Cliometrica manuscript No.
(will be inserted by the editor)

Child Labor Legislation: Effective, Benign, Both, or Neither?

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Received: date / Accepted: date

Abstract This paper explores the relationship between the state-specific child labor legislation and the decline in child labor that occurred in the U.S. between 1880 and 1900. The existing literature that addresses this question uses a difference-in-difference estimation technique. We contribute to this literature in two ways. First, we argue that this estimation technique can produce misleading results due to: (a) the possibility of multiplicity of equilibria and (b) the non-linearity of the underlying econometric model. Second, we develop an empirical strategy to identify the mechanism by which the legislation affected child labor decisions. In particular, besides establishing whether the legislation was effective or not, our analysis may determine if the legislation constituted a benign policy or not, i.e., whether the legislation constrained the behavior of families (not benign) or whether it changed the labor market to a new equilibrium in which families voluntarily respected the law (benign).

Keywords Child labor · Child labor legislation · Treatment effect estimation · Difference-in-difference estimation

1 Introduction

According to the 1880 U.S. census data, 32% of the children in the U.S. with ages between 10 and 15 declared having a gainful occupation. This rate decreased dramatically by the early 1900s. In particular, according to the 1930 U.S. census data, only 2% of this group declared having a gainful occupation[1]. The literature considers that one of the main reasons for this decline was the growing opposition to child labor that ultimately materialized into a body of legislation restricting employers from hiring children below a certain age[2]. According to [Moehling(1996)], [Moehling(1999)], and [Basu(1999)], various degrees of resistance against child labor had always existed in the U.S., but this opposition developed into a well-organized social movement in the 1880s and 1890s. Between 1880 and 1910, this movement was successful in enacting state-wide child labor legislation in many U.S. states. Typically, these laws took the form of state-wide prohibition for children of less than a certain age (typically, 14 years old) to be employed in the manufacturing sector. In particular, the number of U.S. states that prohibited children less than 14 years old to work in manufacturing went from zero in 1880, to 3 in 1890, to 12 in 1900, and to 32 in 1910. After 1910, child labor activists realized

Financial support from the Robert Eisner Memorial Fellowship and the Dissertation Year Fellowship is gratefully acknowledged.

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[1] See [Carter and Sutch(1996)].
[2] For a description of the evolution of this body of legislation, see [Ogburn(1912)] and [Moehling(1999)].

that employers had influence over certain state legislatures which limited the progress that could be made at the state level. Therefore, they decided to shift lobbying efforts from a state to a federal child labor legislation. After several unsuccessful attempts, the Fair Labor Standards Act was enacted in 1938. This is the federal law that currently prohibits employment of minors in occupations considered oppressive.

The objective of this paper is to explore the contribution of the state-specific child labor legislation to the spectacular decline in child labor that occurred in the U.S. between 1880 and 1900. The effectiveness of this legislation has been previously studied in the literature, most notably by [Moehling(1996)] and [Moehling(1999)]. In her dissertation, [Moehling(1996)] uses a difference-in-differences estimation procedure to estimate the effect of child labor legislation using exclusively 1900 U.S. census data. She estimates a binary choice model and computes the difference in the labor market participation of 13 and 14-year-olds (group difference), between states that did and did not issue child labor legislation (spatial difference). Her estimation reveals that child labor laws imposed constraints on child participation in the labor market. [Moehling(1999)] incorporates observations from the 1880 and 1910 U.S. census to study the same problem. The new dataset allows her to use a difference-in-difference-in-differences estimator to evaluate the effectiveness of the legislation. She computes the difference in labor market participation between 13 and 14-year-olds (group difference), between 1900 and 1880 (and also 1910 and 1900) (time difference) and between states that did and did not issue child labor legislation (spatial difference). Her conclusion is that child labor laws were ineffective in reducing child labor. [Moehling(1999)] states: "Although the predicted probabilities for the treatment group–13-year-old boys living in the states that enacted the age minima of 14– fell substantially between 1880 and 1900, so too did the predicted probabilities for the control groups". Throughout this paper, we use "differencing estimators" to refer to the difference-in-difference estimator in [Moehling(1996)] and the difference-in-difference-in-difference estimator in [Moehling(1999)].

We contribute to this literature in two ways. First, we argue that differencing estimators can produce misleading results due to: (a) the possibility of multiplicity of equilibria and (b) the non-linearity of the underlying econometric model. Second, we develop an empirical strategy to identify the mechanism by which the legislation affected child labor decisions. In particular, besides establishing whether the legislation was effective or not, our analysis may determine if the legislation constituted a benign policy or not, i.e., whether the legislation constrained the behavior of families (not benign) or whether it changed the labor market to a new equilibrium in which families voluntarily respected the law (benign).

Even though [Moehling(1996)] and [Moehling(1999)] provide a very detailed study of this problem, we believe there are two problems with their differencing estimation procedure. The first issue is that in non-linear models, like the ones required to model binary explanatory variables such as (child) labor participation, differencing estimator procedures do not identify the object of interest. The second issue is that differencing estimators assume that there is only one labor market equilibrium. However, [Basu and Van(1999)] argue that there might be multiple equilibria in an economy that has elevated levels of child labor participation, as it was the case in the U.S. at the end of the nineteenth century. We develop a structural model along these lines and argue that the differencing estimators can fail in the presence of this kind of multiplicity. The intuition is as follows. A properly enforced prohibition on young child labor naturally leads to a reduction in employment rates of young children. However, according to our model, the legislation can also result in a switch to a new equilibrium with significantly lower employment rates for older children (not targeted by the legislation). While one would consider this legislation very effective in reducing child labor, a differencing estimator that relies on the difference between employment rates of young and old children will fail to do so.

There is a huge body of literature that studies the determinants for child labor market participation and their relationship with child labor legislation. [Sanderson(1974)] uses a cross section of data to compare employment rates between states with and without child labor legislation. This data will be affected by state fixed effects, which one can control for with panel data. Using anecdotal evidence, [Osterman(1979)] provides a detailed description of changes in the unskilled labor market (which includes child labor) at the end of the nineteenth century. [Brown et al(1992)Brown, Christiansen, and Philips] study how changes in economic conditions and in the legislation impacted child labor in the U.S. fruit and vegetable canning industry. [Goldin(1979)] studies the determinants of child labor using 1880 Philadelphia census data. [Margo and Finegan(1996)] examine the effect of compulsory schooling laws and child labor laws on school attendance. Finally, [Nardinelli(1980)] studies the relationship between child labor legislation and child labor in the U.K.

The rest of the paper proceeds as follows. Section 2 explains why differencing estimators used in the literature may be inadequate to estimate the effectiveness of child labor legislation. Section 3 develops a simple model to study the effect of the child labor legislation. Based on this model, Section 4 delineates the empirical strategy. The estimation results are presented in Section 5. Section 6 concludes the paper.

2 Identification of the treatment effect

Our objective is to study the effect of the U.S. state-specific child labor legislation at the end of the nineteenth century on the behavior of the U.S. families. By 1880, arguably none of the U.S. states had established any serious body of legislation, and by 1900, a subset of the U.S. states had already established state-wide prohibition for children under a certain age to be employed in the manufacturing sector.

Under the maintained assumption that this legislation is an exogenous policy, its effect on child labor can be analyzed using the *natural experiment framework*[3]. According to this framework, the effect of the legislation on child labor is called *treatment effect*, 1880 is a *pre-treatment* year, 1900 is a *post-treatment* year, the children affected by the legislation are the *treatment group*, and the remaining children are the *control group*.

In order to discuss the economic model, it is convenient to introduce some notation. We refer to the year 1880 as period 1 and to the year 1900 as period 2. In period 1, no state had issued child labor legislation and, by period 2, there are states with legislation, referred to as B states, and states without legislation, referred to as A states.

	Period 1	Period 2
A states	No C.L.L.	No C.L.L.
B states	No C.L.L.	C.L.L.

The previous notation seems to imply that all children in B states in period 2 were affected by the treatment. As we have mentioned, the treatment consisted in a state-wide prohibition for children of less than a certain age (typically, 14 years old) to be employed in the manufacturing sector. This may lead one to believe that only young children in the manufacturing sector belong to the control group. Using arguments in [Basu and Van(1999)], Section 2.2 argues that all children in a B state in period 2 should be considered as belonging to the treatment group.

Besides the child labor legislation, there are other factors affecting the households' decision to let a child seek employment, such as time fixed effects, i.e., time-specific factors affecting all the states, and state fixed effects, i.e., state-specific factors affecting each state in both periods. By definition, the child labor legislation is exclusively affecting B states in period 2. In order to identify the treatment effect of the legislation we assume that the child labor legislation is exogenously determined, which implies that it is the only factor affecting B states in period 2 in a systematic fashion. We comment further on these assumptions towards the end of this section.

We model the household's child labor decision using a binary response model. Let w denote the binary variable that indicates when the child is employed, let $d2$ denote the binary variable that indicates when the observation corresponds to period 2, and let dB denote the binary variable that indicates when the observation corresponds to a B state. Naturally, $d2dB$ denotes the product of $d2$ and dB. Finally, denote by x the vector of the remaining variables that affect the decision. In the binary response model, the labor decision is given by:

$$w = 1[\alpha_1 d2 + \alpha_2 dB + \alpha_3 d2dB + \beta x \geq \varepsilon], \tag{2.1}$$

where ε denotes an unobserved random term with a known continuous distribution, whose cumulative distribution function (CDF) is denoted by F. Typically, the function F is assumed to be a non-linear function, such as the standard logistic CDF, i.e., logit model, or the standard normal CDF, i.e., probit model. From Eq. (2.1) it follows that:

$$P(w = 1|d2, dB, d2dB, x) = F(\alpha_1 d2 + \alpha_2 dB + \alpha_3 d2dB + \beta x). \tag{2.2}$$

[3] For a rigorous treatment of these issues, see [Meyer(1995)] and [Wooldridge(2002)].

The object of interest, i.e., the treatment effect, is the difference in the likelihood of employment as a consequence of the introduction of child labor legislation while keeping the remaining variables constant. Under our assumptions, the treatment effect can be identified by changing $d2dB = 0$ to $d2dB = 1$ while keeping $d2$, dB, and x constant at certain values of interest. In notation:

$$\begin{aligned} TE(\bar{d2}, \bar{dB}, \bar{x}) &= P(w = 1|\bar{d2}, \bar{dB}, d2dB = 1, \bar{x}) - P(w = 1|\bar{d2}, \bar{dB}, d2dB = 0, \bar{x}), \\ &= F(\alpha_1 \bar{d2} + \alpha_2 \bar{dB} + \alpha_3 + \beta\bar{x}) - F(\alpha_1 \bar{d2} + \alpha_2 \bar{dB} + \beta\bar{x}). \end{aligned} \tag{2.3}$$

where $\bar{d2}$, $\bar{dB}$, and $\bar{x}$ are the constant values in which the treatment effect is evaluated. As Eq. (2.3) reveals, the treatment effect coincides with the sign of α_3 and can be identified by computing differences in probability expressions.

As we have already mentioned, the treatment effect is identified by the assumption that the child labor legislation (i.e. the treatment) is exogenous. The assumption is explicitly imposed in the model by assuming that, conditional on the control variables, the residual term ε is distributed according to F. As usual, this exogeneity of the residual is an assumption on the unobservables of the model and can be subject to criticism. For instance, consider the plausible case in which the passage of child labor legislation was positively correlated with unobserved growing social opposition to child labor that appeared in the more progressive states between 1880 and 1900. In this case, this unobserved attitude towards child labor would be part of the residual term ε, and would generate positive correlation between the residual and the treatment (i.e. the treatment is endogenous). In this scenario, the observed treatment effect would overestimate the treatment effect of the legislation, as it would attribute to child legislation the combined effect of the legislation itself and the social opposition to child labor. Even in this situation, one could still interpret the observed treatment effect as the mixture of these effects, without attempting to distinguish between the two[4].

2.1 Differencing in non-linear models

In order to model the children's labor decision, [Moehling(1996)] and [Moehling(1999)] use a binary choice model similar to the one described in Eqs. (2.1) and (2.2). Instead of estimating the treatment effect based on Eq. (2.3), Moehling proposes a differencing estimator that consistently estimates the difference-in-differences[5], given by:

$$\begin{aligned} &DD(\bar{x}) \\ &= \begin{array}{l} \big(P(w = 1|\bar{d2} = 1, \bar{dB} = 1, d2dB = 1, \bar{x}) - P(w = 1|\bar{d2} = 0, \bar{dB} = 1, d2dB = 0, \bar{x})\big) \\ - \big(P(w = 1|\bar{d2} = 1, \bar{dB} = 0, d2dB = 0, \bar{x}) - P(w = 1|\bar{d2} = 0, \bar{dB} = 0, d2dB = 0, \bar{x})\big) \end{array} \\ &= \left(F\left(\alpha_1 + \alpha_2 + \alpha_3 + \beta\bar{x}\right) - F\left(\alpha_1 + \beta\bar{x}\right)\right) - \left(F\left(\alpha_2 + \beta\bar{x}\right) - F\left(\beta\bar{x}\right)\right). \end{aligned} \tag{2.4}$$

The difference-in-differences is the difference between the time change in the likelihood of employment for the treatment and control groups. While there is a connection between the treatment effect and the difference-in-differences, these two objects are not the same. In particular, we now show that these two coincide in a linear regression model but they do not necessarily coincide in a non-linear regression model in the non-linear models considered by Moehling.

In a linear regression model (i.e. F is the identity function), it is easy to see that:

$$TE(\bar{d2}, \bar{dB}, \bar{x}) = DD\left(\bar{x}\right) = \alpha_3.$$

In other words, the treatment effect is a constant and coincides with the difference-in-differences. On the other hand, whenever the model is non-linear (i.e. F is not the identity function), neither of the previous findings are *necessarily* true[6]. First, a non-linear F implies that the treatment effect might not be constant,

[4] I thank an anonymous referee for this interesting interpretation.

[5] To be precise, the argument used in this section discusses the difference-in-difference estimator like the one used in [Moehling(1996)], but a similar argument can be used for the difference-in-difference-in-difference estimator in [Moehling(1999)].

[6] In particular, neither of these findings are true for typical non-linear models used to model a binary choice, such as probit or logit.

i.e., the treatment effect might be a function of $(\bar{d2}, \bar{dB}, \bar{x})$. Second and most importantly, the treatment effect and the difference-in-differences might not coincide. In fact, it is relatively straightforward to construct examples where difference-in-differences and the treatment effect have opposite signs[7]. As a consequence, in a non-linear model such as the one used to analyze a binary choice, the differencing estimator does not necessarily identify the object of interest, i.e., the treatment effect of the legislation.

To the best of our knowledge, the literature presents very few references documenting this issue. On the one hand, [Ai and Norton(2003)] focus on the interpretation and estimation of "interaction effects", which do not (necessarily) coincide with the treatment effect that is of interest to our paper. Nevertheless, the authors show how the interpretation and estimation of these effects differ depending on whether the model is linear or not. On the other hand, independent work by [Puhani(2008)] uses a different terminology to make a point similar to the one of this section. In particular, he refers to the difference-in-differences of Eq. (2.4) as a "cross difference", and shows that it does not coincide with the treatment effect when the model is non-linear.

One population quantity that might be of interest is the difference in the treatment effect between the treatment and control groups. If we denote by $(\bar{d2}_B, \bar{dB}_B, \bar{x}_B)$ the vector of covariate values in the treatment group and by $(\bar{d2}_A, \bar{dB}_A, \bar{x}_A)$ the vector of covariate values in the control group, then the difference in treatment effects is given by:

$$DTE = TE(\bar{d2}_B, \bar{dB}_B, \bar{x}_B) - TE(\bar{d2}_A, \bar{dB}_A, \bar{x}_A). \tag{2.5}$$

The difference in treatment effects can be considered the analogue of the differences-in-differences in the context of a linear model. From the formula, it is clear that the difference in treatment effects is neither the treatment effect nor the difference-in-differences. In the next section, we explain why the differences in the treatment effect can be used an indication of whether the child labor legislation generated a switch in the labor market equilibrium.

2.2 Differencing in the presence of multiplicity of equilibria

As we have explained, the typical state-wide child labor legislation took the form of state-wide prohibition for children of less than a certain age (typically, 14 years old) to be employed in the manufacturing sector. Based on this, Moehling uses the difference in the employment rate between children who were affected by the law (i.e. aged 13 or younger) and children who were not affected by the law (i.e. aged 14 or older) in order to identify the effect of the legislation. In particular, this gap is one of the differences in the difference-in-differences estimator in [Moehling(1996)] or the difference-in-difference-in-difference estimator in [Moehling(1999)]. The logic behind using this difference is that the child labor legislation can only affect those individuals who are directly prohibited to work. By adapting the model in [Basu and Van(1999)], we provide a general equilibrium channel by which the legislation can affect the employment rate of all children in the model, *regardless of whether their employment is restricted or not.* If this result obtained in the model holds, then the group difference can severely underestimate the true effect of the child labor legislation.

In their seminal paper, [Basu and Van(1999)] developed a reduced form model of child labor with multiplicity of equilibria. The model is based on two main assumptions or axioms. The first one is the *luxury axiom*, by which a household decides to send the children to work only if the household's income from non-child labor sources is sufficiently low. Children have very important opportunity costs of working, such as not receiving education or not enjoying their leisure. As decision makers, the parents are forced to send their children to work only when income from every member of the household is necessary for survival. The second axiom is the *substitution axiom*, by which from a firm's point of view, adult and child labor are substitutes. When these assumptions are incorporated into a household decision model, this model can generate a downward sloping labor supply. If the wage is very low, then families are forced to send their children to work, generating a high aggregate labor supply. If the wage is very high, then working parents can support their

[7] For example, consider $F(x) = \Lambda(x)$, where Λ denotes the logistic cumulative distribution function (i.e. logit model), and set $\bar{x} = \bar{d2} = \bar{dB} = 0$, $\alpha_1 = 1$, $\alpha_2 = -3$, and $\alpha_3 = 0.1$. Since $\alpha_3 > 0$, then $TE(\bar{d2}, \bar{dB}, \bar{x}) > 0$, but calculations reveal that $DD(\bar{d2}, \bar{dB}, \bar{x}) < 0$.

entire household by themselves, resulting in a low amount of labor supply. When combined with a traditional downward sloping labor demand, the model can produce multiplicity of equilibria.

Using the ideas in [Basu and Van(1999)], we develop a structural framework to model the labor market in the U.S. at the end of the nineteenth century. We now summarize its main features, but all of its details are explained in Section 3. In our model, there are households with young children, i.e., 13 years of age or less, and households with old children, i.e., 14 years of age or more. Before the legislation, the economy is in a situation of low wages, forcing every household to send their children to work, regardless of their age. Now suppose a ban on young child labor is introduced. If this legislation is enforced, households with young children are obliged to comply and, consequently, the legislation is effective in eliminating child labor. If nothing else occurs, then the law produced a gap between the old and young child labor. In this case, the difference in treatment effects between young and old children correctly identifies the effect of the law. This is the reasoning followed by [Moehling(1996)] and [Moehling(1999)].

However, the legislation can have other general equilibrium effects. The elimination of young child labor produces an increase in the wage, making every household in the economy wealthier. Provided that this effect is large enough, families with older children might decide to *voluntarily* remove them from the labor market, as the household income based on parental income is sufficient to support the family. Consequently, a legislation targeted exclusively at young children produces an overall reduction in child labor. In this case, child labor legislation should be considered extremely effective, as it reduces the labor participation of all children, and not only young children covered by the law. Moreover, the legislation is benign, because instead of constraining the behavior of economic agents, it causes a change to an equilibrium where agents voluntarily respect the law. In this economy, older children cannot really be considered part of the control group, as their behavior is also affected by the legislation. Finally, any of the differencing estimators that have been discussed (i.e. difference-in-differences, difference-in-difference-in-differences, or difference in treatment effects) will fail to identify the treatment effect of the law[8]. The effect of the legislation can be easily identified by computing the treatment effect in Eq. (2.3), which can be calculated for both young and old children in the economy.

3 Economic model

Consider the following overlapping-generations model. Each household in the economy is composed of two individuals: a parent and a child. An agent in the economy lives four periods. He is a young child in the first period, an old child in the second period, a young adult in the third period and an old adult in the fourth period. In the first two periods of his life, the individual lives under the supervision of the adult, who makes all decisions in the household. At the end of the second period, the old adult dies, the old child becomes a young adult and gives birth to a young child. For the two remaining periods of his life, he will be the decision maker in his household. In every period $2N$ simultaneous families coexist: N young families and N old families[9].

The flow utility of the adult is given by:

$$u(c_{i,a}, c_{i,k}, l_{i,k}) = u(c_{i,a} + c_{i,k}, (\psi + \delta 1[i = y])(1 - l_{i,k})),$$

where $i \in \{o, y\}$ denotes the age of the household, $c_{i,a}$ refers to the adult's consumption, $c_{i,k}$ refers to the child's consumption, and $l_{i,k} \in \{0, 1\}$ is a binary variable that equals one when the child works and zero when he does not. The indicator variable $1[i = y]$ takes a value of one if we are referring to a young household (which includes a young child) and zero otherwise.

In this model, an adult is altruistic in two ways: he cares about his child's consumption and his child's leisure (or, alternatively, his education). When an old child works, his parent suffers a disutility of $\psi > 0$. When a young child works, his parents suffers a disutility of $\psi + \delta$, where $\delta > 0$ represents the extra cost of forcing a young child to work. We assume that the utility function is weakly increasing in both coordinates.

[8] We consider that this general equilibrium effect could explain [Moehling(1999)] finding: "Although the predicted probabilities for the treatment group–13-year-old boys living in the states that enacted the age minima of 14– fell substantially between 1880 and 1900, so too did the predicted probabilities for the control groups".

[9] Even though the age structure in this economy may be unrealistic, our objective is to maintain a constant proportion of young and old children and adults.

Moreover, we assume that the household has a subsistence consumption level, denoted by $\bar{C}$, such that if the household consumes less than this amount, the adult only cares about maximizing consumption and child leisure becomes irrelevant[10]. This part of the model represents the luxury axiom in [Basu and Van(1999)].

A household's wealth is given by labor income. Households are subject to period budget constraints, and we assume, for simplicity, that there is no borrowing or lending:

$$c_{i,a} + c_{i,k} = w_a + w_k l_{i,k},$$

where w_a represents the equilibrium wage for the employed adult and w_k represents the equilibrium wage for the employed child[11].

We now model the production sector in this economy. There is a continuum of perfectly competitive firms, each producing the unique manufactured good according to the following production function:

$$f(L_a^d, L_k^d) = G(L_a^d + L_k^d/\mu),$$

where G is a strictly increasing, marginally decreasing, and twice differentiable function. Labor input is measured in adult labor equivalent units, $L_a^d + L_k^d/\mu$, where L_a^d and L_k^d are the amounts of adult and child labor demanded, respectively. Implicit in the equation is that adults and children are perfect substitutes in production: one working adult produces the same amount as μ working children[12]. This part of the model represents the substitution axiom in [Basu and Van(1999)].

Profit maximization implies that equilibrium adult and child wages are given by:

$$w_a = g((2 + (l_{y,k} + l_{o,k})/\mu)N) \text{ and } w_k = w_a/\mu,$$

where g denotes the derivative of G.

Labor decisions in the household are as follows. As a consequence of the subsistence consumption level, a parent will always decide to work. The only relevant household decision is whether to send their children to work or not. In an old household (with an old child), the optimal decision is given by:

$$l_{o,k} = 1[u(w_a, \psi) \leq u(w_a + w_k, 0)],$$

and in a young household (with a young child), the optimal decision is given by:

$$l_{y,k} = 1[u(w_a, \psi + \delta) \leq u(w_a + w_k, 0)].$$

Notice that if young children are sent to work, then old children will be sent to work as well.

3.1 Equilibria in the model

This model can generate three equilibria, each of which is characterized by the composition of economically active children.

1. **The "all children work" equilibrium.** This is a pooling equilibrium where, as the name indicates, all households force their children to work. Equilibrium wages are given by $w_a = g((1 + 1/\mu)2N)$ and $w_k = g((1 + 1/\mu)2N)/\mu$. This equilibrium exists if and only if the parameters of the model satisfy the following condition:

$$u(g((1 + 1/\mu)2N), \psi + \delta) \leq u(g((1 + 1/\mu)2N)(1 + 1/\mu), 0).$$

2. **The "no children work" equilibrium.** This is another pooling equilibrium where only the parents work. Equilibrium wages are given by $w_a = g(2N)$ and $w_k = g(2N)/\mu$. This equilibrium exists if and only if the parameters of the model satisfy the following condition:

$$u(g(2N), \psi) \geq u(g(2N)(1 + 1/\mu), 0).$$

[10] This feature is not necessary to get the main results of the model, but it helps to strengthen the intuition.

[11] Implicit in the notation is the fact that firms discriminate between adults and children, but not between young and old adults and young and old children. This is mainly assumed for simplicity.

[12] We assume that a child is less productive than a grown up and, therefore, $\mu > 1$.

3. **The "only old children work" equilibrium.** In this last equilibrium, households of different age separate. Equilibrium wages are given by $w_a = g((2+1/\mu)N)$ and $w_k = g((2+1/\mu)N)/\mu$. This equilibrium exists if and only if the parameters of the model satisfy the following condition:

$$u(g((2+1/\mu)N), \psi + \delta) \geq u(g((2+1/\mu)N)(1+1/\mu), 0) \geq u(g((2+1/\mu)N), \psi).$$

We assume that the parameters of the model are such that all of the aforementioned equilibria exist. This situation is depicted in Figure 1. For low wages, all the households of the economy will decide to send their children to work. At intermediate wages, old parents will send their old children to work but young parents will decide not to. Finally, when wages are high enough, all families are wealthy enough to avoid sending their children to work.

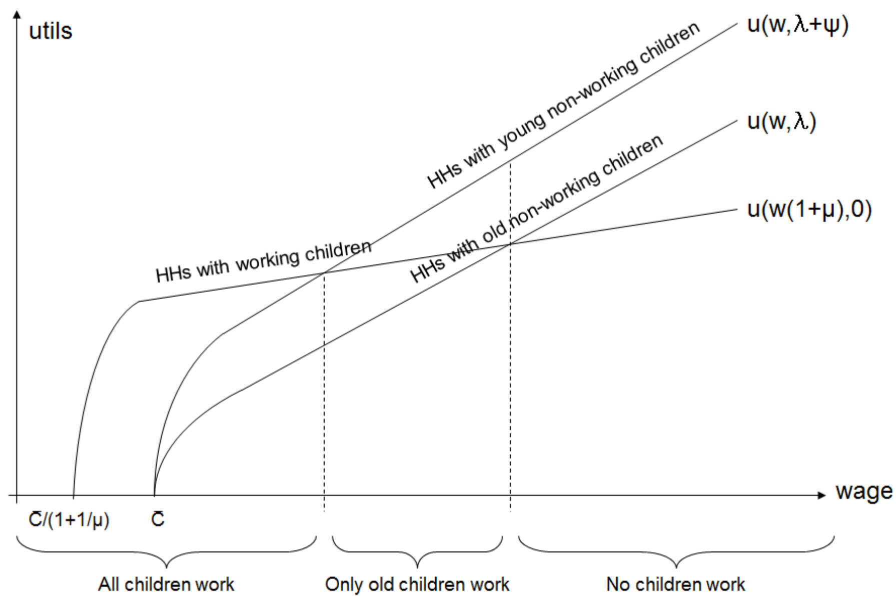

Fig. 1 An economy with three equilibria.

3.2 The effect of child labor legislation

At the end of the nineteenth century, the U.S. labor market was characterized by high levels of child labor participation. On this basis, we assume that pre-legislation economy was in the "all children work" equilibrium. This situation is depicted in Figure 2.

We now introduce child labor laws into the economy. Based on the state-specific legislation introduced in the U.S. at the end of the nineteenth century, we assume that the state government prohibits young children from working. The effect of this ban depends on whether the legislation is properly enforced or not. If there is no enforcement, it is possible to have a completely ineffective legislation (see case 1 below). In order to explore more interesting results, suppose that the legislation is properly enforced. As a consequence of the prohibition, young children are forced out of the labor market and thus, the pre-legislation "all children work" equilibrium is eliminated. The elimination of young child labor supply causes an increase in wages, resulting in general equilibrium effects. Depending on the magnitude of this general equilibrium effect, we have several cases (see cases 2, 3, and 4 below). We now divide the analysis into all the possible cases.

Case 1: Ineffective. The legislation has no effect on child labor participation and the post-legislation situation is identical to the pre-legislation situation. This is shown in Figure 3. This outcome is only possible if the legislation is not enforced.

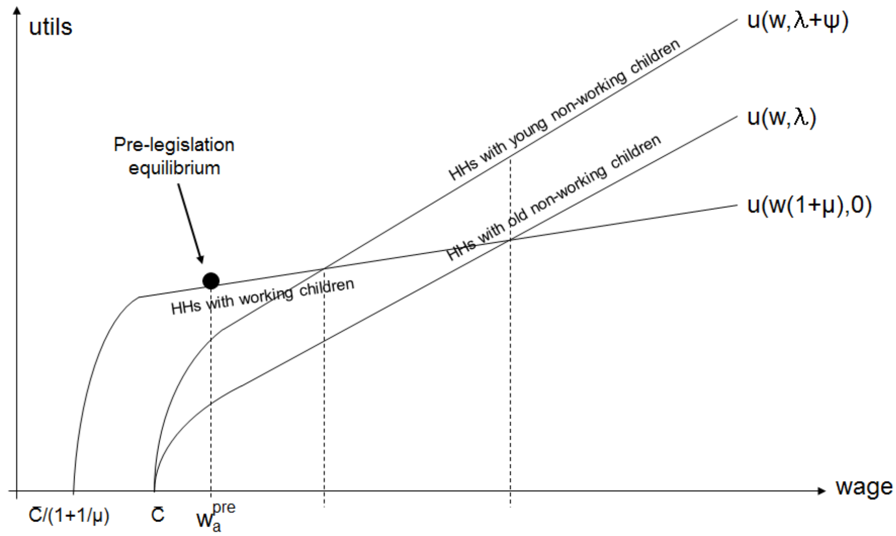

Fig. 2 Pre-legislation situation.

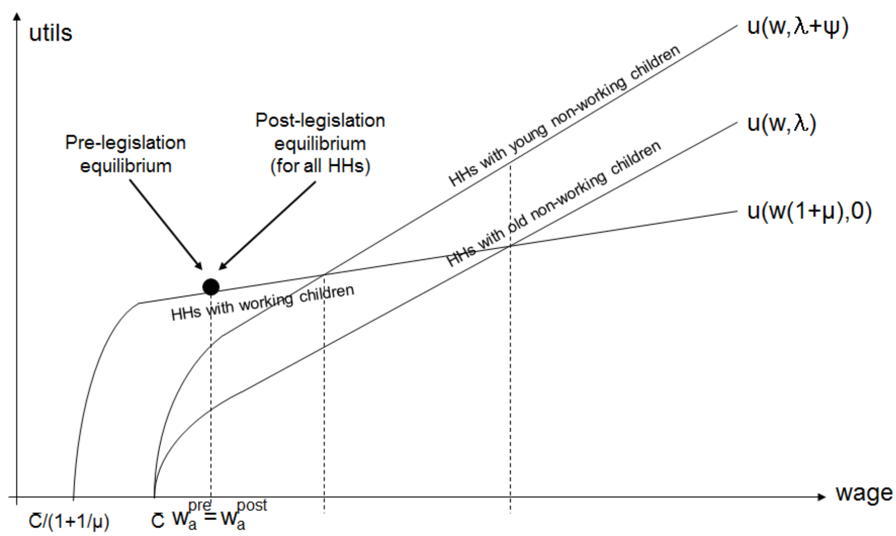

Fig. 3 No effect (case 1).

Case 2: Distortive. The prohibition of young child labor produces a mild increase in equilibrium wages, which is not sufficient to induce changes in households' decisions. Old households still decide to send their old children to work and, in absence of legislation, young households would do so too. The child labor legislation is not Pareto optimal and therefore, not benign. This is shown in Figure 4. The legislation is effective in reducing young child labor and ineffective in reducing old child labor.

Case 3: Small benign effect. The elimination of young child labor produces a greater increase in wages. The rise in family income is large enough to induce young families to remove their children from the labor market, but not enough to convince old families to remove their children from the labor market. The legislation generates a switch from one equilibrium to a different one. In this case, the pre and post-legislation equilibrium are both Pareto optimal situations. This is represented in Figure 5. As a consequence of the child labor laws, young child labor is reduced and old child labor remains high. Notice that in terms of child labor market participation, this case is observationally equivalent to the preceding one.

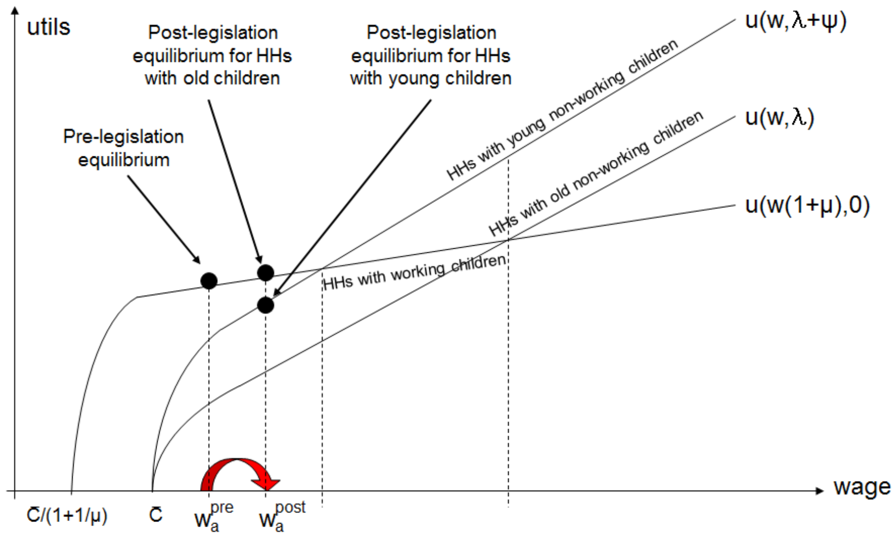

Fig. 4 Distortive effect (case 2).

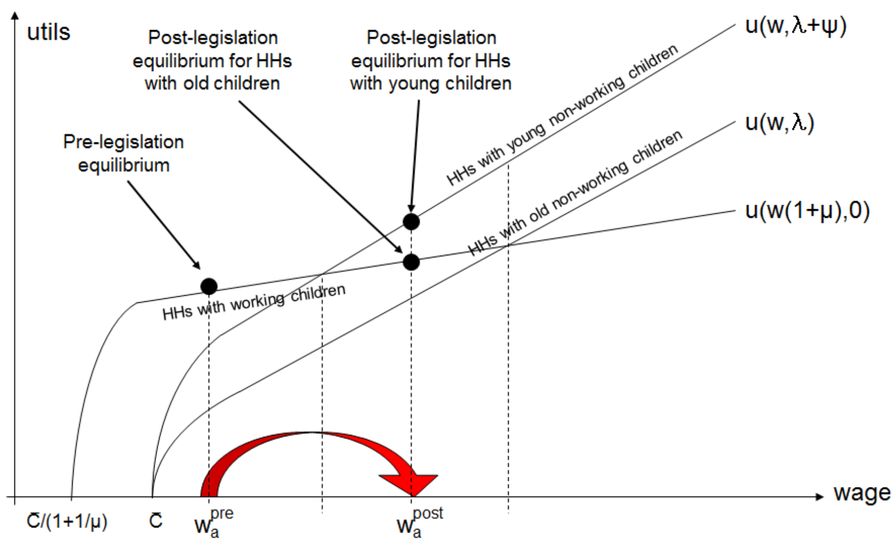

Fig. 5 Small benign effect (case 3).

Case 4: Large benign effect. In this case, the removal of young child labor produces a big increase in wages, causing a significant increase in household income. This induces all families to remove their children from the labor force, regardless of their age. As in the previous case, the legislation causes a switch from one equilibrium to another one, and the post-legislation equilibrium is also Pareto optimal. Figure 6 depicts the situation. The legislation is effective in reducing child labor levels across all ages, even though the legislation is only explicitly targeted at young children. Notice how this case is observationally different from the previous ones.

We summarize the effects of child labor legislation in the following table. For each case, we indicate whether the legislation is: (a) effective in reducing young child labor, (b) effective in reducing old child labor, and (c) benign.

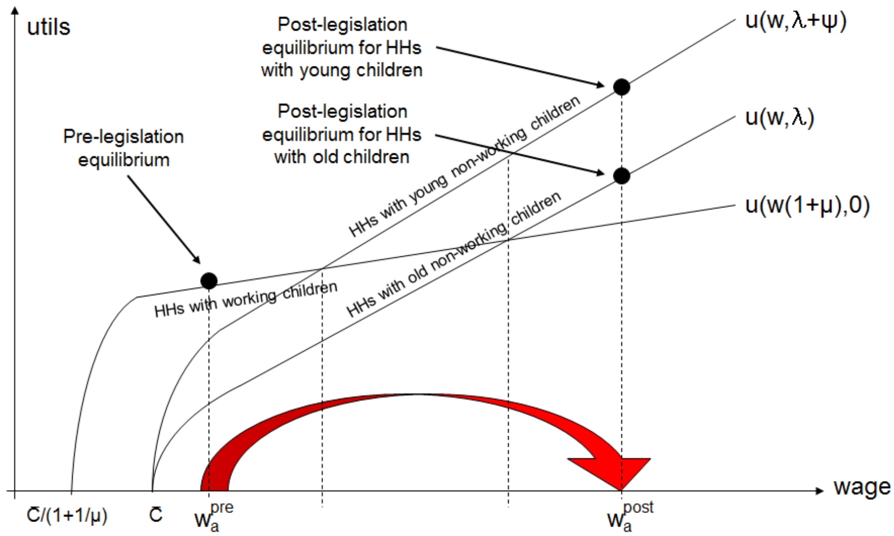

Fig. 6 Large benign effect (case 4).

	Effective in reducing young child labor?	Effective in reducing old child labor?	Benign?
Case 1	No	No	Yes
Case 2	Yes	No	No
Case 3	Yes	No	Yes
Case 4	Yes	Yes	Yes

By definition, the legislation is effective in reducing young (respectively, old) child labor if the treatment effect for young (respectively, old) children is negative. The legislation is benign if its effect is not to restrict the household's behavior but rather changing the pre-legislation equilibrium to a different one, where households voluntarily choose to comply with the legislation. Cases 3 and 4 are examples of this. Case 1 is a special situation where there legislation has no effect and, consequently, it is benign in a very trivial way.

Notice how cases 2 and 3 are observationally equivalent but the effect of the legislation is fundamentally different. In case 2 the legislation is distortive and in case 3 the legislation is not. From this, we can conclude that it might not always be possible to determine whether the legislation is benign or not. On the other hand, the reduction in old child labor in case 4 allows us to distinguish it from the remaining cases. Notice that case 4 is a situation where the legislation is extremely effective as it reduces child labor of all ages, even those that are not directly targeted by the ban. It is paradoxical that this is the case in which the difference in treatment effects (or any other differencing estimator that uses group difference, for that matter) would conclude that the legislation is ineffective.

4 Econometric methodology

In this section, we describe the econometric model in detail and the data used to conduct the inference.

4.1 Econometric model

As we have explained in Section 2, the household's child labor decision is modeled with a binary response model. We now reproduce this for convenience. According to the model, the labor decision is given by:

$$w = 1[\alpha_1 d2 + \alpha_2 dB + \alpha_3 d2dB + \beta x \geq \varepsilon], \tag{4.1}$$

where w is a binary variable that indicates when the child is employed, $d2$ is a binary variable that takes value one when the observation corresponds to 1900 (period 2) and zero otherwise (period 1), dB is a binary variable that takes value one when the observation corresponds to a state that issued child labor legislation in 1900 (B states) and zero otherwise (A states), $d2dB$ is their interaction, x are remaining observable controls, and ε denotes an unobserved random term whose CDF is denoted by F. We assume ε is independent and distributed according to the logistic distribution, i.e., we adopt a logit specification[13]. If we denote the parameters of the model by $\pi = [\alpha_1, \alpha_2, \alpha_3, \beta]'$ and we denote the observable covariates vector by $X = [d2, dB, d2dB, x]$, the probability of employment evaluated at X is given by:

$$P(w = 1|d2, dB, d2dB, x) = F(X\pi).$$

The parameters of the model can be consistently and asymptotically efficiently estimated by maximum likelihood, which we denote by $\hat{\pi}$. Under usual regularity conditions and denoting the sample size by N, $\sqrt{N}\,(\hat{\pi} - \pi)$ is an asymptotically normally distributed vector with zero mean and variance covariance matrix denoted by $Avar(\pi)$. The probability of employment evaluated at X can be estimated by:

$$\hat{P}(w = 1|d2, dB, d2dB, x) = F(X\hat{\pi}).$$

The treatment effect of the legislation corresponds to the change in the probability of employment caused exclusively by the child labor legislation, keeping the remaining covariates at a specific level of interest. As we have explained in Section 2, the treatment effect can be identified by changing $d2dB = 0$ to $d2dB = 1$ while keeping $d2$, dB, and x constant at certain values of interest, that is:

$$TE(d\bar{2}, d\bar{B}, \bar{x}) = F(X_1\pi) - F(X_0\pi),$$

where $X_0 = [d\bar{2}, d\bar{B}, 0, \bar{x}]$, $X_1 = [d\bar{2}, d\bar{B}, 1, \bar{x}]$, and $d\bar{2}$, $d\bar{B}$, and $\bar{x}$ are the constant values where the treatment effect is evaluated. This treatment effect can be consistently estimated by:

$$\widehat{TE}(d\bar{2}, d\bar{B}, \bar{x}) = F(X_1\hat{\pi}) - F(X_0\hat{\pi}).$$

Under the standard assumption that F is continuously differentiable, the Delta method implies that:

$$\sqrt{N}(\widehat{TE}(d\bar{2}, d\bar{B}, \bar{x}) - TE(d\bar{2}, d\bar{B}, \bar{x})) \xrightarrow{d} N(0, Avar(\pi, d\bar{2}, d\bar{B}, \bar{x})), \tag{4.2}$$

where $Avar(\pi, d\bar{2}, d\bar{B}, \bar{x})$ denotes the asymptotic variance of the treatment effect, given by:

$$Avar(\pi, d\bar{2}, d\bar{B}, \bar{x}) = (f(X_1\pi)X_1 - f(X_0\pi)X_0)Avar(\pi)(X_1' f(X_1\pi) - X_0' f(X_0\pi))$$

and f denotes the derivative of F. Under the standard regularity assumptions, $Avar(\pi, d\bar{2}, d\bar{B}, \bar{x})$ is a continuous function of π and can thus be consistently estimated by $Avar(\hat{\pi}, d\bar{2}, d\bar{B}, \bar{x})$.

In the results section, we will be interested in conducting the following hypothesis test:

$$H_0 : TE(d\bar{2}, d\bar{B}, \bar{x}) = 0 \text{ vs. } H_1 : TE(d\bar{2}, d\bar{B}, \bar{x}) \neq 0,$$

for a significance level of $\alpha \in (0, 1)$. Under the null hypothesis of the test, the combination of Eq. (4.2) and Slutzky's theorem implies that:

$$\frac{N(\widehat{TE}(d\bar{2}, d\bar{B}, \bar{x}))^2}{Avar(\hat{\pi}, d\bar{2}, d\bar{B}, \bar{x})} \xrightarrow{d} \chi_1, \tag{4.3}$$

where χ_1 denotes the chi-squared distribution with one degree of freedom. As a consequence, asymptotically valid inference is implemented by rejecting the null hypothesis if and only if the test statistic in Eq. (4.3) exceeds the $1 - \alpha$ quantile of χ_1.

[13] We also conducted the estimation using a probit model and obtained very similar results.

4.2 Description of the data

The data were constructed using individual level records from the 1880 and 1900 U.S. federal censuses which are part of the Integrated Public Use Microdata Series or IPUMS[14]. The 1880 dataset is a 1-in-100 sample containing data on over 107,000 households and 502,000 individuals, and the 1900 dataset is a 1-in-100 sample containing data on over 173,000 households and 760,000 individuals[15].

We follow [Moehling(1999)] closely in terms of the preparation and the construction of the data. We focus our attention on children living in non-agricultural households with at least one parent[16]. We also restrict our analysis to white children, since white and non-white children faced very different labor market opportunities. To simplify the construction of variables, we restrict attention to households that contained only one family and to children who were sons or daughters of the household head. Furthermore, we exclude children living in areas that had not achieved statehood by 1880.[17]

We define children to be individuals of ages 13 to 14, where 13-year-olds play the role of young children and 14-year-olds play the role of old children[18]. Since boys and girls were considered to be very different by the labor market, we run separate estimations for each gender.

The dependent variable of the study is a binary variable that indicates whether the child has a gainful occupation or not. Ideally, we would like to observe if an individual held any type of gainful occupation, whether regular or intermittent but, unfortunately, the census data only reports each individual's *regular* or *usual form of employment*. As a consequence, we will be limited to studying the effect of child labor legislation on children that worked *on a regular basis*. As in [Moehling(1999)], we run two separate estimations. In the first one, the dependent variable indicates if the individual works regularly in any sector[19] and, in the second one, the dependent variable indicates if the individual works regularly in the manufacturing sector[20].

The typical state-wide child labor legislation imposed a variety of restrictions: minimum age limits for employment in the manufacturing sector, maximum work hour limits, minimum school enrollment, and minimum grade completion requirements. Following [Moehling(1999)], we focus on the minimum age for employment in the manufacturing sector as this was the one that imposed greater constraints to households' behavior. Specifically, we define child labor legislation to be the prohibition of children of less than 14 years of age to be employed in the manufacturing sector. By the year 1880, almost none of the U.S. states had passed child labor legislation and, according to [Sanderson(1974)], the existing laws had little publicity and were poorly enforced. By the year 1900, twelve states had issued child labor legislation targeting girls and ten states had issued legislation aimed at boys.

We now proceed to explain the construction of the explanatory variables. The information regarding which states passed child labor legislation between 1880 and 1900 can be found in [Ogburn(1912)] or [Moehling(1999)]. We include the same set of controls as in [Moehling(1999)]. To control for the household's wealth we include the household head's age and squared age. We also include variables indicating whether the head reported having no occupation, whether he had an occupation that required no skills, and whether he had a professional or technical occupation, and whether he had an occupation in the textile sector. We also control for the number of months that the household head has been unemployed in the previous year. We include binary variables that indicate whether the mother and/or the father were absent, whether

[14] The data and its description are publicly available at http://www.ipums.umn.edu.

[15] [Moehling(1999)] uses the same 1-in-100 sample for 1880 and uses a smaller 1-in-760 sample for 1900 (the latter sample is no longer available in the IPUMS). Other than in this aspect, the rest of the specification of the data is exactly as in [Moehling(1999)]. In particular, we restrict the data in the same way and we include the same control variables for the estimation.

[16] Children in agricultural households worked mainly in agriculture, which was not targeted by the child labor movement at the end of the century.

[17] This eliminates all observations from Alaska, Arizona, Hawaii, Idaho, Montana, New Mexico, North Dakota, Oklahoma, South Dakota, Utah, Washington, and Wyoming.

[18] We have also conducted the analysis defining children to be individuals of ages 12 to 15, where 12 and 13-year-olds play the role of young children and 14 and 15-year-olds play the role of old children. This alternative definition produces similar results in terms of treatment effects and leads us to believe that our conclusions are robust with respect to how the sample is defined.

[19] A child will not be considered to have a regular gainful occupation if, according to the 1950-occupation classification, the child is at school, keeps the house, helps his parents, is unemployed or without occupation, is invalid or disabled with no occupation reported, or has any other non-occupation.

[20] A child will be considered to work in the manufacturing sector if, according to the 1950-occupational classification, the child is employed as a craftsman or as an operative.

the child and/or the parents were foreign born, the number of older and younger sisters and brothers, and the household presence of children of less than 6 years of age. To capture the human capital stock of the child, we include binary variables that indicate whether the child could read and/or write. To capture the size of the labor market we introduce binary variables that indicate whether the household lived in an area with high population level (25,000 or more habitants), medium population level (between 2,500 and 24,999 habitants), or low population level (less than 2,500 habitants, omitted). We also included state specific controls like the state unemployment rate, a binary variable that indicates whether the state is a southern one, and gender specific industrial mix variables for both employment in any sector and for employment in the manufacturing sector[21].

Table 1 provides summary statistics of all dependent and independent variables for each gender and age combination in our data.

	Young boys		Young girls		Old boys		Old girls	
Variable	Mean	St.dev.	Mean	St.dev.	Mean	St.dev.	Mean	St.dev.
Works in any sector	0.159	0.365	0.064	0.245	0.329	0.470	0.125	0.331
Works in manufacturing	0.072	0.258	0.037	0.190	0.140	0.347	0.077	0.267
dB	0.466	0.499	0.515	0.500	0.475	0.499	0.517	0.500
$d2$	0.609	0.488	0.614	0.487	0.610	0.488	0.621	0.485
$d2dB$	0.293	0.455	0.324	0.468	0.302	0.459	0.320	0.467
Head's age	45.197	7.691	45.049	7.637	46.023	7.572	45.898	7.704
Head's age^2	2101.937	737.898	2087.702	728.489	2175.455	737.115	2165.999	747.378
Head reads	0.926	0.262	0.927	0.261	0.920	0.272	0.925	0.263
Head writes	0.908	0.289	0.910	0.287	0.899	0.302	0.910	0.286
Head's unemp. Months	0.818	2.052	0.800	2.064	0.769	2.017	0.778	1.986
Head is unskilled	0.810	0.393	0.797	0.402	0.810	0.392	0.785	0.411
Head is professional	0.034	0.180	0.038	0.192	0.032	0.175	0.039	0.194
Head has no occupation	0.121	0.327	0.110	0.313	0.136	0.343	0.124	0.330
Head empl. in textiles	0.026	0.158	0.021	0.144	0.022	0.148	0.023	0.149
No. children under 6	0.454	0.498	0.460	0.498	0.401	0.490	0.414	0.493
Absent mother	0.040	0.196	0.037	0.190	0.035	0.183	0.040	0.195
Absent father	0.127	0.333	0.120	0.325	0.137	0.344	0.133	0.340
No. older brothers	0.712	0.937	0.699	0.920	0.684	0.888	0.668	0.892
No. older sisters	0.661	0.891	0.649	0.888	0.618	0.838	0.607	0.864
No. younger brothers	1.048	1.119	1.078	1.127	1.078	1.165	1.061	1.166
No. younger sisters	1.021	1.119	1.035	1.122	1.080	1.156	1.081	1.170
U.S. born	0.922	0.268	0.928	0.258	0.905	0.293	0.921	0.270
Parents born in U.S.	0.536	0.499	0.540	0.498	0.513	0.500	0.538	0.499
Medium population	0.191	0.393	0.195	0.396	0.194	0.395	0.200	0.400
Big population	0.366	0.482	0.377	0.485	0.401	0.490	0.374	0.484
South	0.159	0.366	0.162	0.368	0.166	0.372	0.165	0.371
State unemployment rate	0.081	0.013	0.081	0.014	0.081	0.014	0.081	0.014
Industrial mix	0.112	0.040	0.064	0.037	0.112	0.039	0.065	0.037
Industrial mix manuf.	0.077	0.040	0.040	0.036	0.076	0.039	0.040	0.037
N	4466		4540		4476		4478	

Table 1 Summary statistics of all variables. *Source:* author's calculations using Integrated Public Use Microdata Series. See Section 4.2 for a description of these variables.

5 Results

The estimation results of the logit model are presented in Tables 2 and 3. Table 2 shows the estimation results when the dependent variable indicates a regular occupation in any sector, whereas Table 3 presents the estimation results when the dependent variable indicates a regular occupation in the manufacturing sector.

[21] For details on the construction of these variables, see [Bower and Finegan(1969)] or [Moehling(1999)].

As we have explained in Section 2, the sign of the coefficient associated to $d2dB$ is the sign of the treatment effect of the child labor legislation on the child labor participation. Our results indicate that the child labor legislation contributed to a reduction in the probability of employment of young children, both in manufacturing and in general. This is an expected result, as young child labor was precisely the target of the legislation. For older children, we obtain results that differ by gender. On the one hand, for old boys, we find that the child labor legislation did not change the likelihood of employment in a statistically significant way. On the other hand, for old girls, we find that child labor legislation significantly reduced the likelihood of employment in any sector. This latter result might be considered unexpected, as older children were not the intended target of the legislation.

Variable	Young boys	Young girls	Old boys	Old girls
$d2dB$	-0.927***	-0.595**	0.054	-0.478**
dB	-0.193	0.153	-0.196*	0.516***
$d2$	-0.244**	-0.225	-0.368***	0.460***
Head's age	0.007	-0.111*	-0.004	-0.095*
Head's age^2	-0.000	0.001*	0.000	0.001**
Head reads	-0.381	0.046	-0.442*	-0.191
Head writes	-0.450*	-0.559	-0.287	-0.466
Head's unemp. months	0.038*	0.044	0.080***	0.062***
Head is unskilled	0.908***	1.844***	0.700***	0.959***
Head is professional	-0.0515	0.777	-0.858**	-0.016
Head has no occupation	-0.308	-0.242	-0.458***	-0.035
Head employed in textiles	0.635***	1.543***	0.304	0.767***
No. children under 6	0.018	-0.523***	-0.029	0.040
Absent mother	0.629***	0.122	-0.067	-0.051
Absent father	1.141***	0.597**	0.898***	0.752***
No. older brothers	0.063	-0.045	0.092**	-0.107*
No. older sisters	-0.075	0.205***	-0.120***	0.087
No. younger brothers	0.161***	0.196***	0.231***	0.138***
No. younger sisters	0.201***	0.306***	0.162***	0.239***
U.S. born	-0.416***	-0.826***	-0.716***	-0.636***
Parents born in U.S.	-0.169	-0.530***	-0.319***	-0.469***
Medium population	-0.235*	0.063	0.066	0.176
Big population	-0.201*	0.608***	0.488***	1.144***
South	0.481***	0.622***	0.301***	0.344**
State unemployment rate	-12.550***	-18.300***	-15.294***	-17.034***
Industrial mix	1.041	5.549***	-0.213	7.396***
Constant	-0.890	-0.107	0.720	-0.422
N	4466	4540	4476	4478

Table 2 Logit estimates of the likelihood of having an occupation in any sector. *Source:* author's calculations using Integrated Public Use Microdata Series. See Section 4.2 for a description of these variables.

While Tables 2 and 3 indicate the sign of the treatment effects, they do not provide their statistical significance or economic relevance. These can be found in Tables 4 and 5. In these tables, we estimate the probability of child employment with and without child labor legislation and, by taking their difference, we obtain the treatment effect of the legislation on child labor. The remaining control variables are evaluated at five different values of interest: (a) the U.S. sample average across both periods, (b) the 1880 sample average in A states, (c) the 1880 sample average in B states, (d) the 1900 sample average in A states, and (e) the 1900 sample average in B states.

The results show that the child labor legislation generated a significant decrease in the probability of employment for all young children. For example, if we evaluate the control variables in the overall sample averages (1880-1900 US), the legislation caused an 8.52 percentage points reduction in the employment rate of young boys and a 1.94 percentage points reduction in the case of young girls. Both of these reductions are economically significant, as they represent a reduction in the pre-legislation employment probability of 56% for boys and 44% for girls, respectively.

The treatment effect of child labor legislation on the employment rate of old children differs by gender. For old girls, the treatment effect is negative, significant, and economically relevant. For example, when

Variable	Young boys	Young girls	Old boys	Old girls
d2dB	-1.416***	-1.134***	0.185	-0.560**
dB	0.296*	0.136	-0.128	0.473**
d2	-0.589***	-0.119	-0.694***	0.223
Head's age	0.108	-0.060	0.004	-0.057
Head's age^2	-0.001	0.001	0.000	0.001
Head reads	-0.076	-0.019	-0.505*	-0.022
Head writes	-0.560*	-0.757	0.066	-0.639
Head's unemp. months	0.022	0.058*	0.061***	0.040
Head is unskilled	1.235***	2.198***	0.931***	1.075***
Head is professional	0.683	0.693	-0.906	-1.138
Head has no occupation	-0.162	-0.073	-0.070	0.216
Head employed in textiles	1.515***	1.935***	1.046***	1.173***
No. children under 6	-0.137	-0.392	-0.099	-0.021
Absent mother	0.559**	0.391	-0.365	-0.123
Absent father	0.932***	0.642*	0.619***	0.428*
No. older brothers	0.063	-0.099	0.015	-0.033
No. older sisters	-0.096	0.208**	0.041	0.132**
No. younger brothers	0.182***	0.187**	0.184***	0.109*
No. younger sisters	0.195***	0.291***	0.093**	0.229***
U.S. born	-0.507**	-0.428*	-0.532***	-0.727***
Parents born in U.S.	0.147	-0.411*	-0.192*	-0.294*
Medium population	-0.305	0.503*	-0.200	0.482**
Big population	-0.167	0.903***	0.144	1.105***
South	1.283***	0.868***	0.768***	0.503***
State unemployment rate	9.655*	-17.225**	0.099	-27.300***
Industrial mix manuf.	8.381***	11.660***	5.799***	11.670***
Constant	-7.398***	-2.992	-2.616**	-1.005
N	4466	4540	4476	4478

Table 3 Logit estimates of the likelihood of having an occupation in manufacturing sector. *Source:* author's calculations using Integrated Public Use Microdata Series. See Section 4.2 for a description of these variables.

	Young boys			Young girls		
	With C.L.L.	No C.L.L.	T.E.	With C.L.L.	No C.L.L.	T.E.
1880-1990 US	6.57%***	15.09%***	-8.52%***	2.49%***	4.43%***	-1.94%**
1880, A states	7.16%***	16.30%***	-9.14%***	3.15%***	5.56%***	-2.41%**
1880, B states	9.98%***	21.87%***	-11.90%***	2.52%***	4.48%***	-1.96%***
1900, A states	4.50%***	10.64%***	-6.14%***	2.72%***	4.82%***	-2.10%*
1900, B states	6.62%***	15.18%***	-8.57%***	1.93%***	3.44%***	-1.51%**
	Old boys			Old girls		
	With C.L.L.	No C.L.L.	T.E.	With C.L.L.	No C.L.L.	T.E.
1880-1990 US	31.26%***	30.12%***	1.14%	6.10%***	9.48%***	-3.38%**
1880, A states	35.38%***	34.16%***	1.22%	6.63%***	10.28%***	-3.65%**
1880, B states	38.33%***	37.06%***	1.26%	2.76%***	4.38%***	-1.62%***
1900, A states	26.41%***	25.38%***	1.03%	10.69%***	16.17%***	-5.49%*
1900, B states	29.33%***	28.23%***	1.10%	5.02%***	7.85%***	-2.83%**

Table 4 Estimates of the likelihood of employment in any sector and the treatment effect of the child labor legislation. These control variables are evaluated at the sample average of the group indicated in the row. *Source:* author's calculations using Integrated Public Use Microdata Series.

other control variables are evaluated at the overall sample averages (1880-1900 US), the legislation caused a reduction of 3.38 percentage points or 36% of the pre-legislation employment probability. For old boys, the treatment effect is not statistically significantly different from zero. From here, one can conclude that the child labor legislation did not change the employment probability of old boys.

The child labor legislation was effective in reducing the employment rate of young girls, who were targeted by the legislation, and old girls, who were not. From the cases described in Section 3.2, these results correspond to case 4, which implies that the legislation was a benign policy for girls. On the other hand, the legislation was effective in reducing the employment rate of young boys, who were targeted, but had no significant effect on old boys, who were not targeted. From the cases described in Section 3.2, these results correspond to either case 2 or 3. This is precisely the situation in which we cannot identify whether the legislation was benign or not[22].

As we have explained in Section 2.1, the treatment effect estimator used in this paper and the difference-in-differences type estimator used in [Moehling(1996)] or [Moehling(1999)] are different estimators and, more importantly, they are consistently estimating different parameters. As a consequence, it should not come as a surprise that the estimation results are different even if the econometric model and the data are identical. Furthermore, as we have mentioned in Section 2.2, the difference-in-differences type estimator used in [Moehling(1996)] or [Moehling(1999)] would include the difference in the likelihood of employment between young and old children. As a consequence, even if the treatment effect estimator and the difference-in-differences estimator would obtain similar results, the interpretation of the results could be completely different.

By comparing our results with those in [Moehling(1999)] it is easy to understand that our conclusions are different due to both of the reasons described in this paper. In order to illustrate this point, we consider the treatment effect of the child labor legislation on the employment in any sector for girls. According to Table 3 in [Moehling(1999)], the estimated probability of employment of young girls was: 7.4% in 1880 A states, 7.9% in 1880 B states, 13.8% in 1900 A states, and 5.2% in 1900 B states. This implies that the time effect is 6.4 percentage points in A states and -2.7 percentage points in B states. By computing the difference between these two, we conclude that the difference-in-differences of the general employment of young girls is -9.1 percentage points. If we interpret difference-in-differences as the treatment effects (which is incorrect in non-linear models such as logit), the effect of the child labor legislation for young girls is a reduction in the likelihood of employment of 9.1 percentage points. This figure has the same sign as in our results, but the magnitude is significantly larger. As both analyses are using the same econometric model and the same data, this discrepancy is solely due to the fact that the difference-in-differences and the treatment effects estimator are different and they are estimating different parameters.

Of course, one can repeat this analysis for old girls. The same difference-in-differences interpretation of the result in [Moehling(1999)] suggests that the effect of the child labor legislation for old girls is a reduction in the likelihood of employment of 15.5 percentage points. Once again, this finding has the same sign as in our results, but the magnitude is significantly larger. By the same reasons as before, this discrepancy is attributed to the fact that difference-in-differences and the treatment effects estimator are different and they are estimating different parameters.

In order to reach to the final conclusion regarding employment for girls, [Moehling(1999)] computes the difference of the results between young and old children. In the case of girls, this difference-in-difference-in-differences is 6.3 percentage points, which is not significantly different from zero. From this result, the author concludes that the child labor legislation had no effect on girls, as the reduction in the employment of girls who were targeted by the legislation (young girls) is smaller than the reduction in the employment of girls who were not targeted by the legislation (old girls). This interpretation is drastically different from our interpretation of the results. As our economic model in Section 3 predicts, a benign child labor legislation can reduce the employment of older children that were not explicitly targeted by the legislation. In fact, the reduction of the employment level of both young and old girls due to the legislation is indicative that the legislation was a benign public policy for girls.

Table 5 describes the effectiveness of the child labor legislation in reducing child labor in the manufacturing sector. The results are qualitatively very similar to those of Table 4: the legislation was effective in reducing the employment in the manufacturing sector for young girls, young boys, old girls, but not for old boys. This implies that the conclusions drawn for general employment can also be applied to employment in the manufacturing sector.

[22] One can extend the model in Section 3 to allow for boys and girls to produce different utility costs when they are sent to work. Such an extension could generate a situation in which the child labor legislation is benign for one gender but not benign for the other.

	Young boys			Young girls		
	With C.L.L.	No C.L.L.	T.E.	With C.L.L.	No C.L.L.	T.E.
1880-1990 US	1.42%***	5.61%***	-4.19%***	0.72%***	2.21%***	-1.49%***
1880, A states	2.23%***	8.60%***	-6.37%***	0.81%***	2.48%***	-1.67%***
1880, B states	2.60%***	9.91%***	-7.31%***	0.70%**	2.15%***	-1.45%***
1900, A states	0.90%***	3.62%***	-2.72%***	0.80%***	2.45%***	-1.65%**
1900, B states	1.11%***	4.43%***	-3.32%***	0.60%***	1.85%***	-1.25%***
	Old boys			Old girls		
	With C.L.L.	No C.L.L.	T.E.	With C.L.L.	No C.L.L.	T.E.
1880-1990 US	12.56%***	10.67%***	1.89%	2.94%***	5.03%***	-2.09%**
1880, A states	17.56%***	15.05%***	2.52%	3.60%***	6.13%***	-2.53%**
1880, B states	21.90%***	18.91%***	3.00%	1.57%**	2.71%***	-1.14%***
1900, A states	7.96%***	6.71%***	1.25%	4.45%***	7.54%***	-3.09%*
1900, B states	10.57%***	8.95%***	1.62%	2.40%***	4.13%***	-1.73%**

Table 5 Estimates of the likelihood of employment in the manufacturing sector and the treatment effect of the child labor legislation. These control variables are evaluated at the sample average of the group indicated in the row. *Source:* author's calculations using Integrated Public Use Microdata Series.

6 Conclusions

This paper explores the relationship between the state-specific child labor legislation and the decline in child labor that occurred in the U.S. between 1880 and 1900. The typical state-wide child labor legislation took the form of state-wide prohibition for children of less than a certain age (typically, 14 years old) to be employed in the manufacturing sector.

In order to analyze the consequences of child labor legislation, we develop a model along the lines of [Basu and Van(1999)], which takes into account the possible multiplicity of equilibria in the labor market. Based on this framework, we develop an empirical strategy to identify the mechanism by which the legislation affected child labor decisions. In particular, besides establishing whether the legislation was effective or not in curtailing child employment, our analysis may determine if the legislation constituted a benign policy or not, i.e., whether the legislation was a constraint to the behavior of families (not benign) or whether it changed the labor market to a new equilibrium in which families voluntarily respected the law (benign). We implement our empirical strategy using a sample of the 1880 and 1900 U.S. federal censuses which are part of IPUMS. We restrict our sample to 13 and 14-year olds, where 13-year olds are young children, targeted by the legislation, and 14-year olds are old children, not targeted by the legislation.

Our results indicate that the child labor legislation was effective in reducing labor market participation of young girls, young boys, and old girls. In contrast, the legislation had no significant effect on old boys. On the one hand, our findings allow us to conclude that the legislation was a benign policy for girls. On the other hand, our results for boys do not allow us to identify whether the legislation was a benign policy for them or not.

Acknowledgements I thank the editor Claude Diebolt and three anonymous referees for comments and suggestions that have significantly helped to improve this paper. I am also thankful for helpful discussions with Esteban Aucejo, Arnau Bages, Joe Ferrie, Jon Gemus, Silvia Glaubach, Joel Horowitz, Viktor Subbotin, and Giovanni Zanalda. Erik Vogt provided excellent research assistance. Any and all errors and omissions are my own.

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