Estimating Parental Demand for Children’s Screen Time in a Model of Family Labor Supply

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Accepted: 16 August 2022 / Published online: 13 September 2022
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Abstract  In a novel approach to model the demand for the children’s screen time as the result of a parent’s optimal labor-leisure choice, the study used a simple model of parental utility maximization subject to the money and time budget constraints to derive Marshallian parental demand functions for two types of child upbringing activities: time-intensive (violin lesson) and time-saving (video games). After the Slutsky decomposition, parental demand for children’s screen time was shown to be similar to a Giffen good. Using the National Longitudinal Survey of Youth 1979 and Adolescent Brain Cognitive Development data, the wage equation was first estimated based on Heckman’s two-step correction procedure. Then, the total effect of an increase in wage rate on the parental demand for screen time was empirically decomposed into the substitution effect and the income effect. The study findings indicate that the substitution effect is positive, the income effect is negative, and the negative income effect dominates the substitution effect. We add to the existing literature by showing that the empirical findings in the public health and psychology literature can be reconciled with the theoretical predictions of the standard economic labor-leisure trade-off paradigm.

Keywords  Parenting · Labor-leisure trade-off · Giffen good

JEL  D12 · J13 · J22

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Introduction

The potential adversity of screen time on a child’s development has become a concern in the modern world. The exposure of children to screen time happens through a variety of ways such as watching the television or videos (e.g., YouTube), playing video games, text messaging, social media, video-chat, web browsing and editing photos. Excessive screen time is considered one of the crucial risk factors that can potentially hamper early developmental processes in children, increasing the likelihood of obesity and mental health deterioration (Nieto & Suhrcke 2021). Such developmental delays can significantly impact the learning process, as well as serve as a barrier to a child’s academic success and healthy life. According to the Common Sense Media (2017) census report, children ages 5 to 8 spend nearly three hours per day using digital devices and screen time grows quickly. Ninety-five percent of families in the United States (U.S.) have a mobile device and nearly 80% of families have a tablet. As concerns regarding excess screen time for children grew, medical associations such as the World Health Organization (WHO), American Academy of Pediatrics (AAP), and Canadian Pediatric Society (CAP) all developed guidelines on the recommended time and rules on screen device exposure for children.

The situation increasingly worsened with the coronavirus disease (COVID-19) pandemic. During long months of lockdown and shuttered schools, many parents overlooked the vastly increasing time that their children were spending on video games and social media. When the outbreak hit, many parents were willing to relax restrictions on screen time to keep frustrated and restless children entertained and engaged. Remaining limits frequently evaporated as computers, tablets and phones became the centerpiece of school and social life. According to Qustodio, a private company that tracks the usage of electronic devices by children ages 4 to 15, children’s one-month average daily screen time doubled by May 2020 compared with the same period a year earlier.1 The data showed that usage increased as time passed. In the U.S., children spent on average 97 minutes on YouTube in March and April 2020, up from 57 minutes per day in February 2020. Similar trends were found in Britain and Spain (Ritchtel 2021).

There are numerous studies on how screen time affects children’s physical health such as obesity, metabolic syndrome and risk for cardiovascular disease, as well as mental health, self-esteem, pro-social behavior, and academic achievement (e.g., Danner 2008; Henderson 2007; Parsons et al. 2005; Mark & Janssen 2008; Sugiyama et al. 2007; see Tremblay et al. 2011 for a systematic review of this literature). However, considerably less attention in the literature has been devoted to investigating the relationship between children’s exposure to screen time and families’ socioeconomic background and structure. Some examples in the latter group are McMillan et al. (2015), Hardy et al. (2006), and Duch et al. (2013) who found significant correlations between children’s screen-time exposure and parents’ income and education, family structure, and residence area.

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1 Because Qustodio is a private company that sells a service through which parents can control their children’s media usage, it is possible that the data provided by the company could be exaggerated, but the general tendencies in children’s screen-time exposure are in line with other findings.
Invariably, all these studies consistently found that families with higher income and educational backgrounds tend to expose their children to less screen time.

These results seem intuitively correct but could contradict the standard economic model of time allocation and labor supply. To simplify the argument, think of two types of parental activities related to child upbringing differentiated by how time-intensive (demanding of parents’ time) they are. The first group of high time-intensive efforts includes activities like taking a child to after-school soccer practice or a violin lesson. The second group of low time-intensive activities includes children watching TV, playing computer games or surfing the internet. Obviously, the demand on parents’ time is substantially higher for the first group of activities than for the second. Invoking the standard labor-leisure microeconomic model, the optimal parental allocation of non-wage-earning time among competing child upbringing activities will, ceteris paribus, be determined by the opportunity cost of their time, in the sense that the increase in wage rate would cause the non-wage-earning time allocation to shift away from violin lessons and toward video games. This line of reasoning corresponds perfectly with Linder (1970) who predicted that rising productivity decreases the demand for commodities the consumption of which is expensive in time or inexpensive in money (Baumol 1973, p. 629). Therefore, one should see lower income parents spending more time driving their children to soccer practices and violin lessons than higher income parents. Yet, the extant empirical literature recorded exactly the opposite. Children from lower-income, less educated, and single-parent families spent more time with screen devices than their more affluent counterparts. Explaining this apparent puzzle is the main motivation for this research.

The economic literature on parental time with children found that mothers with a college education or greater spend about 4.5 hours more per week in childcare than mothers with high school diplomas or less. This robust relationship holds for both non-working and working mothers and working fathers (Guryan et al. 2008). This positive education (as well as income) gradient for childcare is also surprising given that the opportunity cost of time is higher for both highly educated and high wage earners. In light of the fact that education and income gradients are negative for both leisure (watching a movie) and home production (cooking a meal) activities and education and income gradients are clearly positive for childcare, time spent caring for one’s children appears to be fundamentally different from leisure and home production (see Guryan et al. (2008, p. 36–38), and references therein for competing explanations of this result).

One important aspect of the tradeoff between family labor supply and children’s upbringing is the case where parental time in household production is substituted or outsourced. Cortés and Tessada (2011) found that the increase in low-skilled immigrant labor increased both working hours and the probability of working for women in the top quartile of the wage distribution. They also showed that these women decreased the time spent and increased the expenditure on household production. Obviously, the availability of the market-supplied childcare solutions (such as a hired nanny or daycare), or non-market transactions (such as support from a retired grandparent or other adult family member) can affect the family labor supply. However, these situations are too complex to theoretically model in the current paper, and the paucity of relevant data make them very difficult to deal with empirically.
The focus of attention in this paper is the parental decision regarding two child-care activities which are differentiated by their time intensity in production. Based on a simple model of parental utility maximization subject to money and time budget constraints, Marshallian demand functions are derived for two types of child upbringing activities. After a Slutsky decomposition, the study shows that the empirically observed result corresponds to the case where screen time exhibits Giffen-good-like characteristics.\textsuperscript{2} Using two different datasets, the National Longitudinal Survey of Youth 1979 (NLSY) (Bureau of Labor Statistics 2022) and the Adolescent Brain Cognitive Development (ABCD) study (National Institutes of Health 2022), the wage equation is estimated based on the Heckman’s two-step correction procedure. Then, the total effect of an increase in wage rate on parental demand for children’s upbringing activities is empirically decomposed into the substitution effect and the income effect relying on the approach of Ashenfelter and Heckman (1974). For the case of low time-intensive child upbringing activities, such as exposing children to screen time, in line with our theoretical predictions, we found that the substitution effect is positive, the income effect is negative, and the negative income effect dominates the positive substitution effect. Hence the results show that the empirical findings in the public health and psychology literature can be reconciled with the theoretical predictions of the Becker model.

### A Theoretical Model

Following in the footsteps of the time allocation model of Becker (1965), the utility maximization problem of a household is formulated.\textsuperscript{3} A household supplies \( L \) hours of labor and consumes a child upbringing activity \( Z \) and a composite good \( C \). The consumption of good \( Z \) requires per unit time of \( t_Z \) and the consumption of composite good \( C \) requires per unit time of \( t_C \). The prices of goods \( Z \) and \( C \) are denoted as \( p_Z \) and \( p_C \), respectively. The household solves the following utility maximization problem:

\[
\max_{(Z,C)} U = U(Z, C) \\
\text{s.t.} p_Z Z + p_C C = M + wL \\
t_Z Z + t_C C + L = T.
\]

\textsuperscript{2} A Giffen good is a good whose demand curve slopes upward because the negative income effect dominates the substitution effect. In classical demand theory, a Giffen good is rarely of practical interest because it requires a large negative income effect, but the income effects are usually small because, individually, most goods account for only a small part of a consumer’s budget (Pindyck & Rubinfeld 2013, p. 122).

\textsuperscript{3} Traditional models of family behavior assume that family members act as if they are maximizing a single utility function. Other models have challenged this unitary approach and attempted to incorporate divergent or conflicting preferences of individual family members into economic analysis via some type of bargaining or Pareto-efficient sharing allocation mechanisms (Lundberg et al. (1997). We simplify this problem and in the empirical part of the paper assume that all relevant decisions regarding child upbringing are made by their mothers.
By substituting the time constraint into the budget constraint, the problem can be rewritten with only one constraint:

$$\max_{(Z,C)} U = U(Z, C)$$
$$s.t. \left( p_Z + wt_Z \right) Z + \left( p_C + wt_C \right) C = M + wT$$

(2)

where $$M$$ is a non-labor income, $$w$$ is a wage rate, $$T$$ is the household’s total disposable time and $$p_Z + wt_Z$$ and $$p_C + wt_C$$ are full prices of $$Z$$ and $$C$$ consisting of time prices $$wt_Z$$ and $$wt_C$$ and market prices $$p_Z$$ and $$p_C$$ and related goods. The system of first order conditions is solved to obtain the Marshallian demands for $$Z$$ and $$C$$:

$$Z^M = Z^M(p_Z, p_C, w, t_Z, t_C, M, T)$$
$$C^M = C^M(p_Z, p_C, w, t_Z, t_C, M, T).$$

(3)

On the dual side of the problem, the agent minimizes the non-labor income $$M$$ subject to a given level of utility $$u^0$$:

$$\min_{(Z,C)} M = \left( p_Z + wt_Z \right) Z + \left( p_C + wt_C \right) C - wT$$
$$s.t. U(Z, C) = u^0$$

(4)

leading to Hicksian demands for $$Z$$ and $$C$$:

$$Z^h = Z^h(p_Z, p_C, w, t_Z, t_C, u^0)$$
$$C^h = C^h(p_Z, p_C, w, t_Z, t_C, u^0)$$

(5)

and the associated indirect expenditure function:

$$e^*(p_Z, p_C, t_Z, t_C, w, u^0, T) = M^* =$$
$$\left( p_Z + wt_Z \right) Z^h + \left( p_C + wt_C \right) C^h - wT.$$  

(6)

Using the fundamental identity for $$Z$$,

$$Z^h(p_Z, p_C, w, t_Z, t_C, u^0) =$$
$$Z^M(p_Z, p_C, w, t_Z, t_C, e^*(p_Z, p_C, w, t_Z, t_C, u^0, T))$$

(7)

and differentiating with respect to the wage rate, the cross-price Slutsky equation is obtained:

$$\frac{\partial Z^M}{\partial w} = \frac{\partial Z^h}{\partial w} + \left( T - t_ZZ^h - t_C C^h \right) \frac{\partial Z^M}{\partial M}.$$  

(8)

Slutsky decomposition (8) shows that the total effect of a change in the wage rate on the consumption of the child upbringing activity $$\frac{\partial Z^M}{\partial w}$$ can be decomposed into the substitution effect $$\frac{\partial Z^h}{\partial w}$$ and the income effect $$\left( T - t_ZZ^h - t_C C^h \right) \frac{\partial Z^M}{\partial M}$$, neither of which can be unambiguously signed.

As shown by Baumol (1973), the sign of the substitution effect is determined by the effect of the wage rate $$w$$ on relative full prices of $$Z$$ and $$C$$. In particular, the substitution effect will be positive, i.e., $$\frac{\partial Z^h}{\partial w} > 0$$ if and only if an increase in $$w$$ decreases the full price ratio of $$Z$$ to $$C$$.  

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This is the standard case of sliding along a given indifference curve and purchasing more of the good whose relative price became lower. To prove this result, the derivative of the time price ratio with respect to the wage rate must be negative, i.e.:

\[
\frac{d}{dw} \left( \frac{p_Z}{p_C} \cdot \frac{1 + wt_Z/p_Z}{1 + wt_C/p_C} \right) = \frac{p_Z}{p_C} \frac{1}{1 + w(t_C/p_C)} \left[ \frac{t_Z}{p_Z} - \frac{t_C}{p_C} \right] < 0. \tag{9}
\]

Because all the terms on the right-hand-side of (9) are positive, it follows that:

\[
\frac{\partial Z^h}{\partial w} > 0, \text{ if and only if } \frac{t_Z}{p_Z} < \frac{t_C}{p_C}. \tag{10}
\]

Obviously, the reverse result that \( \frac{\partial Z^h}{\partial w} < 0 \) if and only if \( \frac{t_Z}{p_Z} > \frac{t_C}{p_C} \) follows directly. In general, notice that as \( w \) increases, the household will not increase its consumption of less-time utilizing or more expensive alternative \( i \) unless \( \frac{t_i}{p_i} \) is less than the average for its overall consumption. Alternatively, the substitution effect of an increase in wages will decrease the consumption of some good or service if the time needed to consume a dollar worth of that item is greater than the average time needed to consume a dollar worth of all other commodities in the household’s basket.

Because the theoretical prediction about the sign of the substitution effect depends on the normalized full price ratios, one needs to sort out where the types of child upbringing activities belong. If \( Z \) is driving the children to the violin lesson, then the relative time cost to money cost of this activity is likely to be bigger than the average for the rest of the household’s consumption bundle and we have the case where \( \frac{t_Z}{p_Z} > \frac{t_C}{p_C} \) and the substitution effect is negative. Contrary to this, if \( Z \) is having a child playing video games, then the relative time cost to money cost of this activity is likely to be very small (in fact, the parent can engage in other activities while the child plays video games), and hence smaller than the average for the rest of the household’s consumption bundle. This is the case where \( \frac{t_Z}{p_Z} < \frac{t_C}{p_C} \) and the substitution effect is positive.\(^4\)

Let’s turn now to the income effect which will, as always, prevent us from drawing a theoretically unambiguous conclusion about an impact of wages or income on child upbringing. If time-consuming child upbringing activities are

\(^4\) Other examples of activities where relative time costs to money costs are larger than the average for the entire consumption bundle include playing a round of golf, reading *War and Peace*, and season tickets to attend sporting events or theater. For all such activities, the substitution effect is negative. On the other end of the spectrum, there are consumption activities, such as eating beluga caviar, driving a Porsche to work, drinking Dom Perignon or wearing a Rolex watch, where the time cost relative to the money cost is relatively low and hence likely to be less than the average for the entire consumption bundle. For such commodities and activities, the substitution effect will be positive.
not inferior goods, households would want more of them as their income rises. They would be able to spend more money on those activities even if rising wages increase their opportunity cost of time. Also, assuming that the income effect of a rise in wages is likely to be substantial and child upbringing activities are not likely to be inferior, it appears that that demand for high quality child upbringing activities is likely to grow as household wealth grows. However, as pointed out by Baumol (1973), there are two important caveats to such reasoning. First, there are two constraints in the model. The binding one is the time constraint and not the money constraint in the sense that if an individual has more time, she can earn more money, but she is prevented from doing so by the 24-hour limit to her day. It follows that additional time could result in more income, but additional income cannot purchase more time. The second reservation comes from the fact that for a certain class of ambitious people, non-working activities (leisure in a typical sense or raising children as in this model) could be inferior goods and hence the demand for them would not rise with income.

To analyze all possible cases, the various parts of the Slutsky Eq. (8) are labelled as follows:

\[
\frac{\partial Z^M}{\partial w} = \frac{\partial Z^h}{\partial w} + (T - t_zZ^h - t_C^h) \frac{\partial Z^M}{\partial M}
\]

The results are summarized in Table 1. Among the six possible cases presented in Table 1, half represent positive \((A > 0)\) and half represent negative substitution effects \((A < 0)\). Recall that there are two types of child upbringing activities \(Z\): time intensive activities like driving a child to a violin lesson, or time-saving activities like having a child play video games. Since we are only interested in signing the total effect of the wage change on parents’ decision to let their children engage in various screen-time activities, the relevant three cases are those labelled as cases 1, 2, and 3 in Table 1 where the substitution effect is positive \((A > 0)\).

Among three cases where \(A > 0\), there is only one case where the total Marshallian effect of a change in the wage rate on the demand for child upbringing through the increased exposure to screen time is negative. This case is important because all existing empirical literature supports it. The case is characterized by the screen-time type of child upbringing being an inferior activity \((B < 0)\) and the income effect

### Table 1

| Case # | A  | B  | Absolute Value | C  |
|--------|----|----|----------------|----|
| 1      | +  | +  |                | +  |
| 2      | +  | –  | \(|A|>|B|\)     | +  |
| 3      | +  | –  | \(|A|<|B|\)     | –  |
| 4      | –  | –  |                | –  |
| 5      | –  | +  | \(|A|>|B|\)     | –  |
| 6      | –  | +  | \(|A|<|B|\)     | +  |
dominating the substitution effect, $|A| < |B|$. Although an increase in the wage rate would make parents shift their demand towards more screen-time types of activities as their time intensity is less than the average of other goods and services in their consumption bundle, the increase in income due to the wage increase would make the parents demand less of the screen time for their children. That negative effect swamps the substitution effect such that the overall sign of the Marshallian cross-price effect becomes negative. The result in row 3 of Table 1 reminds us of the case of a Giffen good in the classical demand analysis. Because the sign of the income effect cannot be determined \textit{a priori}, it remains an empirical question. The Giffen-good case represents the cornerstone of the empirical analysis that follows. Unlike in the classical demand case (with prices of regular goods changing), here the income effect caused by the change in wages is likely to be large, hence the income effect could more easily dominate the substitution effect and hence the Giffen good type situations should not be that rare.

### Data Sets

Our empirical analyses were carried out using the National Longitudinal Survey of Youth 79 and the National Longitudinal Survey of Youth 79—Child and Youth (together as the NLSY) and the Adolescent Brain Cognitive Development (ABCD) data. The NLSY data are richer in terms of relevant content variables (questions), but the ABCD data are about a decade newer. The use of two data sets provides an automatic robustness check for the results and lends additional credibility to the empirical findings. Table 2 shows the summary statistics of screen times and other demographic variables from these two data sets.

The National Longitudinal Survey of Youth 79 (NLSY79) was conducted by the National Bureau of Labor Statistics. NLSY is a survey from a nationally representative sample of youth (girls and boys) in the U.S. who were between 14 and 22 years old when they were first surveyed in 1979. Within this cohort, children of female respondents were followed in the NLSY79-Child and Youth data (NLSY79CY), and child-mother pairs were matched from these two data sets. The NLSY79CY survey was repeated every two years and this study only used observations from 2006 to 2014 where the age of children ranged from 10 to 14 years old. During this period, there were 1,703 observations (child-mother pairs) without missing values. These observations were collected from 1,057 children and 698 mothers, indicating the fact that some mothers appear with more than one child.

The ABCD data from the National Institute of Mental Health are very recent, with the first wave starting in 2016–2017. The ABCD data have rich information on children’s cognitive ability, physical and mental health as well as their family background. In this study, only data from the third wave (2018–2019) were used, with the age of children ranging from 10 to 14 years. Unlike the NLSY, the ABCD database collects responses from children, although some survey questions, such as family income, are completed by parents. A unique identifier is
assigned to each child, not to the parent, so the sibling relationship cannot be identified. There are 4,068 children-parent pairs.

Although both datasets are from longitudinal studies, they were treated as cross-sectional. In the NLSY interviews, the respondents often skipped interview rounds, such that almost 90% of the mother–child pairs recorded responses in fewer than three waves. The ABCD dataset also consists of annual panel data, but the first two waves of the survey were excluded from our analysis because of the very detailed
definition of children’s screen times that led to implausible results and lack of some critical questions (variables).

Closer inspection of the entries in Table 2 indicates that the two datasets are similar in some respects, but also differ somewhat regarding several other variables of interest. In both data sets, screen times are measured as children’s screen watching time during typical weekdays and weekends. In NLSY, the screen times are defined as the sum of the hours of watching television and hours playing video games, whereas in the ABCD database, children are asked to report total combined screen times (i.e., not separated by screen activity type). Both cases required removing unreasonable screen time responses from the datasets. In the NLSY data, responses with daily screen times greater than 8 hours during the week and greater than 12 hours during the weekends were deemed unreasonably high and hence dropped from the sample, leading to a final number of observations of 1,348 from 901 children. The same approach was used for the ABCD data resulting in 3,986 observations.

Since the ABCD data are more recent, children from this dataset were born five to ten years later than those in the NLSY data. However, they are of comparable average age (12.4 versus 11.9) and the ratio of male to female is about equal in both datasets. Mothers from the NLSY are significantly older than those from the ABCD data by about seven years on average. Weekly family income and the mother’s wage rate are both greater in the ABCD data, due to a decade worth of inflation. Mothers are also on average more educated in the ABCD data than in the NLSY data (17.3 versus 14.5 years of schooling).

The datasets also differ in how they provide information about siblings. In both datasets, information on the number of children in the family was available. The number of children in the household is greater in the NLSY data (3.05) than in the ABCD data (2.52). The NLSY data includes the age of the youngest child in the family whereas in the ABCD data, similar information is provided for the number of younger siblings of the child responding to the survey. The percentage of single-parent families is greater in the NLSY data (30%) than in the ABCD data (20%).

Finally, there are differences in the definitions of mother’s working status and job-related variables. The ABCD dataset asks whether the mother is working full time, half time, or not working at all, and her annual income. For this reason, the number of hours worked is assumed to be 40 if she works full-time, 20 hours for part-time, and zero for not working. The wage rates are defined as the annual income divided by the annual hours worked. The NLSY survey contains more detailed information about employment. The

5 In the NLSY survey the question was: “How much time do you spend watching TV on a typical weekday?” (0–24 hours) and “How much time do you spend playing video games on a typical weekday?” (0–24 hours). In the first two waves of the ABCD, the children were asked to report separate times spent engaged in watching TV, video (like YouTube), playing video games, text messaging, social media, video-chat, web browsing and editing photos. In the third wave the question changed into: “On a typical WEEKDAY (during the school year), how much TIME per day do you spend in TOTAL on a computer, phone, tablet, iPod, or other device or video game? Please do NOT include time spent on school-related work, but do include watching TV, shows or videos, texting or chatting, playing games, or visiting social networking sites (Facebook, Twitter, Instagram)” (0–24 hours). The same question was asked for the weekend.
respondents are asked to record up to five different jobs. The number of hours worked is defined as the sum of working hours for all current jobs. The wage rate is a weighted average of wage rates from all jobs weighted by the hours worked. Tenure reflects the longest duration of employment (in weeks) among all reported jobs. This variable is not available in the ABCD dataset.

**Estimation and Testing**

To establish the link to previous research, a simple model was initially estimated that mimics the empirical models in the existing literature. The estimation results are presented in Table 3. In line with what the previous literature found, our results also indicate a negative and statistically significant relationship between family income and children’s screen time. In the NLSY dataset, a $1,000 increase in weekly family income led to a decrease of 0.18 hours of weekday screen time and 0.10 hours of a weekend screen time. The results with the ABCD dataset show comparable decreases of 0.10 and 0.15 hours, respectively.

The rest of the estimated coefficients show that both the age and sex of the child are important determinants of screen-time exposure. The results show that older children and boys spend more time in front of the screens. Though the age of the mother is insignificant in all specifications, the mother’s employment and education are important determinants of the children’s screen-time exposure. In all specifications, the dummy coefficient on whether the mother is working or not is positive indicating that children of mothers with jobs outside the home tend to have higher screen-time exposure. The education coefficients were mostly negative and significant indicating that the children of more educated mothers tended to spend less time in front of screens.

The remaining two estimated parameters are quite interesting. First, family structure appears to be important in the sense that children from a single-parent family tend to spend more time in front of the screens. These effects are significant in both specifications estimated with the ABCD data and not significant in the NLSY data. Second, the number of children in the family is also important for children’s screen consumption. Interestingly, the results show a negative and significant (except in one case) relationship, indicating that more siblings translate into less screen viewing, which could mean that in larger families, children tend to play more with each other and spend less times watching TV.

**An Econometric Model**

The main objectives of the following empirical analysis is to test whether (a) the substitution effect of the change in wages on the time-saving (screen time) types of child upbringing activities is positive, b) the screen-time activities are inferior goods, and (c) the negative income effect dominates the positive substitution effect, such that the overall effect is negative. To be able to do this, the challenge is to separately estimate the substitution and income effects.
We propose an estimation model where all relevant decisions regarding the children’s upbringing activities in the household are carried out by the mothers. Consequently, this household model applies to mothers who make choices among children upbringing, consumption, and labor supply. Despite its simplification, this approach is not overly restrictive. The literature suggests that the role of the mother is larger than that of the father in the context of child upbringing. For example, Thomas (1990) showed that unearned income in the hands of the mother has a larger effect on her family’s health than income controlled by the father. For child survival probabilities, the effect is almost 20 times bigger. Using a policy change in the United Kingdom (UK) that transferred a substantial child allowance to wives, Lundberg et al. (1997) found strong evidence that a substantial shift occurred towards relatively greater expenditures on women’s and children’s goods that followed that income distribution. The decision to designate the mother as the sole decision maker in the household was also driven by our data. Namely, NLSY79CY only follows the children of female respondents. Thus, their biological father cannot be directly identified. Moreover, in the ABCD data, more than 75% of the parent respondents are mothers, thus the full set of demographic variables on fathers is not available.

| Table 3 | A simple model of children’s screen-time exposure: OLS regression results |
|---------|---------------------------------|
| NLSY    | ABCD                            |
| weekdays| weekdays| weekend| weekend|
| age (child) | 0.0987** | 0.0560 | 0.1934*** | 0.2204*** |
|          | (0.0400) | (0.0476) | (0.0377) | (0.0551) |
| age (mother) | 0.0059 | 0.0186 | 0.0039 | 0.0094 |
|          | (0.0182) | (0.0216) | (0.0045) | (0.0066) |
| male (child) | 0.8268*** | 0.9039*** | 0.1640*** | 0.4158*** |
|          | (0.1019) | (0.1213) | (0.0483) | (0.0705) |
| family income | –0.1803*** | –0.1032*** | –0.1011*** | –0.1543*** |
|          | (0.0145) | (0.0043) | (0.0098) | (0.0240) |
| education (mother) | –0.0392* | 0.0084 | –0.0530*** | –0.0440*** |
|          | (0.0208) | (0.0247) | (0.0123) | (0.0180) |
| single parent | –0.0472 | 0.1565*** | 0.2704*** | 0.3054*** |
|          | (0.1242) | (0.1478) | (0.0666) | (0.0973) |
| # of children | –0.0302*** | –0.0737* | –0.0338* | –0.1219*** |
|          | (0.0359) | (0.0427) | (0.0201) | (0.0294) |
| mother working | 0.0944 | 0.1673*** | 0.1498*** | 0.1496** |
|          | (0.1392) | (0.1656) | (0.0593) | (0.0866) |
| (intercept) | 2.4326** | 1.8084 | 0.7306 | 1.3631* |
|          | (0.9546) | (1.1359) | (0.4889) | (0.7134) |
| Years covered | 2006–2012 | 2018–2019 |
| N         | 1,348 | 1,348 | 3,965 | 3,965 |

Standard errors in parentheses. Family weekly income is in thousands of dollars

*p < 0.1, **p < 0.05, ***p < 0.01
Our approach follows Ashenfelter and Heckman (1974) who proposed an estimation strategy for disentangling the income and substitution effects in the case of family labor supply. Assuming that time prices and aggregate available time are constant, such that $dp_Z = 0$, $dt_Z = 0$, $dp_C = 0$, $dt_C = 0$, and $dT = 0$, the total differentiation of the Marshallian demand (3) for activity $Z$ gives

$$dZ^M = \frac{\partial Z^M}{\partial w} dw + \frac{\partial Z^M}{\partial M} dM.$$ (12)

Replacing $\frac{\partial Z^M}{\partial w}$ from the Slutsky decomposition, one obtains

$$dZ^M = \left[ \frac{\partial Z^h}{\partial w} + H \frac{\partial Z^M}{\partial M} \right] dw + \frac{\partial Z^M}{\partial M} dM,$$ (13)

where $H = (T - t_Z Z^h - t_C C^h) > 0$. Re-arranging the terms, we get

$$dZ^M = \frac{\partial Z^h}{\partial w} dw + \frac{\partial Z^M}{\partial M} [H dw + dM].$$ (14)

Expression (14) can possibly be estimated from the data by treating $\frac{\partial Z^h}{\partial w}$ and $\frac{\partial Z^M}{\partial M}$ as the coefficients of an econometric model. If the unobservable infinitesimal changes in the variables, $dZ^M$, $dw$ and $dM$ are replaced by the observable finite changes $\Delta Z^M$, $\Delta w$ and $\Delta M$, defined as the deviations from the mean $\Delta X_k = X_k - \bar{X}$ for $k^{th}$ observation, and adding an iid error term, the estimation equation has the following form:

$$\Delta Z_k = \frac{\partial Z^h}{\partial w} \Delta w_k + \frac{\partial Z^M}{\partial M} [H_k \Delta w_k + \Delta M_k] + \epsilon_k.$$ (15)

To test the sign of the substitution effect and income effect of an increase in wages on the mother’s demand for screen time, the following equation is estimated:

$$\Delta Z_k = \beta_1 \Delta w_k + \beta_2 F_k + \epsilon_k,$$ (16)

where $H$ is the hours of worked per week and $M$ is the exogenous income per week, defined as all family income other than the mother’s labor income. $H \Delta w + \Delta M$ is denoted as $F$. We expect $\beta_1$ to be positive, and $\beta_2$ to be negative.

First, the wage equation was estimated. Then, the estimated parameters of the wage equation were used to generate in-sample wage predictions. These forecasted wages were subsequently used as a generated regressor in Eq. (16). The distinction between employed and unemployed mothers is critical because unemployed workers not only have lower incomes but also have lower opportunity costs, thus lower relative prices of time and other earnings-intensive commodities (Becker 1965, p. 343). Because the decision to either work outside the home or stay at home is not random, the problem of selection bias needs to be addressed first. The two-step correction procedure (Heckman 1979) was used to estimate the wage equation. In the first step, the probability of the mother’s participation in the labor force was estimated as a function of the mother’s education, the labor market size, the number of children in
her family, the age of the youngest child, and the family structure (married versus single) using probit. The ABCD data do not have information on the size of the labor market or the age of the youngest child. Therefore, the size of the labor market is not in the regression model and the age of the youngest child is replaced with the number of younger siblings of the child being surveyed. The estimation results for the selection equation are presented in Table 4.

As seen in Table 4, most of the estimated probit model coefficients are intuitively correct. Clearly, children are deterrents to a mother’s employment. The coefficient on the number of children in the family is negative and significant in both data sets. Also, the older the youngest child is, the greater the probability of employment (in the NLSY model). Similarly, a greater number of younger siblings has a negative sign on the probability of employment (in the ABCD model). Next, education is obviously important for employment. In both models the education parameter is positive and statistically significant. Older mothers are generally less likely to work outside the home, but the coefficient is not significant in the ABCD data model. Interestingly enough, the mother is more likely to work if she is a single parent. The

| Table 4 | Probit estimates of mothers’ labor force participation |
|---------|--------------------------------------------------------|
|         | NLSY                                                                 | ABCD                                                                 |
| age (youngest child) | 0.0577***                                             | -0.1569***                                                        |
| # of younger sibling | (0.0185)                                               | (0.0248)                                                           |
| # of children | -0.0467* (<0.1)                                         | -0.1187***                                                         |
| (0.0280) | (0.0192)                                                |
| single parent | 0.1172                                                 | 0.1543**                                                          |
| (0.0957) | (0.0603)                                                |
| education (mother) | 0.0909*** (<0.01)                                       | 0.1231***                                                         |
| (0.0169) | (0.0102)                                                |
| age (mother) | -0.0330*** (<0.01)                                       | -0.0023                                                           |
| (0.0160) | (0.0046)                                                |
| market size (medium) | -0.6698*** (<0.05)                                       | -0.9833***                                                         |
| (0.3477) | (0.3460)                                                |
| market size (large) | -0.9833*** (<0.01)                                       | (intercept)                                                       |
| (0.3460) | 1.5137* (<0.05)                                         | -0.8622***                                                         |
| (0.8085) | (0.2264)                                                |
| Years covered | 2006–2012                                              | 2018–2019                                                          |
| N | 1,348                                                   | 3,965                                                              |

Market size: small (control) = population less than 50,000; medium = population between 10,000 and 1,000,000; large = population greater than 1,000,000. Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
size of the market is negatively related to employment in the NLSY data model. The first results could be explained by the economic pressure that households face when single parents must work to secure the financial viability of the family. The second result could be related to the cost of arranging childcare which could be prohibitively high in big cities, making it harder for the mother to work.\(^6\)

In the second step the wage equation is estimated using education, age of the mother, the number of hours worked, the number of children, the size of the labor market, tenure on the current job and the inverse Mill’s ratio (IMR) calculated from the selection equation that controls for selection bias. Tenure and market size are not available in the ABCD data. The results are presented in Table 5. All obtained results are economically meaningful and most are statistically significant. The results show that the hourly wages of working mothers increase with years of education, the number of hours worked, and tenure on the job, and decrease with the number of children she has.\(^7\) This last result is interesting because it indicates that mothers with large families, even if they work outside the home, tend to find less career-oriented and lower paying jobs. Somewhat surprisingly, the market size variable measured by the population size in a given area is not statistically significant. Finally, the coefficients of the IMR are both negative and statistically significant, meaning that selection bias was present and without the correction, the estimates would have been biased downward.

**Hypothesis Testing**

Estimation of Eq. (16) provides the basis for the empirical testing of the proposed hypotheses. We experiment with three different measurements of the dependent variable screen time, \(\Delta Z_k\): weekday screen time, weekend screen time, and the total screen time, which is the sum of previous two. As mentioned in the previous section, the predicted wage rate from the wage equation (Table 5) is used as \(w\). \(F\) is defined as \(H\Delta w + \Delta M\) where \(H\) is the mother’s hours worked and \(M\) is her exogenous income. Exogenous income is calculated as the total household income net of the mother’s labor income. All variables are defined as the deviations from the mean. In Eq. (16), \(\beta_1\) and \(\beta_2\) are the coefficients of interest measuring the substitution effect and the income effect, respectively. Based on our hypotheses (Table 1), the correspondence between Eqs. (15) and (16) is straightforward and given by:

\(^6\) Recall that the market size variable is coded as a 3-level dummy variable: small, medium, large. The small market is left out to avoid perfect multicollinearity. The remaining market coefficients (medium and large) are interpreted relative to the left-out variable (small).

\(^7\) Recall that for the ABCD data, the number of hours worked was approximated as 20 per week for part-time and 40 per week for full-time employment. Admittedly, this specification is rather arbitrary but inconsequential for the results. The Current Population Survey (CPS) published by the Bureau of Labor Statistics (BLS) classifies people as full-time employed if they work 35 or more hours per week and part-time if they work fewer than 35 hours. Therefore, as a robustness check, in an alternative specification we randomly picked a number in the 10–34 hours interval for a part-time worker and a number in the 35–45 hours interval for the full-time worker and re-estimated the wage equation with the ABCD data. The results turned out to be qualitatively identical to the results in Table 5, hence they are not published.
The results are summarized in Table 6. First, the sign of the substitution effect is positive and three out of six coefficients are statistically significant. Recall that the sign of the substitution effect will be positive if and only if an increase in the wage rate decreases the time-price ratio of child upbringing activity over general consumption. Because the child upbringing activity is screen time, as wages increase, the household will increase its consumption of screen time because its time-price ratio is less than the average of its overall consumption. Second, the estimated income effect is negative and statistically different from zero in all six versions of the model indicating that screen time is an inferior good. Five hundred bootstrapped samples were constructed from our original sample. Equation (16) was estimated using each bootstrapped sample. All coefficients and their standard errors were obtained as empirical distributions based on these bootstrapped estimates.

\[
\beta_1 = \frac{\partial Z^h}{\partial w} > 0, \quad \beta_2 = \frac{\partial Z^M}{\partial M} < 0. \tag{17}
\]
Finally, the hypothesis was tested that parental demand for children’s exposure to screen time has the characteristics of a Giffen good. Based on the estimated substitution and income effects, the total price effect of a change in wage rate on the screen time demand was calculated as 

$$\Delta Z_k = \hat{\beta}_1 \Delta w_k + \hat{\beta}_2 (H_k \Delta w_k + \Delta M_k)$$

The mean values and the 5% confidence intervals of the total price effect were also generated from 500 bootstraps. As one can see from the bottom part of Table 6, in three versions of the model the total price effect is negative and falls inside the 5% confidence interval. This result confirms our conjecture that parental demand for children’s screen time is not only an inferior good but also has Giffen-good-like characteristics. As the wage rate of the mother increases, the household’s demand for children’s screen time is decreasing. This result is perfectly in line with what most of the empirical research in other non-economics disciplines have found.

### A Counterfactual Experiment

From the estimated model, one can also predict changes in children’s exposure to screen time when the maternal wage rate changes. Under the assumption that the individual wage increase does not affect the average wage level (recall that $\Delta w_k$ is defined as the deviation from the mean), and assuming that exogeneous income remains constant, one can compute a new $\Delta Z_k^{\text{new}}$:

$$\Delta Z_k^{\text{new}} = \hat{\beta}_1 \Delta w_k^{\text{new}} + \hat{\beta}_2 F_k.$$
Next, 500 bootstraps were generated and for each sampled individual, the $\Delta \text{Z}_{t}^{new}$ was calculated for a 10%, 50%, and 100% increase in maternal wage. Since it was assumed that one individual’s wage increase does not affect the average wage level, the original $\bar{\text{Z}}$ and $\bar{\text{w}}$ were used to calculate $\Delta \text{Z}$ and $\Delta \text{w}$. The results are summarized in Table 7.

The results for changes in weekday screen times are not reliable because the substitution and income effects were not statistically significant in the original model in Table 6. The same is true for the total screen time changes in the ABCD data. Relying only on the simulation results using the NLSY data, children’s weekday screen-time exposure would decrease by 0.6%, 2.71%, and 5.35% in line with the corresponding wage increase of 10%, 50% and 100%, respectively. The predicted percentage increase in children’s exposure to screen time during the weekends is somewhat smaller when the ABCD data are used.

Conclusion

The increasing exposure of children to screen time has worried public health and psychology professionals as well as many parents for quite some time. The situation became increasingly worse with the COVID-19 pandemic. When the outbreak hit, many parents were willing to relax restrictions on screen time to keep their children entertained and engaged during their prolonged confinement in the home. Tracking data on the usage of electronic devices by children ages 4 to 15 showed that children’s screen time doubled by May 2020 compared with the same period a year earlier. There are numerous studies of how screen time affects children’s physical health such as obesity, metabolic syndrome and risk for cardiovascular disease, as well as effects on mental health, low self-esteem, diminished pro-social behavior, and academic achievement. Less attention has been devoted to investigating the relationship between children’s exposure to screen time and families’ socioeconomic background and structure. Some examples in the latter group (Duch et al. 2013; Hardy et al. 2006; McMillan et al. 2015) found significant correlations between children’s screen-time exposure and parents’ income and education, family structure,
and residential area. Invariably, all these studies have consistently found that families with higher income and educational backgrounds tend to expose their children to less screen time.

These results seem intuitively correct but could contradict the standard economic model of the labor-leisure trade-off. Imagine two types of parental activities related to child upbringing: high time-intensive efforts like taking a child to a violin lesson and low time-intensive activities like having a child play computer games. The optimal parental allocation of non-wage-earning time among competing child-upbringing activities will, ceteris paribus, be determined by the opportunity cost of their time in the sense that the increase in wage rate would cause the non-wage-earning time allocation to shift away from violin lessons and towards video games. Therefore, one should see lower income parents spending more time driving children to violin lessons than higher income parents, yet the extant literature shows exactly the opposite. Explaining this apparent puzzle was the main motivation for this paper.

To the best of our knowledge, this is the first study that models the demand for children’s screen time as the result of a parent’s optimal labor-leisure choice. The paper starts by presenting a model that can explain the apparent contradiction between existing empirical results and economic theory. Based on a simple model of parental utility maximization subject to money and time budget constraints, Marshallian parental demand functions were derived for two types of child upbringing activities. After the Slutsky decomposition, the empirically observed result corresponds to the case where screen time exhibits Giffen-good-like characteristics. The empirical work utilized two datasets: the NLSY and ABCD. An estimation model was proposed where all decisions related to children’s upbringing are made by mothers who either work outside the home earning the prevailing market wages or stay at home. In line with this approach, a wage equation was estimated based on Heckman’s two-step correction procedure. Using estimated wages, the total effect of an increase in wage rate on the parental demand for children’s upbringing activities was empirically decomposed into the substitution effect and the income effect relying on the approach of Ashenfelter and Heckman (1974). For the case of low time-intensive child upbringing activities, such as exposing children to screen time, in line with our theoretical predictions, we found that the substitution effect is positive, and the income effect is negative. Moreover, relying on bootstrapped confidence intervals the negative income effect (signaling that parents perceive their children’s screen time as an inferior good) dominates the positive substitution effect causing the sign of the total wage effect to turn negative. Hence, our results show that the empirical findings in the public health and psychology literature can be reconciled with the theoretical predictions of the standard economic labor-leisure trade-off paradigm.

One possible deficiency of our approach to the problem of children’s exposure to screen time becomes apparent with the prolonged lockdowns and school closures during the COVID-19 pandemic worldwide. It is reasonable to believe that with some disciplined time away from screen devices, children can gradually learn to rely less on virtual interactions and more on face-to-face human interactions. However, doing so becomes very complicated because screen devices are now tools for school
as well as social life and gaming. This type of bundling creates particular challenges because different kinds of rewards are mingled together such that it could be hard to separate beneficial impacts from developmental and social costs. Consequently, the parental task of policing children’s screen-time exposure becomes very difficult. If they are doing schoolwork that bores them, children can easily switch to playing a video game, without parents’ awareness or permission. Needless to say, systematic modeling of parental decisions regarding optimal consumption of children’s screen time in such an environment would be even more complicated.

Acknowledgements An earlier version of this paper was presented at the 20th Journees Louis-Andre Gerard-Varet, International Conference in Public Economics in Marseille, France, June 22-24, 2021 and the International Atlantic Economic Virtual Conference, October 7-10, 2021.

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