizable reallocation of resources after children receive subsidies.

Angelucci and Giorgi (2009), Lalive and Cattaneo (2006), and Miguel and Kremer (2004).[8]

The second strand of literature related to our work consists of recent research evaluating the direct impact of particular aspects of health education at the school level on students' health outcomes and behaviors. Cawley et al. (2007) find positive effects of physical education requirements on the amount of time high school students engage in physical exercise, although they do not find any impact on Body Mass Index (BMI) or the probability of students being overweight. Also, McGeary (2009) assesses the effects of state-level nutrition education program funding on the BMI, the probability of obesity, and the probability of above normal weight.[9] Her results suggest that this funding is associated with reductions in BMI and in the probability of an individual having an above-normal BMI. Kahn et al. (2002), Salmon et al. (2007) and van Sluijs et al. (2007) summarize the results of several interventions aimed at evaluating the effectiveness of HED programs in changing children's physical activity. The three articles agree that the interventions reviewed provided insufficient evidence to assess the effectiveness of classroom-based HED and family-based social support interventions in increasing levels of physical activity or improving fitness because of inconsistent results among studies and various limitations in the studies design.[10]

2 Health Education Policies in the US

In the 1970s and 80s, research studies showed that healthy kids did better in school and scored higher on achievement tests. As a consequence, some states started to develop and implement HED programs in public schools. In the 1990s, many educators called for the creation of a set of national health education standards that states could use as a template.

[8] Angelucci and Giorgi (2009) evaluate the spillover effects of an aid program (PROGRESA) on entire local economies (villages) where the program was implemented. Lalive and Cattaneo (2006) find that PROGRESA significantly increases school enrollment among non-eligible families in the villages and that this rise is driven by a peer effect. Using evidence from a randomized experiment, Miguel and Kremer (2004) show that a deworming program substantially improved health and school participation among untreated children in both treatment schools and neighboring schools.

[9] This funding is allocated to public-school systems, public-health clinics, as well as public-service announcements and advertisements. McGeary's analysis goes beyond the effects of education at school, and therefore she computes the estimates for the entire population in each state.

[10] Among the several limitations in the studies the authors single out the lack of information on the randomization procedure, short duration of follow-ups, lack of precision of the physical activity outcome measures, and small sample sizes.

In 1995, the National Committee for Health Education Standards created national health education standards with K-12 benchmarks covering several content areas of health. In 1998, the Congress urged the Centers for Disease Control and Prevention (CDC) to "expand its support of coordinated health education programs in schools" (Wyatt and Novak, 2000).

As Kahn et al. (2002) explain, "*HED classes that provide information and skills related to decision making are usually multicomponent, with the curriculum typically addressing physical activity, nutrition, smoking, and cardiovascular disease. HED classes, taught in elementary, middle, or high schools, are designed to effect behavior change through personal and behavioral factors that provide students with the skills they need for rational decision making*".

State HED programs are typically characterized by two dimensions. The first is the health education curricula indicating the health related topics schools are *required* to teach. Panel A of Table 1 lists the topics included as potential HED requirements. We focus in these five topics because all of them may affect the knowledge about the benefits of being physically active.[11]

The second dimension is specific regulations to guarantee and strengthen the effective and coordinated implementation of health education in schools. We broadly refer to these regulations as *enforcements*. Panel B of Table 1 describes the three specific state requirements enforcing HED we focus on.[12]

In the period 1994 and 1999 school health policies at the state level generally remained unchanged, but important changes were detected between 1999 and 2005.[13] During this period, states either implemented HED programs for the first time or expanded one or both dimensions of pre-existing programs.

2.1 Databases for HED programs: NASBE and SHPPS

The information we use to define which states have HED programs and the degree of development of such programs -i.e., which topics were required and which enforcements were mandatory at different points in time- comes from two complementary sources: the NASBE

[11] Table 10 in the Appendix shows other topics that could potentially be included in an elementary school HED curriculum, but we do not take them into consideration because they are more related to sex education.
[12] The full list of potential requirements is shown in Table 10 in the Appendix.
[13] See Kann et al. (2001) and Kann et al. (2007) for more details on these changes in policies.

Table 1: HED Programs

A) Curricula: Topics covered
1) Alcohol- or Other Drug-Use Prevention
2) Emotional and Mental Health
3) Nutrition and Dietary Behavior
4) Physical Activity and Fitness
5) Tobacco-Use Prevention

B) Enforcements
1) State requires districts or schools to follow national or state health education standards or guidelines
2) State requires students in elementary school to be tested on health topics
3) State requires each school to have a HED coordinator

State School Health Policy Database and the School Health Policies and Programs Study (SHPPS).

The NASBE Database is a comprehensive set of laws and policies of all states in the US on more than 40 school health policies. It began in 1998 and is maintained with support from the Division of Adolescent and School Health (DASH) of the CDC. The database contains brief descriptions of laws, legal codes, rules, regulations, administrative orders, mandates, standards, resolutions, and other written means of exercising authority. While authoritative binding policies are the primary focus of the database, it also includes guidance documents and other non-binding materials that provide a detailed picture of a state's school health policies and activities.

The NASBE Database was designed to build upon the SHPPS, conducted by the CDC every 6 years since 1994. SHPPS is a nationwide survey that gathers detailed and comparable information about the characteristics of HED programs at the state level across elementary, middle, and high schools.[14] While SHPPS collects state policy information by means of survey questionnaires that are completed by state education agency personnel, the NASBE Database provides the legal support for the policies reported in SHPPS.

[14] SHPPS also gathers information about health-related programs at the district, school, and classroom levels. SHPPS analyzes eight components, one of which is the HED component. The remaining seven components are physical education and activity, health services, mental health and social services, nutrition services, a healthy and safe school environment, and faculty and staff health promotion.

Using the information provided by both sources we classified each state as either an *"Experimental State"*, if the state changed the HED program between 1999 and 2005, or as a *"Non-Experimental State"*, if no changes were introduced in the state HED program during the period. Tables 11 and 12 in the Appendix give a detailed description of HED programs in all states in 1999 and 2005.

3 Identification Strategy and Data

Our goal is to identify the spillover effects of elementary school HED policies implemented in certain states (the "experimental states") on the behavior of parents of elementary school-age children (the treatment group). Identifying this effect requires, as stated in Gruber (1994), controlling for any systematic shocks to the parents' outcome behavior in the experimental states that are correlated with, but not due to, changes in HED policies. To do so, we use a "differences-in-differences-in-differences" (DDD) approach that allows us to exploit the variation of HED policies across time (time dimension), across states (geographical dimension), and across different groups of individuals residing in the same state (individual dimension). That is, we compare the treatment individuals in experimental states to a set of control individuals in those same states and we measure the change in the treatments' relative outcome, relative to those of states that did not change HED policies. The identifying assumption requires that there is no contemporaneous shock affecting the relative outcome of the treatment group in the same state-year as the change in the HED policy.

We use a DDD identification strategy instead of the more commonly used "difference-in-differences" (DD) because it does not require the common trend assumption for treatment and control groups. We consider that this assumption will most likely be violated given the characteristics of the policy we are analyzing. In particular, the DD estimator of the spillover effects of HED policies on parents will be biased if the states that increased their HED requirements between 1999 and 2005 were those where health indicators were deteriorating more rapidly. To explore this possibility, we looked at health indicators of the population of adults with children below 18 years of age for pre-treatment periods (1994-1998), using data from the Behavioral Risk Factor Surveillance System (BRFSS).[15] As shown in Table 2, the proportion of individuals at risk because of overweight or obesity has increased more rapidly in experimental states than in non-experimental states. As well, between 1994 and 1998 the proportion of individuals with sedentary lifestyles has increased more in experimental than in non-experimental states. Therefore, the different trends in the outcomes of experimental versus non-experimental states indicate that the implementation of HED policies is correlated with the evolution of the outcome of interest, which makes the use of a DDD estimator crucial here.

Table 2: Lack of common trends between experimental and non-experimental states.

Year	Obesity 1 (%)		Obesity 2 (%)		Sedentary lifestyle (%)	
	Non-exper. states	Exper. states	Non-exper. states	Exper. states	Non-exper. states	Exper. states
1994	33,1	32,8	28,3	28,4	59,5	56,9
	(22824)	(13693)	(22824)	(13693)	(22824)	(13693)
1996	35,7	35,6	30,7	31,5	59,0	59,4
	(24612)	(16470)	(24612)	(16470)	(24612)	(16470)
1998	36,9	39,8	32,4	34,9	57,0	59,1
	(29052)	(20767)	(29052)	(20767)	(29052)	(20767)
Var. % ('94-'98)	11,6%	21,3%	14,4%	22,7%	-4,2%	4,0%

Source: BRFSS 1994, 1996, and 1998. Sample sizes in parentheses. *Definitions:* **Obesity 1 (%)**: Percentage of population (with children under 18 years old) at risk for obesity (greater than 120% of weight for height percent median). **Obesity 2 (%)**: Percentage of population (with children under 18 years old) at risk for overweight based on BMI. At risk defined as: >27.8 for males and >27.3 for females. **Sedentary lifestyle (%)**: Percentage of population (with children under 18 years old) at risk for sedentary lifestyle (sedentary or irregular physical activity profile).

Formally, let y_{it}^1 be the outcome for individual i at time t if she/he is exposed to the treatment. The outcome for the same individual if not exposed to the policy is y_{it}^0. Consequently, the impact of the policy on individual i is $y_{it}^1 - y_{it}^0$. The average treatment effect across treated individuals is $\mathbb{E}(y_{it}^1 - y_{it}^0 | elem = 1, S = 1)$, where $elem = 1$ denotes individuals who have elementary school-age children –the treatment group– and $S = 1$ denotes individuals who reside in a state where HED requirements changed between 1999 and 2005 –the experimental states–. The treated individual has both, $elem = 1$ and $S = 1$. In our setup, the methodological challenge is to obtain a way to estimate the missing counterfactual

[15] Note that we made use of this other dataset to evaluate the pre-treatment trends because the PSID does not contain information on health issues for this period of time.

$\mathbb{E}(y_{it}^0|elem = 1, S = 1, \tau_t = 1)$, where τ_t is a dummy variable, equal to one in 2005.

The population under analysis includes adults who have children living with them. The specification for the outcome is

$$
\begin{aligned}
y_{it} = \beta_0 &+ \beta_1 \tau_t + \beta_2 elem_i + \beta_3 S_i \\
&+ \beta_4 (elem_i \times \tau_t) + \beta_5 (S_i \times \tau_t) + \beta_6 (elem_i \times S_i) \\
&+ \beta_{7i} (\tau_t \times elem_i \times S_i) + u_{it},
\end{aligned} \tag{1}
$$

where $i = 1...N$ indexes individuals, and $t = 0, 1$ indexes time (0=before the policy change, 1999; 1=after the policy change, 2005). As stated before, τ_t is a dummy variable, equal to one in 2005, so it captures a nationwide time trend in the outcome; $elem_i$ is a dummy variable that takes the value one if individual i has at least one child of elementary-school-age, reflecting a group fixed effect in the outcome; and S_i is a dummy variable equal to one if individual i resides in an experimental state, that is, a state where the HED policy has changed between 1999 and 2005, allowing for an experimental-state fixed effect in the outcome. Moreover, the outcome may present differential time trends: (1) between parents of elementary school-age children versus parents of children of other ages and (2) between individuals living in experimental states and those living in non-experimental states. $(elem_i \times \tau_t)$ and $(S_i \times \tau_t)$ are the group-trend and the experimental state-trend respectively. Since parents of elementary school-age children in experimental states may have a different outcome than parents of children below and above elementary school age also living in experimental states, we include the group-state fixed effect captured by the interaction $(elem_i \times S_i)$. Finally, the triple interaction $(\tau_t \times elem_i \times S_i)$ is equal to one only for treated individuals in the after-policy-change time period: these are the parents of elementary school-age children residing in experimental states in 2005.

The treatment effect for individual i is β_{7i}, and the average treatment effect on the treated (ATT) is $\mathbb{E}(\beta_{7i}|elem_i = 1, S_i = 1)$. The ATT can be recovered by sequential differences, up to the unobserved temporary individual-specific shocks u_{it}, that is

$$
\begin{aligned}
ATT &= \mathbb{E}(\beta_{7i}|elem_i = 1, S_i = 1) \\
&= [\mathbb{E}(y_{i1} - y_{i0}|elem_i = 1, S_i = 1) - \mathbb{E}(y_{i1} - y_{i0}|elem_i = 1, S_i = 0)] \\
&\quad - [\mathbb{E}(y_{i1} - y_{i0}|elem_i = 0, S_i = 1) - \mathbb{E}(y_{i1} - y_{i0}|elem_i = 0, S_i = 0)],
\end{aligned} \tag{2}
$$

only if:

$$
\begin{aligned}
&\mathbb{E}(u_{i1} - u_{i0}|elem_i = 1, S_i = 1) - \mathbb{E}(u_{i1} - u_{i0}|elem_i = 1, S_i = 0) \\
&= \mathbb{E}(u_{i1} - u_{i0}|elem_i = 0, S_i = 1) - \mathbb{E}(u_{i1} - u_{i0}|elem_i = 0, S_i = 0).
\end{aligned} \tag{3}
$$

The assumption (3) will hold if the outcome of parents in the treatment group in experimental states relative to the outcome of the same group of parents in non-experimental states is affected in the same way by idiosyncratic temporary shocks as the relative outcome of parents in the non-treatment group in experimental and non-experimental states.

The sample analog of equation (2) is the DDD estimator of the ATT:

$$
\begin{aligned}
\widehat{ATT} &= (\bar{y}_1^{1,1} - \bar{y}_0^{1,1}) - (\bar{y}_1^{1,0} - \bar{y}_0^{1,0}) \\
&\quad - [(\bar{y}_1^{0,1} - \bar{y}_0^{0,1}) - (\bar{y}_1^{0,0} - \bar{y}_0^{0,0})],
\end{aligned} \tag{4}
$$

where $\bar{y}_t^{elem,S}$ is the average of the estimated outcome among individuals in group *elem*, residing in states S, at time t.

We can derive the same estimator for the ATT by recovering the missing counterfactual $\mathbb{E}(y_{it}^0|elem_i = 1, S_i = 1, \tau_t = 1)$, and rewriting the ATT as a function of unobserved counterfactuals using equation (1).

3.1 Database

We analyze the impact of HED policies on the behavior of adults who have children attending elementary school using data from two sources. The information on HED policies is obtained from the NASBE Database and the SHPPS, and the information on individuals comes from the Panel Study of Income Dynamics (PSID).

The PSID is a nationally representative longitudinal survey of individuals in the US (men, women, and children) and the family units in which they reside. In 1999, the PSID has expanded the set of health-related questions for the heads of family units and spouses, gathering information on health status, health behaviors, health insurance, and health care expenditures. We concentrate on the indirect effect of HED policies on levels of physical activity, which is one of the health behaviors reported in this survey. The PSID also provides detailed information about family income, as well as family composition and demographic variables, including the ages of family members, race, marital status, employment status and education. The PSID covers all states.

We base our analysis on the PSID survey years 1999 and 2005, using 1999 as the pre-reform period. The DDD design we use to identify the effect of interest does not require the use of a panel, but the identification is improved by using longitudinal data. Even though we do not specify a model for panel data, in our final sample about 90% of the observations correspond to individuals in a panel.

Our final sample consists of 10,663 observations that include parents of children living with them, who participated in the 1999 and/or 2005 PSID. It is worth noting that for most of the individuals we also have her/his spouse or partner in the sample. Given the way in which the PSID is designed, for some of the individuals we also have another relative in the sample, for instance siblings. This feature of our data makes it important to estimate robust standard errors clustered at the family level.

Besides the PSID, there are other household and individual surveys containing information about health lifestyles. However, these surveys do not include all the variables we require to conduct our analysis for the years in which we can identify HED policy changes. The National Health Interview Survey (NHIS) and the National Health and Nutrition Examination Survey (NHANES) gather rich information about health, health behaviors, and socio-demographic characteristics. However, in both surveys the public-use data files do not include the state identifiers necessary to create HED reform variables at state level. Also, the Behavioral Risk Factor Surveillance System (BRFSS) has information about health behaviors and demographic variables, but its information on the age of children is incomplete.[16] Finally, the National Longitudinal Survey of Youth 1979 (NLSY79) recovers some information about health behaviors, but the information about adult's physical activity is not available for the years for which we can construct the policy reform variables.

In the NASBE Database and in the SHPPS surveys we found that HED policies across states are highly heterogeneous, not only in terms of whether the state has implemented a HED program, but also regarding the scope and effectiveness in the implementation of such programs. Accordingly, we divided the non-experimental and experimental states into several groups. The non-experimental states are those states that did not change their HED policies between 1999 and 2005. We classified the non-experimental states into two groups: (1) States without HED programs in 1999 and 2005; (2) States with HED programs implemented by 1999, and without changes in 2005. We name groups (1) and (2) $S1$ and $S2$, respectively.

The experimental states are those that introduced any HED reforms between 1999 and 2005. There are three types of treatments (policies) that define three types of experimental states. Group $S3$ are states that, while having some topics in their HED curricula in 1999, did not introduce changes in those topics by 2005, but introduced some reforms in enforcements. Group $S4$ are states that, while having some topics required in 1999, increased the number of topics required by 2005, without introducing changes in enforcements. We consider that these two policies involve only minor changes in the already implemented HED programs, so in what follows we refer to these groups of states as "Moderate changes A" and "Moderate changes B", respectively. Finally, we include in the group $S5$ those states that for the first time introduced required topics at state level in their HED programs by 2005. We consider this policy to be a deep reform in HED, so we refer to group $S5$ as "Major changes". Some of the states introduced topics for the first time by 2005, while they did not make changes in enforcements, as were the cases of Arkansas and Florida. New Mexico and Wyoming introduced topics as mandatory by 2005, and simultaneously strengthened their HED policies by introducing new

[16] In the 1999 BRFSS survey, there are some available variables indicating the number of children younger than 5 years old, the number of children between 5 to 12 years old, and the number of children who are 13 through 17 years old within the household. Since November 2004 information about one randomly selected child, including age of the child, is available for some households. Hence, in those households where there is one child only, information about its age is available but there is missing information about the age of the other children in households with more than one child.

Table 3: States classification by changes in HED requirements between 1999 and 2005.

Group		Type of policy	Num. of states	Num. of Observations
Non-	$S1$	Does not have HED in 1999 and 2005	2	707
Experimental	$S2$	Existing HED in 1999 remains unchanged in 2005	18	6,417
	$S3$	Moderate changes A	5	1,099
Experimental	$S4$	Moderate changes B	5	1,156
	$S5$	Major changes	3	1,284
Total			33	10,663

Source: NASBE State School Health Policy Database, SHPSS surveys, and PSID database. The number of observations is the number of individuals in each group of states.

enforcements. A particular case is Texas, where all districts had a mandatory HED program in 1999 designed and implemented following district rules. It was not until 2005 that Texas implemented a coordinated HED program requiring all public schools in the state to have all topics in curriculum that followed national HED guidelines.

The information available in the NASBE database and SHPPS surveys regarding HED in the District of Columbia, Minnesota, and New Hampshire was not conclusive, so we could not classify these states and, consequently do not include them in our sample. We do not use states in our estimations for which the sample size was insufficient to control for temporal and group trends within the state.[17] Table 3 presents the aforementioned state classifications and the sample sizes for the states included in our sample.[18]

We modify the specification in equation (1) to introduce the previous classification of states, and to allow for differential effects of the policy across different types of treatment

[17] States excluded from our database due to small sample size are Alaska, Delaware, Hawaii, Idaho, Maine, Montana, Nevada, New Mexico, North Dakota, Oklahoma, Rhode Island, South Dakota, Vermont, West Virginia, and Wyoming. To check that the exclusion of these states does not drive our results we estimate the effect of interest including the states with small sample size and the results are comparable.

[18] The complete list of states in each group, and the number of observations in each state are reported in Table 13 in the Appendix.

$$
\begin{aligned}
y_{it} = {} & \beta_0 + \beta_1 \tau_t + \beta_2 elem_i + \sum_{k=2}^{5} \beta_{3,k} Sk_i \\
& + \beta_4 (elem_i \times \tau_t) + \sum_{k=2}^{5} \beta_{5,k} (Sk_i \times \tau_t) + \sum_{k=2}^{5} \beta_{6,k} (elem_i \times Sk_i) \\
& + \sum_{k=3}^{5} \beta_{7,k} (\tau_t \times elem_i \times Sk_i) + u_{it},
\end{aligned} \tag{5}
$$

where, as before, $i = 1...N$ indexes individuals, and $t = 0, 1$ indexes time (0=before policy, 1999; 1=after policy, 2005), and now $k = 1, ..., 5$ indexes state groups.[19]

In our setting, treated individuals, those exposed to changes in HED policies, are adults who reside in an experimental state, and who have elementary school-age children (6-10). The PSID does not provide information on whether a child is attending elementary school. However, it provides information on the age of children, allowing us to determine if individuals have school-age children.[20]

The control group consists of individuals who were unaffected by changes in state HED requirements; it includes adults who have elementary school-age children (6-10) living in states that did not change HED policies, that is, living in states that either did not implement HED policies or that, while having HED requirements in 1999, did not introduce any reform during the period. Furthermore, to control for possible correlation of state HED policies with unmeasured state trends in health and health behaviors, we use a sample of adults who have children living with them but not of elementary school age as a within-state comparison group. We group the non-treated individuals in three different control groups. We include in the Treatment-Non-Experimental group (Control 1) individuals with elementary school-age children residing in non-experimental states. The Control-Experimental group (Control 2) includes individuals with children not of elementary school-age residing in experimental states. Finally, in the Control-Non-Experimental group (Control 3) we include individuals with children above and below elementary school age residing in non-experimental states.

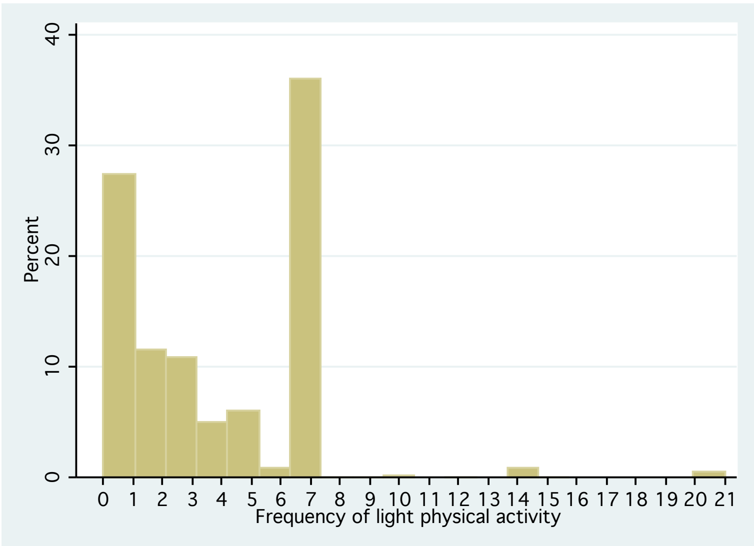
[19] $S1$ is the group of reference.

[20] Note that the dropout rate in elementary school is very low in the US. Therefore, by knowing the age of the children we are able to know whether the child is attending elementary education.

3.2 The outcome variable

Our outcome variable is light physical activity. PSID respondents are asked about their physical activity habits through two questions, the first about how often they do light physical activity and the second about the frequency of these activities (daily, weekly, monthly or annually). Based on these two questions we construct a variable indicating the number of times per week individuals do light physical activity. It is an ordinal variable with 49 different values, from 0 to 21. Its histogram is shown in Figure 1, according to which 15.4% of parents in the sample reported not doing any physical activity at all, while the remaining 84.6% reported engaging in light physical activity some number of times per week. Two well-differentiated mass points, at values 0 and 7, can be identified. As well, more than 12% of the observations lie in the interval (0,2), while another 34% are in the interval [2,7).

Figure 1: Histogram for the variable "frequency of light physical activity" (times per week).



Source: PSID

One limitation to using the number of times per week of light physical activity directly as our outcome variable is that there is no information in the PSID about the amount of time (minutes, hours) individuals spend each time they do physical activity. For example, in our database an individual that reports doing light physical activity three times per week is not necessarily doing more light physical activity than an individual that reports one session per week. This makes it very difficult to compare individuals who are physically active. To overcome this problem, we use as the outcome variable a binary variable that reflects whether an individual reports engaging in light physical activity at least once a week.

In what follows, the outcome variable is

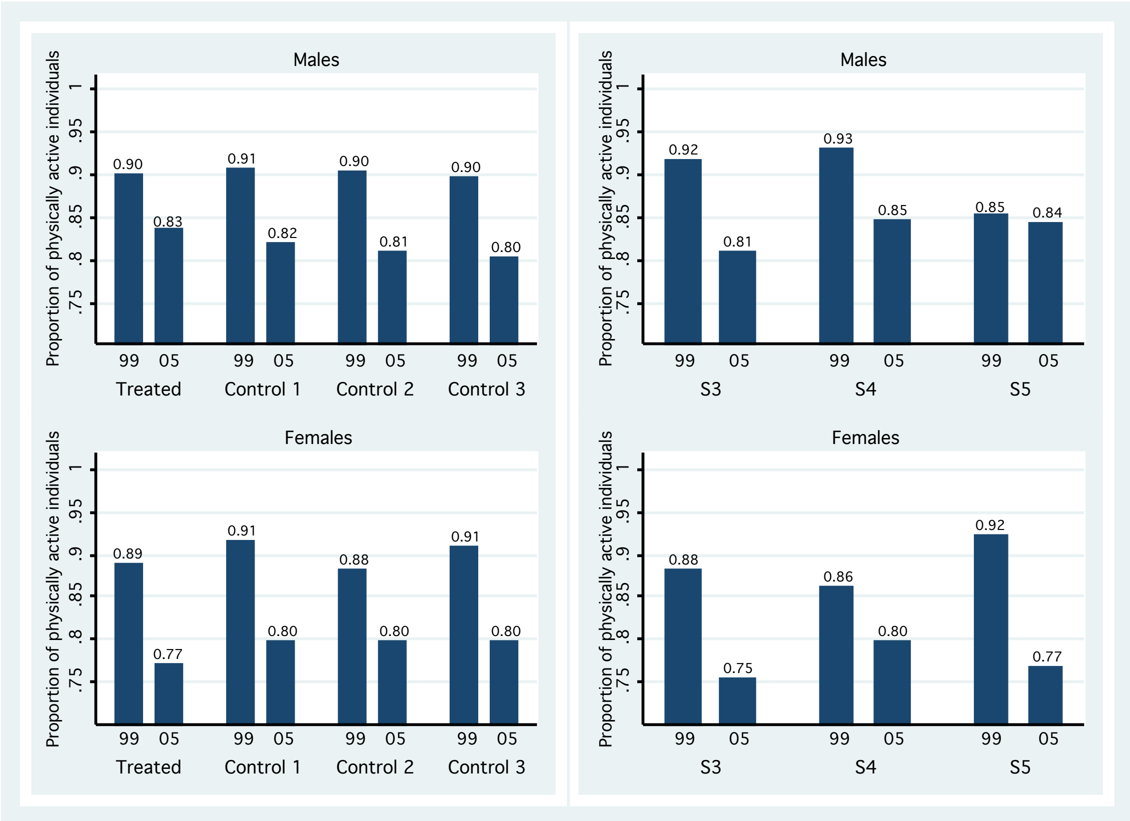
$$y_i = \begin{cases} 1 & \text{if } i \text{ does light physical activity at least once a week,} \\ 0 & \text{otherwise.} \end{cases}$$

The two graphs in the left panel in Figure 2 show the proportion of physically active individuals by gender in 1999 and 2005 for the treated and control groups. We observe a downward trend in all groups for both genders. In particular for the treated groups, the proportion of physically active individuals goes down by 7 percentage points for males, and by 12 percentage points for females. This simple Before-After estimator tells us that HED policies have had a negative impact on the outcome of interest. However, these estimates are obviously biased given that the average of the outcome variable in the three control groups also has a downward trend.

Exploring gender differences, we can see that females in the Treatment-Experimental group (Treated) present a larger drop in the proportion of physically active individuals than that observed for males in the same group. This suggests the need to take gender differences into account when estimating the effect of HED policies.

As we discussed above, the implementation and modification of HED policies between 1999 and 2005 were not homogeneous across states. Therefore, we can expect differences in the temporal evolution of the outcome of interest for treated individuals across the three groups of experimental states. The two graphs in the right panel in Figure 2 show the proportion of physically active treated individuals, by gender and by group of experimental states. In the first graph we see that in states belonging to group $S5$, the states that introduced major HED changes, the downward trend in the proportion of physically active males is substantially smaller than the corresponding downward trend in groups $S3$ and $S4$, the groups of states that introduced moderate HED changes. Moreover, the reduction in the proportion of physically

Figure 2: Proportion of physically active individuals by treated/control groups (left panel), and treated individuals by treatment groups (right panel), and by gender, in 1999 and 2005.



Notes: **Treated:** individuals with elementary school-age children in experimental states. Control 1: individuals with elementary school-age children in non-experimental states. **Control 2:** individuals without elementary school-age children in experimental states. **Control 3:** individuals without elementary school-age children in non-experimental states. The type of policies corresponding to the groups of states Sk are as follows. **S3:** Moderate changes A; **S4:** Moderate changes B; **S5:** Major changes. Source: PSID.

active males in the group $S5$ is lower than the fall in all three control groups. This relatively moderate downward trend for treated males in $S5$ experimental states suggests a positive effect of HED policies on the outcome variable, although it does not seem to be the case for females.

3.3 DDD estimation in a simple linear model

Table 4 presents the DDD estimate of the effect of changes in HED policy on the behavior of fathers for the group of states that introduced major HED changes, $S5$.[21]

[21]In Table 14 in the Appendix we report results for a similar exercise on mothers.

Panel A compares the change in the proportion of physically active males with elementary school-age children residing in $S5$ states to the change for the group of fathers with elementary school-age children in non-experimental $S1$ or $S2$ states. Each cell in the first two columns contains the proportion of physically active individuals for the corresponding group, before and after the HED reform, along with the standard errors and the number of observations. The Before-After estimate (Δ_E^T) of the effect is shown in the third column. There is a non-significant decrease in the proportion of physically active fathers with elementary school-age children in experimental states, and a significant fall in the proportion of physically active fathers with children of the same age in non-experimental states. The diff-in-diff estimator ($\Delta_E^T - \Delta_{NE}^T$), reported at the bottom of Panel A, is positive but non-significant. However, the DD estimate could be downwardly biased because, as we showed with the data from the BRFSS, the policy changes occurred in those states where health outcomes and health behaviors were deteriorating more rapidly. Hence, to control for potential state-specific trends, we additionally look at the evolution of outcomes for a control group within each state.

In Panel B of Table 4 we perform the same exercise for the groups of fathers with children above and below elementary school age. We find a larger fall in the proportion of physically active individuals in the experimental states, relative to the other states, as was expected according to the pre-treatment trends observed in the BRFSS data.

In panel C we compute the difference between the two DD estimators in panel A and B. This non-parametric DDD estimator indicates that there is a 13.8 percentage points significant increase in the relative proportion of physically active fathers of elementary school-age children, compared to the change in the relative proportion of physically active fathers with no elementary school-age children. This statistically significant DDD estimate provides some evidence on the existence of spillovers of HED on the physical activity of fathers.

In the following subsections we discuss how the DDD design can be expressed in a regression framework that will allow us to control for observable differences between individuals in the treated and control groups, as well as explicitly modeling the discrete support of the outcome variable.

Table 4: DDD estimator for males in $S5$.

	Before HED change	After HED change	Time difference	
A. Treatment individuals: with elementary school-age children				
Experimental states	0.851	0.843	-0.009	Δ_E^T
	(0.036)	(0.035)	(0.050)	
	[101]	[108]		
Non-experimental states	0.908	0.821	-0.087***	Δ_{NE}^T
	(0.012)	(0.016)	(0.020)	
	[606]	[563]		
Difference in difference			**0.078**	
			(0.054)	
B. Control Individuals: without elementary school-age children				
Experimental states	0.918	0.766	-0.152***	Δ_E^C
	(0.023)	(0.030)	(0.038)	
	[147]	[201]		
Non-experimental states	0.896	0.803	-0.093***	Δ_{NE}^C
	(0.011)	(0.012)	(0.016)	
	[834]	[1,162]		
Difference in difference			**-0.059**	
			(0.041)	
C. Non-parametric DDD estimator				
$\mathbf{DDD} = (\boldsymbol{\Delta}_{\mathbf{E}}^{\mathbf{T}} - \boldsymbol{\Delta}_{\mathbf{NE}}^{\mathbf{T}}) - (\boldsymbol{\Delta}_{\mathbf{E}}^{\mathbf{C}} - \boldsymbol{\Delta}_{\mathbf{NE}}^{\mathbf{C}})$			**0.138****	
			(0.068)	

Notes: Cells contain proportion of physically active individuals for the group identified. Standard errors are given in parentheses, and sample sizes in brackets. The non-experimental states are groups of states S1 and S2. Significance levels: * = 10%; ** = 5%; *** = 1%.

3.4 Allowing for covariates and gender differences

In Table 5 we report average values and standard errors of the outcome variable, and other demographic and socioeconomic characteristics for treated and control individuals in 1999 and 2005.

For each group, we find evidence of statistically significant differences in some observable characteristics between 1999 and 2005. These differences may produce changes in the observed proportion of physically active individuals between 1999 and 2005 that are not a consequence of changes in HED programs. To avoid a biased estimation of the effect of interest, we use a regression framework that allows us to control for temporal differences in observable

Table 5: Descriptive statistics: All individuals in the sample.

	Treated individuals			Control individuals		
	1999	2005	Difference	1999	2005	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Frequency of light physical	4.31	3.82	-0.49***	4.37	3.75	-0.62***
activity (times per week)	(3.09)	(3.26)		(3.09)	(3.23)	
Body Mass Index	27.11	27.59	0.48	26.53	27.74	1.21***
	(5.77)	(5.67)		(5.30)	(5.96)	
Proportion with Health condition	0.11	0.14	0.03*	0.14	0.17	0.03***
that limits daily activity	(0.32)	(0.35)		(0.34)	(0.37)	
Proportion of Female	0.56	0.57	0.01	0.55	0.57	0.02*
	(0.50)	(0.50)		(0.50)	(0.50)	
Age	36.13	36.15	0.02**	37.17	39.46	2.29***
	(6.34)	(6.84)		(8.25)	(9.92)	
Years of Education completed	13.01	13.22	0.21	12.79	13.05	0.26***
	(2.38)	(2.25)		(2.74)	(2.49)	
Num. of Children	2.62	2.58	-0.04	2.34	2.31	-0.03
	(1.33)	(1.26)		(1.25)	(1.20)	
Num. of Children	1.26	1.28	0.03	0.45	0.31	-0.14***
in elementary school	(0.50)	(0.52)		(0.72)	(0.60)	
Proportion of White	0.53	0.50	-0.03	0.56	0.54	-0.02*
	(0.50)	(0.50)		(0.50)	(0.50)	
Proportion of Married	0.77	0.75	-0.02	0.78	0.76	-0.02**
	(0.42)	(0.43)		(0.42)	(0.43)	
Proportion of Unemployed	0.04	0.04	0.00	0.03	0.04	0.01**
	(0.21)	(0.19)		(0.17)	(0.19)	
Proportion of Retired	0.00	0.00	0.00	0.00	0.01	0.01***
	(0.04)	(0.05)		(0.07)	(0.10)	
Proportion of Disabled	0.01	0.02	0.00	0.02	0.03	0.01***
	(0.12)	(0.14)		(0.14)	(0.17)	
Proportion of Full time	0.74	0.70	-0.03	0.77	0.73	-0.03***
workers	(0.44)	(0.46)		(0.42)	(0.44)	
Labor income	13,621	17,723	4,102***	14,878	19,765	4,887***
per capita	(16,916)	(28,353)		(15,911)	(29,240)	
Total income	16,392	27,805	11,413***	17,721	23,605	5,884***
per capita	(20,049)	(214,424)		(21,151)	(33,232)	
Sample size	679	661		4,061	5,262	

Notes: Standard errors reported in parentheses below the corresponding average. Stars in columns (3) and (6) show statistical significance of differences in proportion or distribution of the referred variable, between years 1999 and 2005. We perform tests of difference in proportion for the dummy variables White, Health condition that limits daily activity, Married, Unemployment, Retired, Disabled, and Full-time workers. We perform tests of differences in distribution for the categorical variables Frequency of light physical activity, Age, Education, Number of Children, and Number of Children in elementary school, and for the continuous variables Body Mass Index, Labor income, and Total income. Significance levels: * = 10%; ** = 5%; *** = 1%.

characteristics.

Given the existence of different time trends on the frequency of light physical activity between females and males observed in Figure 2, in the model that we estimate we include interactions of all the parameters related to the identification of the HED effect with a gender dummy.

The outcome equation with interactions by gender and with covariates has the following form

$$
\begin{aligned}
y_{it} = \beta_0 + \beta_1\tau_t + \beta_2 elem_i + \sum_{k=2}^{5}\beta_{3,k}Sk_i + \beta_4 female_i + \beta_5(\tau_t \times female_i) + \beta_6(elem_i \times female_i) + \\
\sum_{k=2}^{5}\beta_{7,k}(Sk_i \times female_i) + \beta_8(elem_i \times \tau_t) + \beta_9(elem_i \times \tau_t \times female_i) + \sum_{k=2}^{5}\beta_{10,k}(Sk_i \times \tau_t) + \\
\sum_{k=2}^{5}\beta_{11,k}(Sk_i \times \tau_t \times female_i) + \sum_{k=2}^{5}\beta_{12,k}(Sk_i \times elem_i) + \sum_{k=2}^{5}\beta_{13,k}(Sk_i \times elem_i \times female_i) + \\
\sum_{k=3}^{5}\beta_{14,k}(Sk_i \times elem_i \times \tau_t) + \sum_{k=3}^{5}\beta_{15,k}(Sk_i \times elem_i \times \tau_t \times female_i) + \beta_{16}X_{it} + u_{it},
\end{aligned}
\tag{6}
$$

where $i = 1...N$ indexes individuals, $t = 0, 1$ indexes time (0=before policy, 1999; 1=after policy, 2005), and $k = 1, ..., 5$ indexes state groups.[22]

The DDD estimates in this model are the estimates of $\beta_{14,k}$ for males, and $\beta_{14,k} + \beta_{15,k}$ for females. If the parameter $\beta_{15,k}$ is significantly different from zero, there is evidence of a different impact of HED policies between fathers and mothers. X_{it} is a set of observable individual characteristics including age, race, gender, health conditions that limits daily activity, body mass index, marital status, number of children, children of high-school-age, education level, employment status, full-time/part-time employment, total family income, and state of residence.

3.5 Empirical implementation: DDD in a non-linear model

To simplify notation, in this section we use the specification of the outcome equation in (1), which does not include state classification, covariates, and gender interactions.

Considering that the outcome variable is binary, the expectation of the outcome equation

[22] $S1$ is the group of reference.

measures the probability of doing light physical activity any positive number of times per week, and has the following form

$$\begin{aligned}\mathbb{E}[y_{it}|elem_i, S_i, \tau_t] = f\Big[&\beta_0 + \beta_1\tau_t + \beta_2 elem_i + \beta_3 S_i \\ &+ \beta_4(elem_i \times \tau_t) + \beta_5(S_i \times \tau_t) + \beta_6(elem_i \times S_i) \\ &+ \beta_7(\tau_t \times elem_i \times S_i)\Big],\end{aligned} \tag{7}$$

where f is the cumulative distribution function of idiosyncratic shocks (u_{it}).

As remarked in Blundell and Dias (2009), applying DD and DDD methods imposes additive separability of the error term conditional on the observables, an assumption that does not hold when the outcome of interest is a dummy variable. To overcome this limitation, we follow Blundell et al. (2004) by imposing the identifying assumption in equation (3) over the index, rather than over the probability itself. Assuming that the inverse probability function, f^{-1}, is known, the DDD estimator of the ATT is

$$\begin{aligned}\widehat{ATT} = \bar{y}_1^{1,1} - f\Big\{&f^{-1}(\bar{y}_0^{1,1}) + [f^{-1}(\bar{y}_1^{1,0}) - f^{-1}(\bar{y}_0^{1,0})] \\ &+ [f^{-1}(\bar{y}_1^{0,1}) - f^{-1}(\bar{y}_0^{0,1})] - [f^{-1}(\bar{y}_1^{0,0}) - f^{-1}(\bar{y}_0^{0,0})]\Big\},\end{aligned} \tag{8}$$

where $\bar{y}_t^{elem,S}$ is the average of the estimated outcome over individuals in group $elem$, residing in states S, at time t.[23]

Assuming that the idiosyncratic shocks have a normal distribution, f is the normal cumulative distribution function. We estimate the parameters of interest by maximum likelihood and compute robust standard errors clustered at the family level. A report of the estimated coefficients can be found in Table 15 in the Appendix.

With the estimated parameters we compute the Indirect Average Treatment effects on the Treated (IATT), using equation (8), including the state classification (discussed in Section 3.1), gender interactions, and covariates (both presented in Section 3.4).

[23] In Section 6.1 in the Appendix we show how we obtain the expression for the DDD estimator.

4 IATT estimates

Table 6 shows the IATT for the three types of treatment, by gender. The "OLS" column presents the IATT estimates obtained using a linear probability model. The "Probit" column presents the IATT estimates obtained using equation (8) and assuming a normal distribution for idiosyncratic shocks.

Table 6: IATT by type of treatment, and by gender.

Group of experimental states	**Male**			**Female**		
	OLS	**Probit**	**# obs**	**OLS**	**Probit**	**# obs**
S3: Moderate changes A	-0.009	-0.039	3,628	-0.042	-0.028	4,595
	(0.071)	(0.080)		(0.065)	(0.085)	
S4: Moderate changes B	-0.035	-0.055	3,678	0.023	0.034	4,602
	(0.064)	(0.065)		(0.059)	(0.081)	
S5: Major changes	**0.122***	**0.199***	3,722	-0.056	-0.088	4,686
	(0.068)	(0.107)		(0.054)	(0.061)	

Notes: Robust standard errors reported in parenthesis clustered at the family level. Robust standard errors computed by bootstrap using 1000 replications in Probit specification."OLS" columns present the IATT estimates obtained using a linear probability model. The "Probit" columns present the IATT estimates obtained using equation (8) and and probit specification. The regressions include the following covariates: age, race, gender, health status, marital status, number of children, children of high school-age, education level, employment status, full-time/part-time employment, total family income level, and state of residence. Significance levels: * = 10%; ** = 5%; *** = 1%.

We find evidence of a positive effect of HED education at the elementary school level on the probability of parents engaging in light physical activity. A noteworthy change in the HED program ($S5$ group of states) raises the probability of fathers doing physical activity. Looking at the results of the probit column we can see that the probability of fathers affected by this policy doing physical activity is 19.9 percentage points higher than that of fathers not affected by the policy. The positive and statistically significant effect on fathers is also obtained by using a linear probability model. The effect on the probability that mothers engage in light physical activity is never statistically significant, but the signs are the opposite to those found for fathers.

The estimated effects are not statistically significant for males and females residing in the group of states $S3$ and $S4$. These results suggest that moderate changes in HED programs do not produce indirect effects.

The interpretation of the estimated IATT can be clarified by looking at the averages of the estimated outcomes in Table 7. Let's consider the results for treated fathers residing in the group of states S_5. On average, the estimated percentage of physically active fathers in the pre-treatment period, 1999, is 84.9%. In 2005, after major changes in HED programs, we estimate that 84.3% of fathers were engaged in light physical activity. Nevertheless, if HED programs had not been subject to profound changes in this group of states, we estimate that only 64.4% of fathers of elementary school-age children would have engaged in light physical activity in 2005. In other words, due to the major changes in HED programs, the percentage of physically active fathers fell from 84.8% to 84.3%, instead of falling to 64.4% had HED not been modified. The effect of major reforms on HED was to soften the declining trend in the proportion of physically active fathers.

Table 7: IATT and averages of the estimated outcomes for treated individuals, by type of treatment and gender.

Group of experimental states		**IATT**	**Estimated Average Outcomes for Treated Individuals** Post-treatment period with treatment	Post-treatment period without treatment	Pre-treatment period without treatment
S3: Moderate change A	Male	-0.039	0.810	0.848	0.919
	Female	-0.028	0.759	0.787	0.884
S4: Moderate change B	Male	-0.055	0.848	0.903	0.928
	Female	0.034	0.796	0.762	0.863
S5: Major change	Male	**0.199**	**0.843**	**0.644**	**0.849**
	Female	-0.088	0.766	0.854	0.924

Notes: IATT and estimated outcomes obtained using equation (8) and a probit specification. Each cell contains the estimated proportion of physically active individuals. Pre-treatment period is 1999, and post-treatment period is 2005. The IATT is obtained as the estimated average outcome in the post-treatment period under treatment minus the missing counterfactual, that is, the estimated average outcome in the post-treatment period without treatment.

We conclude that there are positive spillovers of introducing major changes in existing HED programs on the probability of fathers engaging in light physical activity, while for mothers we do not find a statistically significant effect of these reforms.

4.1 Plausible explanations for our results

We can think of two channels to explain our results. When children start receiving HED at school their parents are confronted with two new sets of factors that might potentially affect their health-related behaviors. First, parents may optimally react to HED in schools by complementing this education with the incorporation of healthy lifestyles into their own daily activities. We refer to this potential channel as "role modeling". On the other hand, there is the effect of the arrival of new information that the child receives at the school. In particular, parents are confronted with knowledge that the child brings to the household from the health education curricula given at the school, and they may adjust their health behaviors in response to it. We refer to this potential channel as "information sharing". In what follows we provide evidence of the existence of both channels.

4.1.1 Role models

Parents may do more physical exercise in response to the knowledge children acquire via HED, not because they were not already aware of the benefits of exercising but because they want to complement the instruction received by the child so as to form the desired healthy lifestyle in the child.

The estimates from the model interacting the policies with a dummy variable for gender provide some insights on the operation of the "role model" channel. Parents usually spend more time with their children doing gendered activities. Figure 3 in the Appendix shows some evidence on this respect with data from the American Time Use Survey (ATUS). Women spend roughly twice as much time in childcare as do men, a pattern which holds true for all subgroups and for almost all types of childcare, except for "Recreational" childcare. This type of childcare activity includes playing games with children, playing outdoors with children, attending a child's sporting event or dance recital, going to the zoo with children, taking walks with children, etc. In the case of "Recreational" childcare, mothers allocate relatively less of their time with children than do fathers. Thus, this is evidence that fathers are more likely to do stereotypically male activities with their children, among them physical activity. Accordingly, the impact of HED reforms on physical activity is more likely to appear for fathers rather than for mothers.

4.1.2 Information sharing between children and parents

Individuals with a lower stock of information are expected to be more affected by HED changes. We explore the existence of the information-sharing channel by analyzing the differential impact of HED reforms on individuals with low and high education levels and with low and high income levels. Since lower levels of education and socioeconomic status are related to less knowledge about health (Kenkel, 1991; Tinsley, 2003), we expect to obtain a greater effect of HED reforms on individuals with lower levels of education and income.

Exploiting the non-linearity of the model specified we estimate the IATT evaluated at particular values of the covariates of interest. We report the results in Table 8 for treated fathers residing in states that belong to group $S5$. According to these results, the policy has a higher effect on lower educated males relative to higher educated males, on non-white males relative to white males, and on males that have a lower income than those having a higher income. The policy raises the probability of lower educated males being physically active relative to higher educated males in 4.9 percentage points, while the increment is 4.2 percentage points for non-white males relative to white males.

Table 8: Differences in IATT estimates evaluated at particular values of the covariates, for males in $S5$.

Income	**IATT**	**Education**	**IATT**	**Race**	**IATT**
Low	0.198*	**Low**	0.211*	**No White**	0.207*
(20th percentile)	(0.108)		(0.114)		(0.116)
High	0.193*	**High**	0.162*	**White**	0.165*
(80th percentile)	(0.106)		(0.096)		(0.099)
Difference	**0.005***		**0.049****		**0.042****
	(-0.003)		(0.021)		(0.020)

Notes: The IATT is obtained using equation (8) and a probit specification. Robust standard errors in parentheses clustered at the family level, and computed by bootstrap using 1000 replications. We find no differences for males in health status (measured using the existence of a health condition that limits the daily activity and the body mass index), family size, labor force participation, full-time/part-time employment, and marital status. There are no differences for females in all the dimensions analyzed. Significance levels: * = 10%; ** = 5%; *** = 1%.

5 Robustness

5.1 Validity of the identifying assumption

Our identifying assumption requires that, in the absence of HED reforms, state specific trends of the proportion of parents physically active in the treatment group (those with elementary school-age children) is the same as that of parents in the control group (those with children bellow or above elementary school-age). This assumption will be violated if there is a shock contemporaneous to HED reforms that systematically affects the relative outcome of parents of elementary school-age children.

In order to check the robustness of our identifying assumption we perform two tests. First, we estimate the effect of the HED reform on the labor force participation of parents. Labor participation is a decision that should be not affected by the policy under analysis. If HED changes are not the only shock that affects the relative outcomes of treated versus control individuals between 1999 and 2005, we may observe that the labor force participation among individuals in the treatment group changes relative to that of individuals in the control group. Results for the group of states $S5$ are presented in Table 9. The two estimates tell us that between 1999 and 2005 there were no significant changes in the relative decision of participating in the labor market of treated and control parents. This constitutes evidence that there was no other labor market related shock systematically affecting the relative outcomes of treated and control parents between 1999 and 2005.

Second, we estimate the effect of HED reforms in elementary school on individuals that are not likely to be affected by such reforms: the group of adults without children. If there had been no other shock contemporaneous to the HED reforms, the outcome of adults without children relative to a control group should remain unchanged between 1999 and 2005. To perform this test, we keep only individuals without children. Individuals in a given state are then assigned to one of two groups, the "placebo" treatment and the "placebo" control group. The classification is done in such a way that the "placebo" treatment group resembles, at least in observable characteristics, the true treatment group of adults with children in elementary school. This classification is necessary to have a within state control group (the third dimension) in the sample of adults without children, required to implement a DDD estimator. If our classification is correct, we should find no effect of HED reforms on the "placebo" treated individuals. Details on how we select the "placebo" treated individuals can be found in the Appendix in Section 6.2. We present the results using the non-parametric DDD estimator computed in Section 3.3 for the group of states S_5.[24] The effect of HED on the "placebo" treated males is 0.062 (standard error: 0.097), and the effect on the "placebo" females is -0.047 (standard error: 0.097). Reassuringly, the estimated coefficients are smaller than those in the baseline model and not significantly different from zero.[25]

5.2 Sensitivity analysis

Parents in the treatment group, that is parents of elementary school-age children, may also have other children below and/or above elementary school age. In order to have individuals in the control group comparable to those in the treatment group in the same state, we consider that the appropriate group of control individuals should include parents of children of ages below and above elementary school age. Nevertheless, to determine whether our results are sensitive to this definition, we perform two tests. First, we use parents with at lest one child below elementary-school-age as non-treatment individuals. Second, we use parents with at least one child above elementary-school-age as non-treatment individuals. Estimates of the effects of HED reforms on the group of states $S5$ are very similar to those obtained with the baseline model, as can be seen in Table 9.[26]

6 Conclusion

We find evidence for positive spillovers of HED imparted in elementary schools on the probability of parents engaging in light physical activity. However, our results suggest that fathers and not mothers are those affected by the HED reforms. We also analyze the differential impact of HED reforms on fathers and mothers as a way to explore the nature of the channels

[24] We cannot obtain the estimates of the probit or OLS models because the sample size of adults without children is not large enough.

[25] We also perform the placebo test for the group of states $S3$ and $S4$ and results and conclusions are similar to those obtained with the group of states $S5$.

[26] We perform both tests for the group of states $S3$ and $S4$ and results and conclusions are similar to those obtained with the group of states $S5$.

Table 9: Robustness check: Effect of HED reforms on labor market participation (Panel A), and Sensitivity of control groups (Panel B and C), for group of states $S5$.

	Male			**Female**		
	OLS	**Probit**	**# obs**	**OLS**	**Probit**	**# obs**
	PANEL A: *Effect of HED reforms on* ***labor market participation***					
IATT	0.029	0.107	3,722	0.029	0.017	4,686
	(0.054)	(0.098)		(0.065)	(0.066)	
	PANEL B: *Using as* ***control*** *individuals only parents of children* ***below*** *elementary-school-age*					
IATT	0.098	0.220	2,360	-0.012	-0.010	2,930
	(0.073)	(0.144)		(0.070)	(0.093)	
	PANEL C: *Using as* ***control*** *individuals only parents of children* ***above*** *elementary-school-age*					
IATT	0.135*	0.188	2,894	-0.083	-0.117*	3,735
	(0.081)	(0.113)		(0.061)	(0.062)	

Notes: The IATT in columns "OLS" are obtained using a linear probability model. The IATT in columns "Probit" are obtained using equation (8) and a probit specification. Robust standard errors reported in parenthesis clustered at the family level. Robust standard errors computed by bootstrap using 1000 replications in Probit specification. The regressions in Panel A include the following covariates: age, race, gender, health status, marital status, number of children, children of high school-age, education level, total family income level, and state of residence. The regressions in Panel B and Panel C include the previous covariates and employment status, and full-time/part-time employment. Significance levels: * = 10%; ** = 5%; *** = 1%.

driving the spillovers.

We argue that a "role model" channel can explain the differential impact on fathers and mothers. The idea is based on the different role models that mothers and fathers play for their children. Parents usually spend more time with their children doing gendered activities. Since physical activity can be included in the group of typically male-activities, the effect of promoting the advantages of doing physical activity is more likely to appear for fathers rather than for mothers. We also explore the existence of a second channel driving our results -the "information sharing" channel- by analyzing the differential impact of HED reforms on individuals with lower and higher education levels, and obtain the expected greater effect on less educated individuals and individuals with lower socioeconomic status.

Our results also highlight the importance of clearly distinguishing the existence of several dimensions in the implementation of a policy. In our case, it is important for policy evaluation to consider the two dimensions in HED reforms, changes in topics and enforcements, as well as the distinction between "Moderate changes" and "Major changes" in HED requirements.

Our main result shows spillovers only in states that carried out profound reforms in their HED programs.

Spillovers of HED on parents' lifestyles indicate that the interaction between children and parents plays a role in the formation of healthy lifestyles within the household. Therefore, taking these spillovers into account is important in the cost-benefit analysis of health education in schools. In addition, the conclusion that implementing minor reforms in existing HED programs is not enough to obtain spillovers at the family level helps to properly design policy interventions aimed at increasing the adoption of healthy lifestyles.

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Appendix

Table 10: HED topics and enforcements. Full list.

Topics List
1) *Alcohol- or Other Drug-Use Prevention*
2) *Emotional and Mental Health*
3) *Nutrition and Dietary Behavior*
4) *Physical Activity and Fitness*
5) *Tobacco-Use Prevention*
6) Human immunodeficiency virus (HIV) prevention
7) Accident or injury prevention
8) Sexually transmitted disease (STD) prevention
9) Pregnancy prevention
10) Suicide prevention
11) Violence prevention, for example bullying, fighting, or homicide

Enforcements List
1) *State requires districts or schools to follow national or state health education standards or guidelines*
2) *State requires students in elementary school to be tested on health topics*
3) *State requires each school to have a HED coordinator*
4) State uses staff development for HED teachers to improve compliance with HED standards or guidelines
5) State uses written reports from districts or schools to document compliance with HED standards or guidelines
6) State provides a list of one or more recommended elementary school HED curricula
7) State provides a chart describing the scope and sequence of instruction for elementary school HED
8) State provides lesson plans or learning activities for elementary school HED
9) State provides plans for how to assess or evaluate students in elementary school HED
10) State adopts a policy stating that newly hired staff who teach HED at the elementary school level will have undergraduate or graduate training in HED
11) State offers certification, licensure, or endorsement to teach HED
12) State adopts a policy stating that teachers will earn continuing education credits on HED topics to maintain state certification, licensure, or endorsement to teach HED

Notes: The topics and enforcements considered for the analysis are in italics.

Table 11: HED programs: health topics required, by state and year.

	1999					2005				
State	**topic 1**	**topic 2**	**topic 3**	**topic 4**	**topic 5**	**topic 1**	**topic 2**	**topic 3**	**topic 4**	**topic 5**
Alabama	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Alaska	no	no	no	no	no	no	no	no	no	no
Arizona	no	no	no	no	no	no	no	no	no	no
Arkansas	no	no	no	no	no	yes	no	yes	yes	yes
California	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Colorado	no	no	no	no	no	no	no	no	no	no
Connecticut	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Delaware	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
District of Columbia	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Florida	no	no	no	no	no	yes	yes	yes	yes	yes
Georgia	yes	yes	yes	no	yes	yes	yes	yes	yes	yes
Hawaii	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Idaho	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Illi0is	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Indiana	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Iowa	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Kansas	.	.	.	.	.	.	.	.	.	.
Kentucky	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Louisiana	yes	no	no	no	yes	yes	yes	yes	yes	yes
Maine	yes	yes	yes	no	yes	yes	yes	yes	yes	yes
Maryland	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Massachusetts	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Michigan	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Minnesota	.	.	.	.	.	.	.	.	.	.
Mississippi	no	no	no	no	no	no	no	no	no	no
Missouri	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Montana	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Nebraska	yes	no	no	no	yes	yes	no	yes	yes	yes
Nevada	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
New Hampshire	.	.	.	.	.	yes	yes	yes	yes	yes
New Jersey	yes	no	no	yes	yes	yes	no	yes	yes	yes
New Mexico	no	no	no	no	no	yes	yes	yes	yes	yes
New York	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
0rth Carolina	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
0rth Dakota	yes	no	no	no	yes	yes	no	no	yes	yes
Ohio	yes	no	yes	yes	yes	yes	no	yes	yes	yes
Oklahoma	no	no	no	no	no	no	no	no	no	no
Oregon	yes	no	no	no	yes	yes	no	no	no	yes
Pennsylvania	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Rhode Island	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
South Carolina	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
South Dakota	no	no	no	no	no	no	no	no	no	no
Tennessee	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Texas	.	.	.	.	.	yes	yes	yes	yes	yes
Utah	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Vermont	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Virginia	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Washington	yes	no	yes	yes	yes	yes	yes	yes	yes	yes
West Virginia	yes	no	yes	yes	yes	yes	no	yes	yes	yes
Wisconsin	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Wyoming	no	no	no	no	no	no	yes	no	no	no

Source: NASBE Database and School Health Policies and Programs Study (SHPPS).
Notes: The data contained in this table was constructed cross-checking the information from both sources, and in most of the cases survey information from SHPPS coincides with the legal information summarized in NASBE. In those cases in which there is no coincidence, we rely on NASBE information only. In few cases NASBE does not provide complete information -i.e., cases in which the regulations contained in NASBE are not informative about the characteristics of the policy the state implements-, then we rely on SHPPS. Missing values indicate that the information cannot be recovered from any of the two sources.
Topic 1:Alcohol or other drug-use prevention; **Topic 2**: Emotional and mental health; **Topic 3**: Nutrition and dietary behavior; **Topic 4**: Physical activity and fitness; **Topic 5**: Tobacco-Use prevention.

Table 12: HED programs: enforcements required, by state and year.

	1999			2005		
State	**enf 1**	**enf 2**	**enf 3**	**enf 1**	**enf 2**	**enf 3**
Alabama	yes	no	no	yes	no	yes
Alaska	no	no	no	no	no	no
Arizona	yes	no	no	yes	no	no
Arkansas	yes	no	no	yes	no	no
California	no	no	no	no	no	no
Colorado	no	no	no	no	no	no
Connecticut	no	no	no	no	no	no
Delaware	yes	no	yes	yes	no	yes
District of Columbia	.	.	.	.	.	.
Florida	yes	no	no	yes	no	no
Georgia	yes	no	no	yes	no	no
Hawaii	yes	no	no	yes	no	no
Idaho	no	no	no	no	no	no
Illinois	yes	no	no	yes	no	no
Indiana	yes	no	no	yes	no	no
Iowa	no	no	no	no	no	no
Kansas	.	.	.	.	.	.
Kentucky	no	yes	no	yes	yes	no
Louisiana	yes	no	no	yes	no	no
Maine	yes	yes	no	yes	yes	no
Maryland	yes	no	no	yes	no	no
Massachusetts	yes	no	no	yes	no	no
Michigan	yes	no	no	yes	no	no
Minnesota	.	.	.	.	.	.
Mississippi	no	no	no	no	no	no
Missouri	yes	yes	no	yes	yes	no
Montana	yes	no	no	yes	no	no
Nebraska	no	no	no	no	no	no
Nevada	yes	no	no	yes	no	no
New Hampshire	.	.	.	yes	.	.
New Jersey	.	.	.	yes	.	.
New Mexico	no	.	.	yes	.	.
New York	no	.	.	no	.	.
north Carolina	yes	no	no	yes	no	no
north Dakota	no	no	no	no	no	no
Ohio	.	.	.	.	.	.
Oklahoma	no	no	no	no	no	no
Oregon	no	no	no	yes	no	no
Pennsylvania	yes	.	.	yes	.	.
Rhode Island	yes	yes	no	yes	yes	yes
South Carolina	yes	no	no	yes	yes	no
South Dakota	no	no	no	no	no	no
Tennessee	yes	no	no	yes	no	no
Texas	no	no	no	yes	no	no
Utah	yes	no	no	yes	yes	no
Vermont	yes	no	no	yes	yes	no
Virginia	yes	no	no	yes	no	no
Washington	yes	yes	no	yes	yes	no
West Virginia	yes	no	no	yes	no	no
Wisconsin	no	no	no	no	no	no
Wyoming	no	no	no	yes	no	no

Source: NASBE Database and School Health Policies and Programs Study (SHPPS).
Notes: The data contained in this table was constructed cross-checking the information from both sources, and in most of the cases survey information from SHPPS coincides with the legal information summarized in NASBE. In those cases in which there is no coincidence, we rely on NASBE information only. In few cases NASBE does not provide complete information -i.e., cases in which the regulations contained in NASBE are not informative about the characteristics of the policy the state implements-, then we rely on SHPPS. Missing values indicate that the information cannot be recovered from any of the two sources.
Enforcement 1: State requires districts or schools to follow national or state health education standards or guidelines.
Enforcement 2: State requires students in elementary school to be tested on health topics.
Enforcement 3: State requires each school to have a HED coordinator.

Table 13: States classified by groups Sk.

NON-EXPERIMENTAL		EXPERIMENTAL	
State	# of obs.	State	# of obs.
S1		**S3**	
Alaska	14	Alabama	138
Colorado	246	Kentucky	169
Mississippi	521	Oregon	208
Oklahoma	62	Rhode Island	10
South Dakota	59	South Carolina	564
		Utah	100
S2		Vermont	7
Arizona	178		
California	1,218	**S4**	
Connecticut	79	Georgia	414
Delaware	14	Louisiana	209
Hawaii	4	Maine	30
Idaho	25	Nebraska	106
Illinois	397	New Jersey	336
Indiana	363	North Dakota	16
Iowa	264	Washington	218
Kansas	81		
Maryland	450	**S5**	
Massachusetts	258	Arkansas	278
Michigan	613	Florida	450
Missouri	340	New Mexico	16
Montana	13	Texas	691
Nevada	72	Wyoming	18
New York	493		
North Carolina	605		
Ohio	505		
Pennsylvania	476		
Tennessee	238		
Virginia	373		
West Virginia	24		
Wisconsin	183		

Notes: We do not include the District of Columbia, Minnesota, and New Hampshire since the information regarding HED policies for these states is not precise in terms of when HED was implemented, making impossible their classification.

Table 14: DDD estimator for females in $S5$.

	Before HED change	After HED change	Time difference	
A. Treatment individuals: with children in elementary school				
Experimental states	0.922	0.767	-0.155***	Δ_E^T
	(0.024)	(0.035)	(0.042)	
	[128]	[146]		
Non-experimental states	0.914	0.798	-0.116***	Δ_{NE}^T
	(0.010)	(0.015)	(0.018)	
	[758]	[753]		
Difference in difference			**-0.039**	
			(0.046)	
B. Control Individuals: without children in elementary school				
Experimental states	0.874	0.785	-0.089**	Δ_E^C
	(0.025)	(0.025)	(0.035)	
	[183]	[270]		
Non-experimental states	0.910	0.796	-0.114***	Δ_{NE}^C
	(0.009)	(0.011)	(0.014)	
	[984]	[1,464]		
Difference in difference			**0.025**	
			(0.038)	
C. Non-parametric DDD estimator				
$\mathbf{DDD} = (\boldsymbol{\Delta}_{\mathbf{E}}^{\mathbf{T}} - \boldsymbol{\Delta}_{\mathbf{NE}}^{\mathbf{T}}) - (\boldsymbol{\Delta}_{\mathbf{E}}^{\mathbf{C}} - \boldsymbol{\Delta}_{\mathbf{NE}}^{\mathbf{C}})$			**-0.063**	
			(0.060)	

Notes: Cells contain proportion of physically active individuals for the group identified. Standard errors are given in parentheses, and sample sizes in brackets. The non-experimental states are groups of states S1 and S2. Significance levels: * = 10%; ** = 5%; *** = 1%.

The upper part of the Table shows important falls in temporal trends of the proportions of physically active mothers of elementary school-age children residing in both, experimental and non-experimental states. As a consequence, the difference-in-difference estimator is not statistically significant. We can observe a similar pattern for mothers of children below and above elementary school age. Finally, the triple difference estimator does not provide evidence of an effect of HED on the proportion of physically active mothers.

Table 15: Probit Model: Probability of doing light physical activity at least once a week.

Number of obs= 10,663	Wald chi2(83) = 795.28
	Prob > chi2 = 0.0000
Log pseudo-likelihood = -4157.416	Pseudo R2 = 0.0914
	(Std. Err. adjusted for 1818 clusters at family level)

Variable	**Coefficient**	**(Std. Err.)**	**Variable**	**Coefficient**	**(Std. Err.)**
τ	-0.183	(0.215)	married	0.05	(0.059)
elem	0.201	(0.214)	widowed	-0.192	(0.187)
S2	-0.18	(0.280)	separated	0.011	(0.073)
S3	0.062	(0.281)	divorced	-0.077	(0.087)
S4	-0.044	(0.311)	fulltime	-0.088**	(0.044)
S5	-0.022	(0.282)	nchildren	0.027*	(0.015)
$elem \times \tau$	-0.081	(0.122)	pclabinc	0.032***	(0.008)
$S2 \times \tau$	-0.206	(0.220)	limit	-0.053	(0.046)
$S3 \times \tau$	-0.238	(0.281)	bmi	-0.005*	(0.003)
$S4 \times \tau$	0.025	(0.290)	on leave	-0.113	(0.140)
$S5 \times \tau$	-0.426	(0.280)	unemployed	-0.075	(0.078)
$S2 \times elem$	-0.088	(0.212)	retired	-0.261	(0.168)
$S3 \times elem$	-0.027	(0.322)	disabled	-0.568***	(0.094)
$S4 \times elem$	-0.029	(0.350)	housekeeper	0.035	(0.065)
$S5 \times elem$	-0.514*	(0.308)	student	0.284**	(0.144)
$S3 \times elem \times \tau$	-0.094	(0.345)	stated3	-0.227	(0.253)
$S4 \times elem \times \tau$	-0.206	(0.357)	stated5	0.169	(0.181)
$S5 \times elem \times \tau$	0.583*	(0.317)	stated7	-0.132	(0.281)
$\tau \times female$	-0.067	(0.265)	stated10	-0.12	(0.130)
$elem \times female$	0.135	(0.262)	stated11	-0.182	(0.160)
$S2 \times female$	0.236	(0.223)	stated14	0	(0.193)
$S3 \times female$	0.077	(0.272)	stated15	0.032	(0.211)
$S4 \times female$	0.13	(0.305)	stated16	0.08	(0.209)
$S5 \times female$	-0.141	(0.280)	stated18	-0.246	(0.187)
$elem \times_{\tau} \times female$	-0.003	(0.157)	stated21	0.037	(0.193)
$S2 \times \tau \times female$	-0.071	(0.268)	stated22	-0.187	(0.212)
$S3 \times \tau \times female$	0.148	(0.355)	stated23	-0.014	(0.189)
$S4 \times \tau \times female$	-0.13	(0.364)	stated25	-0.367**	(0.160)
$S5 \times \tau \times female$	0.367	(0.343)	stated26	0.044	(0.190)
$S2 \times elem \times female$	-0.228	(0.254)	stated31	-0.314*	(0.187)
$S3 \times elem \times female$	-0.317	(0.409)	stated33	-0.136	(0.191)
$S4 \times elem \times female$	-0.548	(0.410)	stated34	0.031	(0.199)
$S5 \times elem \times female$	0.538	(0.395)	stated36	0.011	(0.189)
$S3 \times elem \times \tau \times female$	-0.027	(0.457)	stated38	-0.173	(0.203)
$S4 \times elem \times \tau \times female$	0.371	(0.406)	stated39	-0.104	(0.195)
$S5 \times elem \times \tau \times female$	-0.924**	(0.396)	stated41	-0.305**	(0.152)
jhs	0.067*	(0.039)	stated43	0.113	(0.211)
gender	-0.096	(0.212)	stated44	-0.005	(0.125)
age	-0.002	(0.014)	stated47	-0.1	(0.202)
age^2	0.000	(0.000)	stated48	-0.171	(0.176)
white	0.376***	(0.043)	stated50	0.410*	(0.229)
edu	0.065***	(0.007)	Intercept	0.431	(0.344)

Notes: Significance levels: * = 10%; ** = 5%; *** = 1%.
Variable names: *tau*: time fixed effect; *elem*: group of parent's of elementary school-age children fixed effect (group fixed effect); *Sk*: groups of states k fixed effect (region fixed effect); $elem \times \tau$: group time trend control (group-time interaction); $Sk \times \tau$: group of states' time trend control (region-time interaction); $Sk \times elem$: region-group interaction; $Sk \times elem \times \tau$: triple interaction (region-group-time interaction); all variables of the form $X \times female$ are X variables interacted with the gender dummy $female$; *jhs*: dummy variable equal to one if the individual has at least one children of junior-high-school age; *age*: age in years; age^2: square of age; *white*: white race dummy; *edu*: year of education completed; *married*: married or permanently cohabiting dummy; *widowed*: widowed dummy; *separated*: separated dummy; *divorced*: legally divorced dummy; $fulltime$: equal to one if the individual works less than 36 hours a week during the last year; *nchildren*: number of children (all ages); *pclabinc*: per-capita family labor income in dollars; *limit*: health condition that limits daily activity dummy; *bmi*: body mass index; *onleave*: only temporarily laid off, sick leave or maternity leave dummy; *unemployed*: looking for work, unemployed dummy; *retired*: retired dummy; *disabled*: permanently or temporarily disabled dummy; *housekeeper*: housekeeper dummy; *student*: student dummy; *statedj*: state j fixed effect.

6.1 Average Treatment Effects: More details

ATT as a function of missing counterfactuals

We can recover the missing counterfactual $\mathbb{E}(y_{it}^0|elem_i = 1, S_i = 1, \tau_t = 1)$ using equation (1), since if we assume that equation (3) holds, we have

$$\begin{aligned}\mathbb{E}(y_{it}^0|elem = 1, S = 1, \tau_t = 1) = \mathbb{E}(y_{it}^0|elem = 1, S = 1, \tau_t = 0)&\\ + [\mathbb{E}(y_{it}^0|elem = 1, S = 0, \tau_t = 1) - \mathbb{E}(y_{it}^0|elem = 1, S = 0, \tau_t = 0)]&\\ + [\mathbb{E}(y_{it}^0|elem = 0, S = 1, \tau_t = 1) - \mathbb{E}(y_{it}^0|elem = 0, S = 1, \tau_t = 0)]&\\ - [\mathbb{E}(y_{it}^0|elem = 0, S = 0, \tau_t = 1) - \mathbb{E}(y_{it}^0|elem = 0, S = 0, \tau_t = 0)].&\end{aligned} \tag{9}$$

We can rewrite the ATT as a function of the unobserved counterfactual $\mathbb{E}(y_{it}^0|elem_i = 1, S_i = 1, \tau_t = 1)$

$$\begin{aligned}ATT = \mathbb{E}(y_{it}^1|elem = 1, S = 1, \tau_t = 1) - \mathbb{E}(y_{it}^0|elem = 1, S = 1, \tau_t = 0)&\\ - [\mathbb{E}(y_{it}^0|elem = 1, S = 0, \tau_t = 1) - \mathbb{E}(y_{it}^0|elem = 1, S = 0, \tau_t = 0)]&\\ - [\mathbb{E}(y_{it}^0|elem = 0, S = 1, \tau_t = 1) - \mathbb{E}(y_{it}^0|elem = 0, S = 1, \tau_t = 0)]&\\ + [\mathbb{E}(y_{it}^0|elem = 0, S = 0, \tau_t = 1) - \mathbb{E}(y_{it}^0|elem = 0, S = 0, \tau_t = 0)].&\end{aligned} \tag{10}$$

The sample analog of equation (10) is the DDD estimator of the ATT

$$\begin{aligned}\widehat{ATT} = (\bar{y}_1^{1,1} - \bar{y}_0^{1,1}) - (\bar{y}_1^{1,0} - \bar{y}_0^{1,0})&\\ - [(\bar{y}_1^{0,1} - \bar{y}_0^{0,1}) - (\bar{y}_1^{0,0} - \bar{y}_0^{0,0})],&\end{aligned} \tag{11}$$

where $\bar{y}_t^{elem,S}$ is the average of the estimated outcome over individuals in group $elem$, residing in states S, at time t.

ATT in a non-linear model

We rewrite the identifying assumption as follows

$$
\begin{aligned}
& f^{-1}[\mathbb{E}(u_{it}|elem=1,S=1,\tau_t=1)]-f^{-1}[\mathbb{E}(u_{it}|elem=1,S=1,\tau_t=0)] \\
& \quad -\{[f^{-1}[\mathbb{E}(u_{it}|elem=1,S=0,\tau_t=1)]-f^{-1}[\mathbb{E}(u_{it}|elem=1,S=0,\tau_t=0)]\} \\
& = f^{-1}[\mathbb{E}(u_{it}|elem=0,S=1,\tau_t=1)]-f^{-1}[\mathbb{E}(u_{it}|elem=0,S=1,\tau_t=0)] \\
& \quad -\{f^{-1}[\mathbb{E}(u_{it}|elem=0,S=0,\tau_t=1]-f^{-1}[\mathbb{E}(u_{it}|elem=0,S=0,\tau_t=0)]\}.
\end{aligned}
\tag{12}
$$

If equation (12) holds, the missing counterfactual is

$$
\begin{aligned}
\mathbb{E}(y^0_{it}|elem=1,S=1,\tau_t=1) = f\Big\{ & f^{-1}[\mathbb{E}(y^0_{it}|elem=1,S=1,\tau_t=0)] \\
& + \{f^{-1}[\mathbb{E}(y^0_{it}|elem=1,S=0,\tau_t=1)]-f^{-1}[\mathbb{E}(y^0_{it}|elem=1,S=0,\tau_t=0)]\} \\
& + \{f^{-1}[\mathbb{E}(y^0_{it}|elem=0,S=1,\tau_t=1)]-f^{-1}[\mathbb{E}(y^0_{it}|elem=0,S=1,\tau_t=0)]\} \\
& - \{f^{-1}[\mathbb{E}(y^0_{it}|elem=0,S=0,\tau_t=1)]-f^{-1}[\mathbb{E}(y^0_{it}|elem=0,S=0,\tau_t=0)]\}\Big\},
\end{aligned}
\tag{13}
$$

and the $ATT = \mathbb{E}(y^1_{it}|elem=1,S=1,\tau_t=1)-\mathbb{E}(y^0_{it}|elem=1,S=1,\tau_t=0)$, can be estimated replacing the expected values by their sample analogs

$$
\begin{aligned}
\widehat{ATT} = \bar{y}^{1,1}_1 - f\Big\{ & f^{-1}(\bar{y}^{1,1}_0)+[f^{-1}(\bar{y}^{1,0}_1)-f^{-1}(\bar{y}^{1,0}_0)] \\
& +[f^{-1}(\bar{y}^{0,1}_1)-f^{-1}(\bar{y}^{0,1}_0)]-[f^{-1}(\bar{y}^{0,0}_1)-f^{-1}(\bar{y}^{0,0}_0)]\Big\},
\end{aligned}
\tag{14}
$$

where $\bar{y}^{elem,S}_t$ is the average of the estimated outcome over individuals in group $elem$, residing in states S, at time t.

6.2 Robustness: effect of HED on "placebo" treated individuals

To simulate the effect of HED reforms in elementary school on adults without children we need to assign to each individual without children an artificial number of children. Additionally, we need to simulate whether each individual has elementary school-age children and/or of junior-high-school age.

To predict the **number of children** we proceed as follows:

1. Using the sample of parents we estimate by OLS the parameters in the equation

$$
nchildren = X\alpha + u,
$$

where X includes age, race, gender, marital status, education level, employment status, full-time versus part-time job, total family income level, a set of variables reflecting health status, and state of residence.

2. Using the estimated parameters we predict the number of children in the sample of adults without children

$$\widehat{nchildren} = X\hat{\alpha},$$

3. To obtain an integer number of children we correct the previous estimation

$$\widehat{nchildren} = \begin{cases} 0 & \widehat{nchildren} < 0.5 \\ a & a - 0.5 \leq \widehat{nchildren} < a + 0.5 \text{ for } a = 1, 2, ..., 12. \end{cases}$$

To predict the dummy variable jhs, that is a variable equal to one if the individual has at least one child of **junior-high-school-age**, we proceed as follows:

1. Using the sample of parents we estimate with a probit model the parameters in the equation

$$Pr(jhs = 1|X) = \Phi(X\gamma),$$

where Φ is the standard normal cumulative density function, and X includes number of children, age, race, gender, marital status, education level, employment status, full-time versus part-time job, total family income level, a set of variables reflecting health status, and state of residence.

2. Using the estimated parameters we predict the probability of having at least one child of junior-high-school age in the sample of adults without children as

$$Pr(\widehat{jhs = 1}|X) = \Phi(X\hat{\gamma}),$$

3. To obtain a binary variable we correct the previous estimation

$$\widehat{jhs}_i = \begin{cases} 1 & Pr(\widehat{jhs_i = 1}|X_i) > \frac{\sum Pr(\widehat{jhs_i=1}|X_i)}{N} \\ 0 & \text{otherwise} \end{cases}$$

Where $\frac{\sum Pr(\widehat{jhs_i=1}|X_i)}{N}$ is a group of states and gender specific average. To predict the dummy variable $elem$, that is a variable equal to one if the individual has at least one child of **elementary-school-age**, we proceed as follows:

1. Using the sample of parents we estimate with a probit model the parameters in the equation

$$Pr(elem = 1|X) = \Phi(X\delta),$$

where Φ is the standard normal cumulative density function, and X includes number of children, indicator of child of high-school-age, age, race, gender, marital status, education level, employment status, full-time versus part-time job, total family income level, a set of variables reflecting health status, and state of residence.

2. Using the estimated parameters we predict the probability of having at least one child of elementary-school-age in the sample of adults without children as

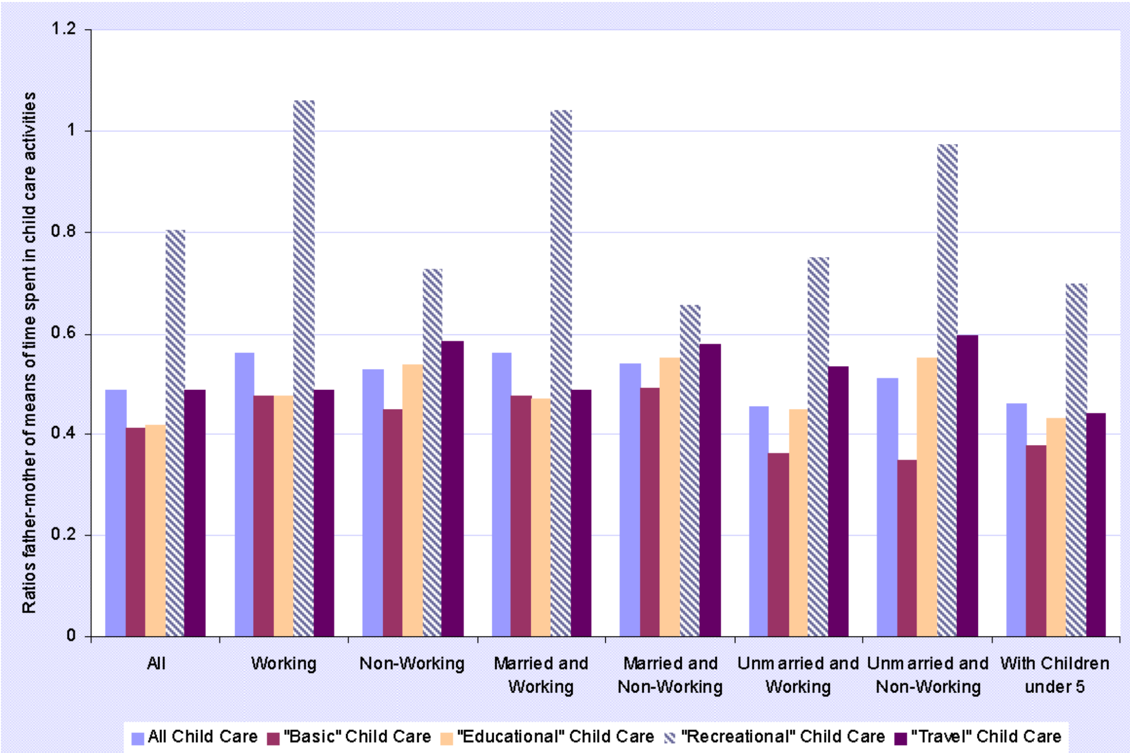
$$Pr(\widehat{elem =} 1|X) = \Phi(X\hat{\delta}),$$

3. To obtain a binary variable we correct the previous estimation

$$\widehat{elem}_i = \begin{cases} 1 & Pr(\widehat{elem_i =} 1|X_i) > \frac{\sum Pr(\widehat{elem_i=}1|X_i)}{N} \\ 0 & \text{otherwise} \end{cases}$$

Where $\frac{\sum Pr(\widehat{elem_i=}1|X_i)}{N}$ is a group of states and gender specific average.

Figure 3: Ratios father-mother of means of time spent in childcare activities (hours per week), by demographic subgroups.



Source: Ratios computed using data in Table 1 in Guryan et al. (2008) based on the 2003-2006 waves of the American Time Use Survey (ATUS). Childcare activities are classified into: "Basic" childcare (breast feeding, rocking a child to sleep, general feeding, changing diapers, providing medical care to child, grooming child, etc.); "Educational" childcare (reading to children, teaching children, helping children with homework, attending meetings at a child's school, etc.); "Recreational" childcare (playing games with children, playing outdoors with children, attending a child's sporting event or dance recital, going to the zoo with children, taking walks with children, etc.); "Travel" childcare (any travel related to any of the three other categories of childcare). Samples include all individuals between the ages of 21 and 55 (inclusive) who had time diaries summing to a complete day and at least one child under the age of 18.