ABSTRACT

OH, SOHAE. Three Essays in Demand Analysis. (Under the direction of Tomislav Vukina).

This dissertation analyze preference and demand of households. Chapter 1 quantifies the welfare effect of egg-laying hen cage ban in California. In November 2018, California passed the so-called Proposition 12 that completely bans selling eggs produced in any type of cages by the end of 2021. The objective of this study is to estimate the welfare effects of Proposition 12 in a partial equilibrium setup where both the supply and the demand side of the market are simultaneously modelled. Our estimates show that the implementation of Proposition 12 would result in welfare losses for both buyers and sellers of eggs in California. The state-level expected annual welfare loss to households amounts to $72 million, whereas the industry level losses at the retail level amount to 18% of their original quasi profits.

In Chapter 2, a simple model of parental utility maximization subject to the money and time budget constraints is suggested to derive Marshallian parental demand functions for two types of child upbringing activities (violin lessons and screen time). After the Slutsky decomposition, I show that parental demand for children's screen time corresponds to the case similar to Giffen good. Using National Longitudinal Survey of Youth 1979 (NLSY) and Adolescent Brain Cognitive Development (ABCD), I first estimate the wage equation based on the Heckman's two-step correction procedure and then empirically decompose the total effect of an increase in wage rate on the parental demand for screen time into the substitution effect and income effect. I found that the substitution effect is positive and the income effect is negative and that the negative income effect dominates the substitution effect. Hence our results shows 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.

Finally, in Chapter 3, I estimate the effects of children's screen time on their obesity by modeling a mother's dynamic decision making on time and money allocation between different activities related to child-rearing: namely, allowing their children to watch screen devices, preparing healthy food, participating in the labor force, and taking an active role in assuring her children's health. Using 2017-2019 Adolescent Brain Cognitive Development data, I found that the percentage of children who are overweight or obese will increase from 32.6% to 36.4% in two years, if they spend one additional hour on watching screen daily. Such a result may be interpreted as the total marginal effect of screen time on children's obesity. Additionally, restricting the daily screen usage time has been effectively correlated

with a decreased likelihood of a mother working in full-time employment.

Three Essays in Demand Analysis

by
Sohae Oh

A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Economics

Raleigh, North Carolina
2022

APPROVED BY:

Raymond Guiteras	Zheng Li
Thath Men Gutierrez Li	Tomislav Vukina Chair of Advisory Committee

DEDICATION

To my parents, my husband, and my daughter for their love and supports

ACKNOWLEDGEMENTS

I would like to express my deepest and sincerest gratitude to my advisor Dr.Tomislav Vukina for his dedicated support and guidance. Words cannot describe all my appreciation to him. I am also deeply indebted to Dr.Raymond Guiteras, Dr.Zheng Li, and Dr.Alejandro Gutierrez-Li for their valuable comments and encouragements. I also extend my gratitude to Dr.Xiaoyong Zheng for his mentoring and support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER

1

THE PRICE OF CAGE-FREE EGGS: SOCIAL COST OF PROPOSITION 12 IN CALIFORNIA

1.1 Introduction

In January of 2015, California's Prevention of Farm Animal Cruelty Act and Assembly Bill 1437, together known as "Proposition 2", went into effect. Proposition 2 banned the use of the so called battery cages for egg-laying hens of all the table eggs produced and sold in California. In November 2018, Californian voters passed "Proposition 12" that completely bans selling eggs produced in any type of cages by the end of 2021.

Ensuring animal friendly environment for hens in table egg production is part of a larger global trend following the European Union laws that banned battery-cages in 2012. A growing number of states, including Massachusetts, Michigan, Ohio, Oregon, and Washington, have already passed laws that will eventually limit the use of battery cages (Mullally and Lusk (2018)). Since Proposition 12 is one of strongest animal welfare laws, it became the center

of attention and concerns from various interest groups around the country. The objective of this study is to estimate the welfare effects of the Proposition 12. Our estimates based on the revealed preference data show that the implementation of Proposition 12 would result in sizeable welfare losses to both buyers and sellers of eggs in California. Understanding how Proposition 12 impacts the market of table eggs in California could provide a basis for predicting the effects of future animal welfare legislation in different markets.

Previous studies have investigated the economic impact of regulation of minimum space requirements for egg-laying hens on egg production, prices and social welfare. Most of the studies did not look at the supply side issues or analyzed two sides of the market separately without addressing the equilibrium adjustments following the implementation of the regulation. Malone and Lusk (2016) measured price changes and consumer welfare loss due to Proposition 2 using wholesale price spreads between the United States and California before and after the effective date of Proposition 2 (January 2015). They found that Californians pay $0.48 - $1.08 per dozen more than they would have paid without the ban. This amounts to a 33% - 70% price increase or the annual consumer welfare loss (as a form of changes in consumer surplus) of between $400 million and $850 million. Mullally and Lusk (2018), found that both egg production and the number of egg-laying hens were about 35% lower than they would have been in the absence of the new regulations. For consumers, based on the five years of scanner data, they found that the average price per dozen eggs from 2014 to 2016 was about 22% higher than it would have been in the absence of Proposition 2. Their results suggest that California consumers can expect to experience annual welfare losses of at least $25 million in future years from higher retail egg prices alone. Carter et al. (2021) developed a conceptual model for analyzing the effects of Proposition 2 by comparing market equilibria under two regulatory scenarios: with and without the regulation. They modeled the demand and supply of conventional and California-compliant eggs and numerically solved for equilibrium prices and quantities under two scenarios. However, they did not empirically estimate their structural model but proceeded with the reduced form estimation of the price effects based on the time series data. They found a long-term increase in California egg prices of 39 cents per dozen eggs (about 14%) and increase in wholesale egg prices in the rest of the U.S. of 7 - 10 cents per dozen (about 4% - 6%).

To the best of our knowledge, no study so far has directly measured the potential welfare effects of Proposition 12. However, there are studies that quantified welfare changes under a hypothetical regulatory scenario where all types of cages were banned. For example, Norwood and Lusk (2011) employed equilibrium displacement models using non-hypothetical

auction data and estimated the cage-free premium to be $0.47 - $0.55 per dozen. They projected that converting all cage eggs to cage-free eggs in the United States would result in a US$ 1,872.7 million decline in consumer surplus and a US$ 187.3 million decline in producer surplus, assuming no consumer demand shift in response to change in the type of eggs sold. Allender and Richards (2010) accounted for unobserved heterogeneity in consumer preferences in their demand estimation but also failed to take into account the equilibrium price effects. Instead they assumed that prices would increase by approximately 20% due to higher production costs, as estimated by Sumner et al. (2008), and perfectly inelastic demand for eggs such that the cost increase would be passed 100% to consumers. They estimated the willingness to pay for cage-free eggs over conventional eggs of $0.54 per dozen and the welfare loss due to animal welfare legislation mandating cage-free egg production in California of $106 million.

To address the failure of the existing literature to deal with market equilibrium effects of animal welfare regulations, we show that any public policy intervention targeting consumer products should take firms' optimal price responses and their effect on consumer welfare into account. So far, the only study that does this is Kotschedoff and Pachali (2020) who, in a partial equilibrium setting similar to ours, estimated an individual-level demand model for eggs differentiated by animal welfare. Using German household data, they demonstrated that prices for majority of higher quality eggs fell after Germany banned the sale of battery eggs, which lead to a redistribution of consumer welfare from households that do not value animal welfare to households that are willing to pay a premium for it. Regardless of the fact that K&P evaluated the same type of regulation in a similar structural econometrics framework, our study is different because it analyzes a completely different market environment. The absence of mandatory and standardized animal welfare labels on egg products in the U.S. compared to the E.U.,[1] makes the comparison of egg products across retailers more complicated and softens competition due to further product differentiation by non-standardized egg labels. Consequently, the type of data used in two studies is also different which lead to certain differences in estimation. First, K&P imputed prices for non-chosen alternatives, whereas we use purchase date and store code in which particular shopping trip is made to match the consumer panel data with retail scanner data which enables us to identify the choice set consumers face during each trip thereby knowing prices and other product attributes even if the consumer had not purchased these products during this particular trip. Secondly, the scanner data also allows us the inclusion of observ-

[1] https://ec.europa.eu/food/animals/animal-welfare/other-aspects-animal-welfare/animal-welfare- labelling_en

able product attributes (color, Omega-3, grade, etc.), and the interaction of product and consumer demographic characteristics. This is an important contribution in light of the previous study (Chang et al. (2010)) that found that about 42% of the observed premium for cage-free eggs over conventional eggs can be attributed to egg color rather than differences in hens' living conditions.

Using the combination of the 2015-2017 Nielsen consumer panel and retail scanner data, obtained from the Kilts Marketing Center of University of Chicago's Booth Business School[2], we investigate consumer preferences for cage-free eggs with the objective to evaluate the ex-ante welfare effect of the forthcoming Proposition 12. In modeling the demand side of the market we use random coefficient logit (mixed logit) model and find that consumers prefer cage-free eggs but the magnitude of the effect is, on average, very small. On the supply side, we use a Bertrand Nash oligopoly model for heterogeneous products, and together with the estimated demand side, predict the new counterfactual equilibrium prices of all egg products under Proposition 12 where conventional eggs are banned. The results show that the new marginal costs of what used to be conventional eggs would increase, on average, by 56%. The prices of originally conventional eggs would increase by 65% and the prices of cage-free eggs would decrease by 3.4% and the overall welfare, measured as the sum of consumer and producer surplus, would decrease. The state-level expected annual welfare loss to households amounts to $72 million and the industry welfare loss at the retail level amounts to 17.6% of their original quasi profits. Because of its partial equilibrium framework, and the use of the matched household Homescan and store scanner data sets, our study contributes significantly to the literature on quantifying the welfare effects of animal welfare laws.

In the next section we provide a background on the egg industry and animal welfare regulation in California. In the third section we present our econometric model of demand and supply. In the next two sections we discuss the construction of the working data set, followed by the description of the estimation procedure. In the sixth section we present the demand estimation results, willingness to pay and marginal costs estimates. The seventh section contains the counterfactual simulation results and robustness checks and the last section concludes.

[2]https://www.chicagobooth.edu/research/kilts/datasets/nielsen.

1.2 Egg Industry and Animal Welfare Regulation in California

According to the Association of California Egg Farmers (CEF) website[3], 40 million Californians consume a total of 12 billion eggs annually, or about 300 eggs per person. According to the same source, in 2018, Californian egg farmers housed 13.7 million hens producing 3.9 billion eggs, making California the 7th largest producer of eggs in the U.S. The comparison of these numbers with Table 1.1 production numbers based on the USDA official statistics show some discrepancies, although the numbers are reasonably close. Relying on the CEF consumption numbers, it follows that California lacks about 8.1 billion eggs annually that need to be imported just to cover domestic consumption. Another way of proving that California relies heavily on the out-of-state egg production is to realize that based on the data in Table 1.1, Californian producers housed only between 3.64% in 2016 and 4.52% in 2017 of the total number of laying hens in the country.

The proportion of cage-free table egg layers in the U.S. rapidly increased from 8.6% in 2015 to 23.4% in 2019. This is due to the aggressive cage-free facility investments of some of the top egg producers in the nation. California has around 20 percentage point higher cage-free egg production ratio than the national average. According to CEF, in 2018, the first year for which their data is available, 38% of all eggs produced in California were cage-free and the proportion went up to 47% in 2019. The source also claims that by 2025, 100% of eggs produced in California will be cage free, regardless of Proposition 12.

The national table egg industry is quite competitive as we can see from the list of leading US table egg producers and their production shares (see the right panel of Table 1.2). The top-4 firms concentration ratio is only 31% and the top-15 producers cover about 63% of the total national table eggs production. The comparison of the size and concentration of egg industry with the food retailing sector (left panel in Table 1.2) where most of eggs are sold leads to a David and Goliath type of story. In terms of annual sales, the No. 15 national retailer chain (Wegmans) with $8.3 billion in annual sales is 4 times bigger than the largest egg producer in the country (Cal-Main Foods). The No. 1 ranked retailer (Walmart) with its $308 billion in annual sales is more than 150 times larger than Cal-Main Foods.[4] The retail sector is also more concentrated than the egg sector. The top-4 firms concentration ratio in 2017 was 67% and cumulative share of top 15 firms approached 88%.

[3] http://californiaeggfarmers.org/

[4] If we take the average production of 296 eggs per hen and multiply it by 41.1 million Cal-Main's layers and assume an average price of $2 per dozen eggs, gives us about $2 billion in annual sales.

The comprehensive and reliable list of the largest egg producers and retailers in California is not available from the public domain sources. Therefore, we have to rely on the 2016 summary statistics based on our retailer scanner data, the details of which will be discussed later in the text.[5] As seen from Table 1.3, the raw scanner data records the sales of 114.05 million dozen-egg cartons, which compared to the total consumption of 12 billion eggs in California reported by CEF, amounts to a fairly representative 11.4% coverage. A 3-level classification of retail outlets (company-banner-store) reveals the fact that 3 largest companies (B,E,G), with two banners each and 584 stores, control the sales of 56.5% of all eggs sold in the state. These large retail chains predominantly rely on their store (private) brands. As seen from the left panel of Table 1.4, private label eggs owned by these three companies (B1,B2,G1,G2,E1,E2) account for 49.5% of all eggs sold. In aggregate, private labels outsell national brands by more then 5 times (85% to 15%). In the right panel, we list the largest national brands, topped by Eggland's Best with a market share of 7.7%.[6] The individual market shares of other highest ranked national brands are tinny compared to the store brands.

Personal interviews with egg industry participants and extension specialists produced an opaque picture of fragmented and idiosyncratic market, complicated by the presence of various intermediaries (brokers and dealers) and the absence of centralized procurement schemes among large retailer banners. Nevertheless, two pricing patterns clearly emerged. For non-specialty (conventional) eggs, the dominant pricing mechanism seems to be a negotiated long-term contract (2-3 years) where the price for the delivery in a specific week is based on the Urner-Barry regional quote for that week (say California, Tuesday).[7] The negotiated percent departure away from the Urner-Barry quote largely depends on the transportation arrangements. There seems to be no particular difference between private (store) labels and national brands pricing arrangements, as most of the egg producers would simultaneously operate under both types, selling some portion of their egg production under a given store label and some portion under their own brand. When it comes to specialty eggs (nutritionally enhanced, cage-free, free-range, organic, etc.) the dominant type of contract seems to be a long term (several years) fixed price arrangement (i.e., not

[5]We chose to present the data for 2016 because it is more representative of the entire state because, according to their manual, Nielsen reduced the coverage of stores in 2017.

[6]Eggland's Best is not a traditional egg producer as they own no chickens but rather franchise the production to other companies who supply specific regions of the country. They developed and patented a diet which results in an altered nutrient composition of the egg.

[7]Urner-Barry is an American business publisher that provides market information on the food industry on the subscription basis. It focuses on market information related to red meat, poultry, eggs and seafood through its reports and websites.

based on the current Urner-Barry quote) with stipulated provisions for extraordinary input price volatility. Fixed price contracts provide egg producers with higher insurance against income volatility which may be necessary to induce a sufficient number of them to switch to riskier production of specialty eggs needed to satisfy continuously increasing demand. With specialty eggs, it seems like producers tend to rely more on brand names then store brand contracts, although specialty eggs private labels are quite ubiquitous as well.

California has been in the center of national attention because of its animal welfare legislation. In November 2008, California voters passed Standards for Confining Farm Animals, known as Proposition 2, as an initiated state statute. The measure was approved with 63.5% of voters support. This law bans the confinement system that prohibits animals from turning around freely, laying down, standing up, and fully extending their limbs. This applied to egg laying hen cages, veal crates and sow gestation crates. The law was set to go into full effect on January 1, 2015. Proposition 2 itself does not prohibit sales of eggs in the state originating from states that do not comply with the regulation.

Right after the passage of Proposition 2, serious concerns emerged that this law would lead to the total destruction of California egg production caused by the domination of cheap out-of-state imports. For this reason, Assembly Bill 1437 which banned the state-wide sale of eggs produced under conditions that do not comply with Proposition 2 was passed and signed into law in July 2010. The AB 1437 was also set to go into effect as of January 2015.

Proposition 2 does not specify the minimum space requirement for raising egg laying hens. Instead, the requirement is based on the behavior and movement of animals which could be too vague to trigger compliance and enforcement. For this reason, in May 2013, the California Department of Food and Agriculture (CDFA) provided the specific rules for sufficient spacing of the egg laying-hens of a minimum of 116 square inches of space per bird. The conventional battery type cage broadly used in the layer production at that time, which housed 6-7 birds with only 67-86 square inches per hen did not meet the standard. Instead the enriched colony cage system, with 60 laying hens housed together in a cage ensuring 116 square inches per hen replaced the traditional battery cage system.

In the November 2018 general election, Californian voters also passed with more than 60% of the votes the Farm Animal Confinement Initiative, amending California Health and Safety Code Section 25990-25993, known as the Proposition 12. Based on the official ballot summary that was given to voters it is clear that Proposition 12: (a) establishes new minimum space requirements for confining veal calves, breeding pigs, and egg-laying hens; (b) requires egg-laying hens be raised in cage-free environment after December 31, 2021; (c) prohibits certain commercial sales of specified meat and egg products derived from animals

confined in noncomplying manner; (d) defines sales violations as unfair competition; (e) creates good faith defense for sellers relying upon written certification by suppliers that meat and egg products comply with new confinement standards; and (f) requires State of California to issue implementing regulations. The implementation of Proposition 12 would proceed in two phases. First, housing egg-laying hens in the environment with less than 144 square inches of usable floor space per hen is banned at the beginning of 2020. Second, all types of cages are banned for the laying hens by the beginning of 2022. A cage-free housing system is defined as an indoor or outdoor controlled environment within which hens can roam freely and are provided enrichments that allow them to exhibit natural behaviors, including scratch areas, perches, nest boxes, and dust bathing areas; and within which farm employees can provide care while standing inside the hens' usable floor space.

As one of our central objectives is to investigate the distributional effects of Proposition 12, before proceeding with the formal analyses, it is useful to present some model free evidence. In Table 1.5 we present the summary of the average annual consumption of fresh eggs by households in California based on the home scanner panel data. The raw data evidence clearly points to the conclusion that the consumption of cage-free eggs is heavily biased towards female, more educated, more affluent and younger households. For example, in households headed by a highly educated (advanced degree) person, 11.15% of the eggs consumed in 2015-2017 period were cage-free whereas this percentage is only 5.34% in households headed by a person with high school diploma or less. During the same time span, the most affluent households (above $100K annual income) consumed 15.72% cage-free eggs, whereas for the households in the $25K to $50K income range this share was only 5.54%. Similarly, the percentage share of the consumption of cage-free eggs in total egg consumption among younger households is more than double that of the older households.

1.3 A Model

To assess the effects of the laying-hen cage ban on the market, we estimate a structural model of demand and supply of table eggs. We model the supply side as a Bertrand-Nash oligopoly pricing game where multi-product retailers compete with each other in the regional markets for fresh egg products. Following McFadden (1973) and Train (2003), on the demand side, we assume that the head of a household makes a discrete choice decision about which table eggs product to buy among the choices she faces during a trip

to the grocery store. Table eggs are differentiated by their characteristics such as size, grade, color, total count per carton, and whether the laying-hens are raised in cage-free or cage environments. Retailers set prices of their table eggs by maximizing their total profits in each market. Across space, a market is defined as a geographical region and across time a market is defined as one week.

1.3.1 Demand Side

Formally, household i obtains utility U_{ijt} from purchasing the jth egg product in grocery market t (recall, a market is defined as a region/week combination):

$$U_{ijt} = \gamma_{it}(y_i - p_{jt}) + X_j\beta_{it} + \epsilon_{ijt}, \tag{1.1}$$

where y_i is household i's income, p_{jt} is the price of product j in market t, X_j is a $1 \times K$ vector of observable characteristics of product j and ϵ_{ijt} is an independently and identically distributed error term that follows the Type-I extreme value distribution. The household faces J_t number of egg products in market t and purchases the product that yields the highest utility. We also allow a consumer to not purchase table eggs in a particular market. In this case, household i obtains utility U_{i0t} from purchasing the outside or the $numéraire$ good:

$$U_{i0t} = \gamma_{it} y_i + \epsilon_{i0t} \tag{1.2}$$

where γ_{it} represents household i's marginal utility of income when shopping in market t. Since the marginal utility of income is non-negative, γ_{it} is assumed to follow the log normal distribution with log mean $\overline{\gamma}$ and log variance σ^2_γ. By including a $numéraire$ (composite) good that represents all other goods, we can measure the correct welfare effect (LaFrance and Hanemann (1989)).

The $K \times 1$ vector of parameters β_{it} describes household i's tastes for observable product attributes. We divide observable product characteristics into to two groups, depending on the value consumers place on various attributes. The vertical product differentiation group (e.g. weakly positive characteristics) includes characteristics such as the cage-free attribute where consumers either do not care about animal welfare (zero preference) or like cage-free eggs (positive preference), whereas negative feelings are unlikely. The second group includes horizontal product differentiation group with taste differences such as, for example, egg color where a consumer either likes brown eggs (positive preference) or dislike brown eggs (negative preference). Accordingly, depending on x^k_j, we assume that the k^{th}

element of β_{it}, β_{it}^k follows either the log-normal distribution with log mean $\overline{\beta}^k + Z_i\theta^k$ and log standard deviation σ_k, or the normal distribution with mean $\overline{\beta}^k + Z_i\theta^k$ and standard deviation σ_k. We assume that both β_{it} and γ_{it} are random.

Finally, Z_i is a $1 \times D$ vector of demographic characteristics of the household, and θ^k is a $D \times 1$ vector of corresponding parameters. By specifying preferences for some chosen product attributes to depend on consumer's demographic characteristics, our model is more general and realistic than other discrete choice frameworks that do not adopt random coefficients (McFadden and Train (2000)).

Incorporating these assumptions, (1.1) can be written as

$$U_{ijt} = \exp(\overline{\gamma} + \sigma_\gamma u_{it}^\gamma)(y_i - p_{jt}) + \sum_{k \in K_1} \exp(\overline{\beta}^k + Z_i\theta^k + \sigma_k u_{it}^k) x_j^k + \sum_{k \in K_2} (\overline{\beta}^k + Z_i\theta^k + \sigma_k u_{it}^k) x_j^k + \epsilon_{ijt} \tag{1.3}$$

where x_j^k is the k^{th} product attribute of product j, and K_1 and K_2 refer to two different product characteristics groups ($K_1 \cup K_2 = K$). u_{it}^γ and u_{it}^k for $k = 1, \ldots, K$ are independently and identically distributed standard normal random errors. The average marginal willingness-to-pay (WTP) for product attribute k is $\frac{\overline{\beta}^k + Z_i\theta^k}{\exp(\overline{\gamma} + \sigma_\gamma^2/2)}$ if β^k follows normal distribution and $\frac{\exp(\overline{\beta}^k + Z_i\theta^k + \sigma_k^2/2)}{\exp(\overline{\gamma} + \sigma_\gamma^2/2)}$ if β^k follows log-normal distribution.

Based on McFadden (1973), the probability for household i in market t choosing product j is given by

$$s_{ijt}(u_{it}) = \frac{\exp(V_{ijt})}{1 + \sum_{g=1}^{J_t} \exp(V_{igt})} \tag{1.4}$$

where

$$V_{ijt} \equiv -\exp(\overline{\gamma} + \sigma_\gamma u_{it}^\gamma) p_{jt} + \sum_{k \in K_1} \exp(\overline{\beta}^k + Z_i\theta^k + \sigma_k u_{it}^k) x_j^k + \sum_{k \in K_2} (\overline{\beta}^k + Z_i\theta^k + \sigma_k u_{it}^k) x_j^k. \tag{1.5}$$

Consequently, the probability of household i purchasing product j in market t can be written as:

$$s_{ijt} = \int \frac{\exp(V_{ijt})}{1 + \sum_{g=1}^{J_t} \exp(V_{igt})} f(u_{it}) d\, u_{it} \tag{1.6}$$

where $f(\cdot)$ is the joint density of $u_{it} = (u_{it}^\gamma, u_{it}^k), k = 1, \cdots, K$, and the average market share of product j in market t can be written as:

$$s_{jt} = \frac{1}{N_t} \sum_{i=1}^{N_t} s_{ijt} \tag{1.7}$$

where N_t is the number of consumers in market t.

1.3.2 Supply Side

On the supply side, we assume that F_t retailers are competing in market t to sell differentiated products (eggs) by engaging in a Bertrand-Nash type of oligopoly pricing game. We assume that each retailer behaves as a vertically integrated firm with respect to its own private labels and acquires brand name products at competitive prices. In absence of brand loyalty for eggs, we assume that egg producers have no market power and sell their eggs to retailers at marginal cost. Formally, a seller f sells J_{ft} lines of products in market t, hence $\sum_{f=1}^{F_t} J_{ft} = J_t$ gives the number of products household i faces in market t. Firm f's profit function in market t is given by

$$\Pi_{ft} = M_{ft} \sum_{j=1}^{J_{ft}} s_{jt}(p_{jt} - c_{jt}), \tag{1.8}$$

where M_{ft} is the size[8] of market t and c_{jt} is the marginal cost of product j in market t. Firm f maximizes profit (1.8) with respect to the prices of all its products in this market, taking the prices of other products in the same market as given. Then, the first order conditions are

$$s_{jt} + \sum_{g=1}^{J_{ft}} \frac{\partial s_{gt}}{\partial p_{jt}}(p_{gt} - c_{gt}) = 0, \quad j = 1, \ldots, J_t, \tag{1.9}$$

which can be expressed in a vector form as:

$$s_t + \Omega_t(p_t - c_t) = 0. \tag{1.10}$$

where s_t, p_t, and c_t are $J_t \times 1$ vectors collecting individual shares s_{jt}, prices p_{jt}, and marginal costs c_{jt}, respectively. Ω_t is a $J_t \times J_t$ matrix whose $(j,r)^{th}$ individual cells are $[\Omega_t]_{(j,r)} = \Phi_{jrt} * \frac{\partial s_{jt}}{\partial p_{rt}}$, and Φ_{jrt} equals 1 if product j and r are sold by the same retailer and 0, otherwise.

1.4 Construction of the Working Data Set

For the purposes of the estimation we match two before mentioned data sets: the consumer panel data and the retail scanner data. The consumer panel data is used to record the

[8] Imagine a regional market where 1 million households reside and each household buys one carton of eggs per week, then the aggregate market size that needs to be split between f firms is M = 1 mil. cartons.

actually purchases that households made. The panelists in the consumer panel data use in-home scanners provided by Nielsen to scan the Universal Product Code (UPC) of all their purchased products intended for personal, in-house use. This electronic scanner automatically records the purchase date, the retail store where the products were purchased, the UPCs of the products, their quantities, and the prices paid. In addition to their purchase information, panelists also provide their demographic and geographic information. This consumer panel data is longitudinal. We use data on consumers' purchase decisions from grocery trips made from January 4th, 2015 to December 30th, 2017. Because the panel is only 3 years long and unbalanced, in our estimation we treat households as independent cross-sections[9].

The retail scanner data provide weekly pricing and sales information of products sold at each store at the UPC level generated by the point-of-sale (POS) systems. It also contains information about store type and location. Using the purchase date and the store code in which a particular grocery trip is made, we match the consumer panel data with the retail scanner data. Because from the retailer scanner data we know the prices and product attributes of all products regardless of whether they have been purchased on this trip or not, matching the two data sets enable us to identify the entire choice set consumers face during each grocery trip they made. Since the prices of products in the retail scanner data are weekly, we assume that, within one week, the product offerings and their prices stay the same.

The construction of the working data set used in the estimation proceeded in several steps. First, after dropping unspecified retailers from both data sets, we constructed the summary Tables 1.3, 1.4 and 1.5. At this point we had 595,708 trips and 249 egg UPCs. Among the purchased product categories, we only consider the fresh eggs group and ignore products like liquid, dehydrated, quail eggs and similar. Next, because of the complications related to the construction of outside options, we deleted drug stores and dollar shops (discount stores) and retained only regular grocery stores. The next step was to divide the trips into those where people purchased table eggs and trips where no eggs were purchased. The latter trips form the outside options category. In defining what constitutes an outside option we had to eliminate the trips where purchasing an egg product was not being considered at all. Possible scenarios include vegans and consumers who already bought eggs very recently. Following this argument, we deleted trips that were made by consumers who never bought any eggs in the sample and trips that were made within the same week

[9]Out of 4,374 household observations used in estimation, 45.6% appeared in all 3 years, 28.5% appeared in only 2 years, and 25.9% of households appeared in only 1 year.

of the trip where eggs were already purchased.

In the next step, we match the household trips data with the retail scanner data. The main problem was missing observations. For example, imagine consumer A purchasing product 1 in store k in week w, consumer B purchased product 2 in store k in week w and consumer C purchased product 3 in store h in week w. In the retail scanner data, POS information only has product 2 in store k and week w. In this scenario, the ideal matching would discard consumer C but also consumer A because even though the store is matched, there is no matching information in retail scanner data for product 1. However, since this would cause tremendous loss of observations, we manually inserted product 1 information from the consumer panel data into the retail scanner data, thereby saving consumer A observation and only dropping consumer C. Retailer scanner and consumer panel data share the same product dictionary (for every UPC), so we have all product characteristics and prices, so the above imputation is precise and does not introduce any measurement error. Finally, some trips were excluded because they have negative or zero prices. These are due to entry mistakes on prices paid or because the applied coupon value was greater than the original price.

In the final step, we restrict the number of egg products purchased per trip to two cartons of one type of product. In about 4% of observations, the households bought multiple UPCs of eggs and/or more than two cartons (units) of the same UPC. These observations were also dropped. Finally, we also had to delete observations where the price information on chosen products from other markets in the same week was not available. The reason for this decision is the fact that, as will be later explained, price information on the same product from other markets is used as an instrumental variable in estimating the demand equation. The final usable number of trip observations is 250,540, where 26,478 are egg trips and the rest are outside option trips and the final number of egg products is 170 UPCs.

There are several important features of the working data set. First, because our matching procedure matches households with stores where eggs (or other things) were purchased, we need to organize stores into markets where retailers compete. In order to define regional markets in California we use ten Census 2020 regions.[10] As seen from Table 1.6, we have 8 retail companies competing in 10 markets but a lot of cells in the table are empty indicating that not all companies maintain presence in all markets. The individual cells in the table indicate the number of stores that each company operates in each of the 10 regions. Notice that the number of stores associated with each banner is smaller than in Table 1.3. These

[10]For the precise coverage of regions see the note below Table 1.6 and Figure 1 in the Appendix.

are stores patronized by households from the survey data, whereas those in Table 1.3 are all stores from the retail scanner data representing the full set of available alternatives. A related issue to the definition of the markets is the definition of the prices. Because our model assumes that consumers have perfect information about products available in their regional markets, stores locations are ignored, and some degree of retail banner loyalty is possible, we need to enforce the law of one price within a retailer and a market. Specifically, in cases where in any given market (region and week), the same UPC sold at different prices in various stores owned by the same company we use the average price across stores as the relevant price for this UPC sold by that company in that market.

Table 1.7 presents the summary statistics of the consumer choice set. From the table entries we see that 36% of 170 table egg products are cage-free eggs and the average posted price for those eggs was $5.25 per dozen, more than 2 dollars higher than the price of conventional eggs. The reported cage-free price is the average price across all markets (156 weeks and 10 regions), and all 61 cage-free UPCs. The average price in the choice set can be compared to the raw retail scanner data. If we divide the total sales with the total eggs sold in Table 3, we get an average price of $2.75 per dozen which is lower than the average price of $3.94 a dozen in our constructed choice set. This is an obvious consequence of the fact that we dropped drug stores and dollar shops and consequently some of the less expensive UPCs. Another interesting point to note is that 56% of all egg products in the choice set are private (store) labels. If we compare this percentage with the data in Table 4, we see that our choice set under-represents the importance of private labels since the actual percent share of private labels in the raw retail scanner data for 2016 was 85%.

Another way of summarizing our working data set is to focus on the actual purchases that California households made during this time period. The top portion of Table 1.8 repeats the structure of Table 1.7. The first thing to notice is that the total number of eggs purchased per egg trip is 14.83. The fact that there were 26,478 egg trips made by 4,374 households, gives us an average egg consumption of 90 eggs per household during the three-year period 2015-2017 or 30 eggs per year. The comparison with the raw data in Table 5 of 113 eggs per household indicates that in the process of constructing our working data set, we lost about two dozen eggs per household. Furthermore, the comparison with the CEF statistics which claims that Californians eat 12 billion eggs annually, or 923 eggs per household, indicates that our household data represents only about 3.3% of actual egg consumption in the state. This issue will have to be adequately dealt with when computing the change in consumer surplus due to regulation.

When it comes to eggs prices, notice that the average price actually paid by consumers

of $2.88 a dozen is lower than in the choice set and much closer to the raw data retail price from Table 3. The share of cage-free eggs in total egg purchases is only 13%, also significantly lower than in choice set (36%). The share of private labels (83%) is higher than in the choice set and very close to the raw retail scanner data in Table 1.4. Finally, the lower panel of Table 8 presents the summary statistics of the panelists' demographic characteristics. Panelists are predominantly married (60%), with college or advanced degree (88%), two thirds of them are middle age (35-64 years old) and two thirds of them have annual income in excess of $50,000 with 28% of them with income in excess of 100K dollars. The average household size is 2.4 persons.

1.5 Estimation Procedure

Our model in Section 1.3 assumes that on each shopping trip, a household purchases one unit of one UPC out of many table eggs products available in the store. This is a standard assumption in the discrete choice modelling literature (Train (2003))[11]. In reality, however, a household may purchase multiple UPCs and/or multiple units of the same UPC. To deal with this issue, we allow for the possibility that a consumer would buy two units of an egg product (2 cartons) instead of only one. Suppose on a shopping trip t, there are L_t table eggs products (UPCs) on the shelf. Then, the choice set would include a total of $J_t = 2L_t + 1$ choices, two for each UPC plus an outside choice.

The vector of our observable product characteristics, X_j, includes brown color (vs. white), private label (vs. national brand), omega3 (yes or no), organic (yes or no) cage-free (vs. conventional), grade AA (vs. A or lower), extra large (vs. large or smaller) and total count per carton. As discussed in Section 1.3.1, coefficients for omega3, organic, cage-free, and AA are assumed to be distributed log-normally and coefficients for other characteristics, brown, private, extra large and total count, normally. Variables in the vector of household demographic variables Z_i include: household type (male or female for the single person households or married for a married couple); two categories of education levels (high school or less and college or advanced degree); four income brackets in dollars (less than 25K, 25-50K, 50-100K and more than 100K); three age groups (under 34, 35-64 and 65 and older) and household size (number of persons).

To reduce computational burden in the estimation, we limit the interaction terms

[11] Although Hendel (1999) and Dubé (2004) proposed estimation methods for handling data where multiple UPCs and/or multiple units of the same UPC are purchased, these methods are complicated and rely on additional and often non-testable assumptions.

between product characteristics and consumer demographic characteristics to those with cage-free characteristic only. Recall that the model-free evidence pointed to the fact that the consumption of cage-free eggs is biased towards female, more educated, more affluent and younger families. We also stipulate that large households would be more reluctant to purchase cage-free eggs than small households simply because they consume a lot of eggs and since cage-free eggs are more expensive they would tend to substitute them for cheaper eggs even if they care about animal welfare. We estimate parameters θ^k that correspond to these product-household characteristic interactions in equation (1.3) and restrict the coefficients for all other interaction terms to be 0. We expect all above tendencies to be confirmed by the estimated model coefficients.

As with most demand estimations, we have to deal with the possibility that the price variable p_{jt} might be endogenous. A common endogeneity concern is that supply side reactions (price changes), to the unobserved demand shocks may bias the price parameter estimate. As an example, we could have a problem with some time-varying unobserved product characteristics such as advertising/promotion campaigns that are captured in the error term ϵ_{ijt}. These activities are likely to be correlated with the price variable as both are the retailers' decision variables, rendering the price variable endogenous.

To address this concern, we use the control function approach (Wooldridge (2015)), particularly suitable for discrete choice models that allow for heterogeneous effects. First, we estimate the following regression,

$$p_{jt} = \Lambda_{jt}\Pi + \upsilon_{jt}, \tag{1.11}$$

where Λ_{jt} is a vector of exogenous variables which includes a constant, a vector of observed product characteristics X_j, and an instrument for price p_{jt}^{IV} constructed as the average price of product j in other markets. In order to construct p_{jt}^{IV}, we divide California into same ten geographic regions used to define regional markets and define p_{jt}^{IV} as the average price of product j in one of the randomly selected regions other than the one in which trip t took place. The origins of this approach can be traced back to Hausman (1997) and Nevo (2001) and it is valid under two assumptions. First, the instrument needs to correlated with the endogenous price variable conditional on other exogenous variables in the model, and second the error terms in (1.3), ϵ_{ijt}, must not be correlated across different regions. Testing the first assumption is straightforward, however, the second assumption cannot be directly tested and needs to be convincingly argued and verified. We deal with these issues in the next section.

In the second step of the control function approach, we include the residuals $\hat{v}_{jt}$ from the first-stage regression as an additional variable in the main model to control for the potential price endogeneity, that is, (1.3) is modified to become

$$\hat{U}_{ijt} = \exp(\overline{\gamma} + \sigma_\gamma u_{it}^\gamma) y_i + \hat{V}_{ijt} + \epsilon_{ijt}, \tag{1.12}$$

where

$$\hat{V}_{ijt} = -\exp(\overline{\gamma} + \sigma_\gamma u_{it}^\gamma) p_{jt} + \sum_{k \in K_1} \exp(\overline{\beta}^k + Z_i \theta^k + \sigma_k u_{it}^k) x_j^k + \sum_{k \in K_2} (\overline{\beta}^k + Z_i \theta^k + \sigma_k u_{it}^k) x_j^k + \eta \hat{v}_{jt}. \tag{1.13}$$

From the above, the probability for consumer i to purchase product j during trip t (1.6) becomes

$$\hat{s}_{ijt} = \int \frac{\exp(\hat{V}_{ijt})}{1 + \sum_{g=1}^{J_t} \exp(\hat{V}_{igt})} f(u_{it}) d\, u_{it}. \tag{1.14}$$

As a result, the log likelihood function for the estimation problem can be written as,

$$LL = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{j=1}^{J_t} d_{ijt} \log \hat{s}_{ijt}, \tag{1.15}$$

where J_t is the number of choices available at trip t, T_i is the number of trips consumer i makes and N is the number of households. $d_{ijt} = 1$ if household i purchases product j during trip t and 0, otherwise.

The log likelihood function in (1.15) cannot be estimated directly because of the unobservable household characteristics, $u_{it}^\gamma, u_{it}^k, k = 1, \ldots, K$. Thus we resort to the simulated maximum likelihood estimation (SMLE) method and estimate the simulated version of (1.15):

$$SLL = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{j=1}^{J_t} d_{ijt} \log \tilde{s}_{ijt}, \tag{1.16}$$

with $\tilde{s}_{ijt} = \frac{1}{R} \sum_{r=1}^{R} \hat{s}_{ijt}(u_{it}^{(r)})$; see Choi et al. (2013). We set the number of simulations to $R = 300$ and $u_{it}^{(r)}$ are random numbers drawn from the standard normal distribution.

Once the parameter estimates in (1.13) are obtained, the market shares s_{jt} and the semi-elasticities $\frac{\partial s_{jt}}{\partial p_{rt}}$ can be computed. Integrals in (1.14) are computed using same type simulations as in the estimation procedure. Finally, the demand and the supply side of the model are brought together by using the computed market shares semi-elasticities to recover the marginal costs of each product on each market by inverting the first order

condition for profit maximization (1.10):

$$c_t = p_t + \Omega_t^{-1} s_t. \tag{1.17}$$

1.6 Estimation Discussion and Results

In this section we first present and discuss the demand side estimation results including the control function, the mixed-logit and the price elasticities, followed by the presentation of the willingness to pay (WTP) estimates and finally the marginal costs.

1.6.1 Demand Side Results

We first discuss the estimation of the control function (1.11). Besides product characteristics and instruments, the specification also includes the dummy variable for the year 2015 and retail banners' fixed effects. The 2015 dummy is supposed to capture the effect of the avian flue. The 2015 bird flu (HPAI) outbreak had an enormous impact on the U.S. egg industry (see e.g. Greene (2015)). Arguably this has been the single largest disruption in the U.S. egg history with 13-15% of the laying flock (35 million hens) destroyed but its impact has been extremely unevenly distributed across industry participants. Hardest hit has been Iowa, where the number of laying hens was down 26% from a year earlier. However, egg producers whose flocks were not infected, including California, benefited nicely from high egg prices. Retailer banners' fixed effects were included to capture the idiosyncrasies of the individual retail chains' eggs procurement contracting with egg producers. All explanatory variables included in the control function are statistically significant. The significance of the Hausman-Nevo p_{jt}^{IV} ($priceiv$) confirms that the instrument is strongly correlated with the potentially endogenous price variable. The estimation results are presented in the main model's columns of Table A.1 in the Appendix.

The idea behind the Hausman-Nevo instrumental variable relies on the Bertrand pricing which implies that the price in a given market is a function of marginal cost and demand shape in that market. This is to say that marginal costs of various products are likely correlated across markets and thus the price in a market t can be instrumented by the cost in another market, say k. As we don't observe costs in market k, we can use the fact that the price in market k depends on its marginal costs and thus the price in market t will be correlated with the price in k through the fact that their marginal costs are correlated. That said, the only weakness of this approach is that prices depend also on the demand

shape and thus if the demand has shocks that are correlated across markets, prices in other markets will not only be correlated to prices in market t because they have correlated costs but also because prices depend on demand shocks that are correlated across markets.[12]

There is no simple solution to this problem but the answer is to try to control as much as possible with observed variables that explain demand variations across markets. To that effect, we augment our demand model with Easter and Christmas seasonal dummies. Easter holiday is characterized by traditionally high demand for eggs because of the eggs coloring tradition that many households adhere to. There are two possible pricing strategies that retailers can play during Easter season. They can set prices high because the expected demand is high and even less elastic than during the rest of the year. Alternatively, they can set prices low to attract holiday shoppers who would run up large grocery bills with eggs being only a small portion of the total purchased basket. Similar marketing strategies can be pursued during Christmas season, another peak egg demand period in the calendar year. This time high demand for eggs is caused by baking Christmas cookies tradition and the fact that more and larger meals are eaten at homes and also in larger gatherings.

Another dimension of price variation across markets is caused by the differentiation across retails chains. Some chains specialize in fresh produce and local foods, some target ethnic food customers, yet some other carry cheaper profile of products. We control for that dimension by including individual banners' preference parameters that affect the likelihood of purchasing a particular egg UPC at a particular retailer. Next, anticipating that the avian flu episode could have impacted the demand for cage-free eggs by changing the consumer perception about the safety of cage-free eggs, we included the interaction between 2015 dummy and cage-free attribute. Finally, we argue that because retail banners to a large degree engage in local procurement of eggs, prices for the same egg product in different regions correlate only through common cost shocks and not because of the national pricing policies.

Table A.2 in the Appendix (see main model columns) shows the estimation results from the mixed logit demand model. Several results are worth highlighting. First, the coefficient for the cage-free variable follows the log-normal distribution with log mean $\overline{\beta} + Z_i \theta^k$ and log standard deviation σ_k. Evaluated at mean of Z_i, the average of β_{it}^{free} indicates that consumers do care about animal welfare and prefer cage-free eggs. The rest of the group of weakly positive characteristics include grade AA and organic, for all of them consumers expressed their preference over the alternatives. From the estimates of the horizontal

[12]For the alternative approaches to deal with the endogeneity of prices problem, see the robustness section towards the end of the paper.

product differentiation group of attributes we conclude that, on average, consumers prefer white eggs to brown eggs, private labels to brand names and smaller size eggs to extra-large eggs. Also, all estimated standard deviations of coefficients for product characteristics (except total count) are statistically significant, lending support to our model specification in which consumers have heterogeneous tastes.

Next, all estimates of the product attributes with households demographic characteristics interaction terms are in line with the model-free evidence on cage-free eggs consumption presented earlier in Table 1.5. Female-headed households are more likely to buy cage-free eggs than households with married couples, and male-headed households are less likely. Consumers with a college degree prefer cage-free eggs more than those without a college degree. Younger people are more likely to buy cage-free eggs and older people are less likely to buy cage-free eggs relative to the middle age group. The relationship between income and the propensity to buy cage-free eggs is non-monotonic in the sense that $25,000-$50,000 income group (income group 1) is less likely to buy cage-free eggs than the lowest income group with less than $25,000 (base group), whereas the other two higher income groups are more likely to buy cage-free eggs than the lowest income group. Finally large households (with more members) appear to be less likely to buy cage-free eggs, but this coefficient is not statistically significant.

Next, the seasonal dummy for Easter, defined as a three week periods preceding the actual holiday, shows that the likelihood of households purchasing any type of eggs is larger during the holiday season than during the rest of the year. Christmas dummy is not significant. Also, notice the different role that the banner dummies play in the demand model in comparison to the control function regression. Here, they play the roles of individual retail chain preference parameters that affect the probability of purchasing a certain egg UPC at a particular retail chain. The fact that they are all statistically significant points to a conclusion that households exhibit certain degree of retail chain loyalty. Finally, the coefficient on the interaction term between cage-free eggs and 2015 dummy shows that during the avian flue episode households were less likely to buy cage-free eggs than during the 2016 and 2017.

One benefit of using the mixed logit model is that it leads to more flexible and realistic substitution patterns among alternatives since it does not exhibit the independent of irrelevant alternatives (IIA) property as the simple multinomial logit model does (Train (2003)). The own- and the cross-price elasticities for household i in trip t can be derived

from (1.14) as:

$$E_{it,jj} = \frac{\partial s_{ijt}}{\partial p_{jt}} \frac{p_{jt}}{s_{ijt}} = \frac{p_{jt}}{s_{ijt}} \times \int \left[\exp(\overline{\gamma} + \sigma_\gamma u_{it}^\gamma) \frac{\exp(\hat{V}_{ijt})}{1 + \sum_{g=1}^{Jt} \exp(\hat{V}_{ijt})} \left[\frac{\exp(\hat{V}_{ijt})}{1 + \sum_{g=1}^{Jt} \exp(\hat{V}_{ijt})} - 1 \right] \right] f(u_{it}) d\, u_{it} \tag{1.18}$$

and

$$E_{it,jr} = \frac{\partial s_{ijt}}{\partial p_{rt}} \frac{p_{rt}}{s_{ijt}} = \frac{p_{rt}}{s_{ijt}} \int \left[\exp(\overline{\gamma} + \sigma_\gamma u_{it}^\gamma) \exp(\hat{V}_{irt}) \frac{\exp(\hat{V}_{ijt})}{\left[1 + \sum_{g=1}^{Jt} \exp(\hat{V}_{ijt})\right]^2} \right] f(u_{it}) d\, u_{it}. \tag{1.19}$$

The results for selected ten widely available dozen eggs UPCs are reported in Table 1.9. A mix of conventional and cage-free UPCs are selected among top 20 UPCs in terms of the number of cartons sold in the retail scanner data. These elasticities are averaged across 833 markets where all these ten products were available.

Looking at the main diagonal cells of Table 1.9 we see that all own-price elasticities are negative ranging from -1.485 to -2.979. We can also see that, on average, the cage-free products are less elastic than the conventional products. In light of the fact that the demand for table eggs is known to be inelastic, these numbers seem to be quite large. Of course, demand elasticities estimated at the UPC level are always going to be much higher than the demand elasticities of more aggregated products because the individual UPCs are very close substitutes to each other. For comparison purposes, Allender and Richards (2010) estimated own-price elasticities of different egg products ranging from -0.4362 to -1.5489. Their numbers are smaller than ours for two reasons: first, their choice set includes only 13 most popular brands and others are aggregated into a single choice and used as the outside option. Secondly, their eggs are aggregated into brand-level products and eggs with different attributes such as size, grade, and color within the same brand are not distinguished. Our estimates are based on 170 UPCs where all attributes can vary freely. The inspection of the off-diagonal elements of Table 1.9 reveals that they are all positive confirming the intuition that various egg UPCs are substitutes. The numbers are also quite small indicating inelastic demand when it comes to cross-product substitution patterns.

1.6.2 Willingness to Pay

Recall that for the product attribute cage-free we assumed that β_{it}^{k} follows the log-normal distribution. Consequently, the average marginal willingness-to-pay (WTP) for cage-free eggs is given by $\frac{\exp(\overline{\beta}^{k}+Z_i\theta^{k}+\sigma_k^2/2)}{\exp(\overline{\gamma}+\sigma_\gamma^2/2)}$. Clearly, the result depends of the marginal utility of income parameter γ_{it}. Marginal utility of money is also assumed to follow the log-normal distribution with log mean $\overline{\gamma}$ and log standard deviation σ_γ. This implies that the mean and the standard deviation of γ_{it} take the form of $\exp(\overline{\gamma}+\sigma_\gamma^2/2)$ and $\exp(2\overline{\gamma}+\sigma_\gamma^2)*[\exp(\sigma_\gamma^2)-1]$ respectively. Both the mean and the standard deviation of the marginal utility of income coefficients are statistically significant. In Table 1.10 we present the WTP estimates over the entire distribution of household heterogeneity (observed and unobserved). Because the number of households in various socio-economic groups is uneven, the presented first two moments and quantiles of the distribution are based on 1,000 bootstraps. The average marginal WTP for all households in the survey is quite small and amounts to only 5.9 cents per package. The distribution of the average WTP is tight where for the lower 5% of the households it amounts to 5.8 and for the top 5% only 6 cents per package. However, the distribution of marginal WTP across various socio-economic groups show large differences. For example the mean WTP for the age group younger than 34 is 10.8 cents whereas for the age group older than 65, it is only 3.2 cents per package.

1.6.3 Marginal Costs

The structure of the model allows us to compute the marginal cost for each product on each market, i.e., each region-week combination. We selected a mixture of cage-free, conventional, private labels and brand names widely purchased UPCs and present their average prices, marginal costs and price-cost margins across all markets and for different retail companies in Table 1.11.[13] Notice that even among the most widely available UPCs, not all companies carry all of them. This is the reason why we see some blank (N/A) cells in the table matrix. Although general results are hard to establish, several interesting tendencies are worth mentioning.

First, as expected, the marginal costs of cage-free eggs (shaded UPC numbers) are always larger than of conventional eggs but their price-cost margins are similar in magnitude.

[13]Because of numerical problems in computing the inverse of the ownership matrix caused by the very small market shares of certain UPCs, in less than 1% of the cases where the estimates of marginal cost were either negative or twice larger than the associated price, we replace the anomalous values with the average marginal cost of UPCs that share the same product characteristics and are sold by the same retail company.

Recall that retailers acquire specialty eggs via fixed price purchasing contracts which provide producers with more income insurance but not at the expense of reduced margins for retailers. Second, the comparison of price-cost margins between brand names (marked by #) and private labels show that brand name egg products tend to have higher margins. This result is somewhat unexpected in light of what has been said about the similarity of purchasing arrangements between brand names and private labels. Recall that egg producers frequently sell some of their production under a given store label and some under their own brand, hence the producers' margins on these two type of products should be similar. Therefore, higher margins for brand name eggs should be attributable to retailers' market power. Next, the comparison of results across retailers indicates that their price-cost margins are similar. For example, comparing large companies such as B with a small ones such as H shows no detectable tendency in favor of either, indicating that a retailer's market power is not necessarily related to size. Finally, the comparison of price-cost margins across various UPCs with their own-price elasticities in Table 1.9 indicates healthy retail competition in California. Relative to the monopoly pricing rule, where the price-cost margin should equal the inverse of the own price elasticity of demand, our results show that margins are uniformly smaller relative to their monopoly benchmarks.

1.7 Counterfactual Analysis

In this section, we utilize the estimated structural model to quantify the potential welfare effects of the forthcoming Proposition 12. To do this, we set the new marginal costs under the counterfactual scenario where all table egg producers convert their confinement system to cage free and solve for the new market equilibrium prices. Then, using the new prices, we calculate the expected changes in consumer and producer surplus. Because of the extraordinary computational burden, we will conduct the counterfactual simulation only for 2017. We believe that 2017 is a typical year where all possible market disruptions due to avian flu in 2015 has dissipated.

Under a scenario where cages are banned, we assume that the marginal cost will increase for conventional egg producers but will remain the same for cage-free egg producers. To estimate the new marginal costs, c_{jt}^{new}, we match the marginal costs of cage-free egg products and the originally conventional egg products. In theory, the closest match would be between a pair of cage-free and conventional eggs in which all other product attributes and retailer characteristics are the same. We classify all the products into several subgroups

according to the combination of the calendar year and retailer/product characteristics and take the difference between the average marginal cost of cage-free and conventional eggs within the same subgroup. If we denote the difference between the average marginal cost of cage-free and conventional eggs in subgroup m as $\delta_{jtm} \equiv \overline{c}_{jt}(m, free = 1) - \overline{c}_{jt}(m, free = 0)$, then the new marginal costs are set as $c_{jt}^{new} = c_{jt}$ if product j is cage-free and $c_{jt}^{new} = c_{jt} + \delta_{jtm}$ if product j is conventional and belongs to subgroup m.

In terms of retailer characteristics, we use the size of the banner measured by that banner's market share from Table 1.3 to define three groups of retailers (small, medium, large). In terms of product characteristics, we assume that the distinction based on color (brown versus white) and label (private versus brand name) has no impact on marginal cost of production, and besides cage-free versus conventional, only the egg size, grade and whether eggs are Omega-3 or not are important determinants of the cost structure.[14] Therefore, the total number of potential subgroups are cage-free (2) × retailer (3) × year (3) × omega-3 (2) × aa (2) × xl (2) =144. However, some subgroups are empty and direct matching is not possible. In this case, the new marginal costs for the conventional eggs are matched to those of the next closest subgroup. For example, if there is no cage-free product that is large, grade AA and sold by the medium size retailer, in 2017, the conventional egg in the counterpart subgroup is matched to the cage-free subgroup that is large, grade AA eggs, sold in a medium size market in 2016.[15] Based on this calculation, the new marginal cost of originally conventional eggs before the ban will increase by 56.5% on average. This results is in line with Sumner et al. (2008) who found that the costs of production in non-cage systems are 41% - 70% higher than the costs of the common cage housing systems, due to higher variable costs of feed, pullets, and labor, as well as increased hen mortality.

1.7.1 Counterfactual Prices and Producer Surplus

With the new marginal costs as well as the estimated parameters, the new market equilibrium prices can be solved using (1.10):

$$s_t^{new} + \Omega_t^{new}(p_t^{new} - c_t^{new}) = 0, \tag{1.20}$$

[14] Another important determinant of cost structure is the organic production. However this product attribute has no bearing on our new cost computation since all organic eggs are automatically cage-free and hence there are no such organic eggs whose cost of production need to be adjusted from cage to cage-free production.

[15] The closeness between subgroups is defined by the hierarchy of product and retailer attributes. The order is: year, retailer, grade, size, omega-3.

where p_t^{new} is the vector of new market equilibrium prices, s_t^{new} is the vector of new market shares, and Ω_t^{new} is the $J_t \times J_t$ matrix with its $(j,r)^{th}$ cell as,

$$[\Omega_t^{new}]_{(j,r)} = \Phi_{jrt} * \frac{\partial s_{jt}^{new}}{\partial p_{rt}^{new}}.$$

The new market share of household i for product j in market t where all products are cage-free is,

$$s_{ijt}^{new} = \int \frac{exp(\hat{V}_{ijt}^{new})}{1+\sum_{g=1}^{J_t} exp(\hat{V}_{igt}^{new})} f(u_{it}) d\, u_{it}, \tag{1.21}$$

and the new average market share of product j in market t under new marginal cost is

$$s_{jt}^{new} = \frac{1}{N_t} \sum_{i=1}^{N_t} s_{ijt}^{new} \tag{1.22}$$

where

$$\begin{aligned} \hat{V}_{ijt}^{new} = &-\exp(\overline{\gamma} + \sigma_\gamma u_{it}^{\gamma}) p_{jt}^{new} + \sum_{k \in \{K_1 \setminus free\}} \exp(\overline{\beta}^k + Z_i \theta^k + \sigma_k u_{it}^k) x_j^k \\ &+ \sum_{k \in K_2} (\overline{\beta}^k + Z_i \theta^k + \sigma_k u_{it}^k) x_j^k + \exp(\overline{\beta}^{free} + Z_i \theta^{free} + \sigma_{free} u_{it}^{free}) x_j^{free} + \eta \hat{v}_{jt}, \\ & x_j^{free} = 1, j = 1, \ldots, J_t. \end{aligned} \tag{1.23}$$

The price differences between p_{jt} and p_{jt}^{new} are presented in Table 1.12, for both the originally conventional eggs and cage-free eggs. Under the counterfactual scenario, all eggs sold are cage-free and their average price would be \$5.12 per dozen. Standard deviation are calculated as dispersion across all UPCs and all markets (region/week). Compared to current prices, these new prices are 65% higher relative to the originally conventional eggs prices and 3.4% lower relative to the originally cage-free eggs. The result showing that the price of cage-free eggs will fall after the ban is interesting and somewhat controversial. Previously mentioned studies on banning cage produced eggs (e.g. Malone and Lusk (2016); Mullally and Lusk (2018)) found an increase in prices for cage-free eggs but Kotschedoff and Pachali (2020) found that the prices will fall.

The decrease in prices of higher quality eggs after the ban of battery cage eggs jives with the theoretical literature on minimum quality standards (e.g., Panzar and Savage (2011)). We found that the price of omega-3 eggs would also fall, same as the average price of all cage-free UPCs. However, the price of organic eggs would increase in the post-ban scenario

in contrast to what the theory would predict. The likely explanation has to do with the fact that all organic eggs prior to the ban were already cage-free due to the existing organic labeling requirements and hence the ban did not require any conversion from cage to cage-free production for this category of eggs.

With the new marginal costs and prices, the changes in the retail level producer surplus due to the implementation of Proposition 12 can be calculated as,

$$\Delta\Pi_{ft} = M_{ft}\frac{1}{R}\sum_{r=1}^{R}\Big[\Big[\sum_{j=1}^{J_{ft}} s_{jt}^{new}(u_{it}^{(r)})[p_{jt}^{new} - c_{jt}^{new}] - \sum_{j=1}^{J_{ft}} s_{jt}[p_{jt} - c_{jt}]\Big]\Big]. \tag{1.24}$$

Again, s_{jt}^{new} is computed using simulations. The change in total producer surplus for firms who sell in market t is,

$$\Delta\Pi_t = \sum_{f=1}^{J_{ft}} \Delta\Pi_{ft}. \tag{1.25}$$

The producer surplus before and after the imposed regulation are reported in the lower panel of Table 1.12. The average producer surplus for 2017 across all retail chains and all markets prior to the ban on cages was estimated at 14 cents per dozen eggs and after the ban at 9.4 cents per dozen eggs indicating a drop of 32.7%. The pre-ban producer surplus of 14 cents per dozen eggs could seem high to most egg producers. However, it is important to realize that producer surplus (quasi profit) is a welfare measure where fixed costs have not been netted out and, moreover, it is computed at the retail level which means that it reflects the possible combination of the production and retailing margins.

In order to scale up these estimates to the state level, we have to rely on the CEF data indicating the consumption of 76.9 dozen of eggs per household.[16] Then, based on the 2020 Census data, the number of households in each the 10 regions/markets gives us the aggregate egg consumption by region, which corresponds to the value of M_t. Based on the regional competition matrix in Table 6, we can compute the egg sales shares of each retailer in each regional market, which multiplied by the size of the market in each region gives the value of M_{ft} from equation (24) for each retailer in each market. Following the outlined procedure we compute the aggregate loss in producer surplus at the retail level due to Proposition 12 for the entire state of California in the amount of 23.2 million dollars or 17.6%.

[16] Recall that our data under-represents the consumption of eggs, hence the reason for relying on the outside data to compute the aggregate welfare effects on the state level.

1.7.2 Consumer Surplus

In the discrete choice framework, the utility household i gets from the grocery trip t is the maximum among the utilities from all products that are available at trip t, denoted as $\max_j(\hat{U}_{ijt})$. Thus, the consumer surplus for a consumer in dollar terms is:

$$CS_{it} = \frac{1}{\gamma_{it}} \max_j(\hat{U}_{ijt}). \tag{1.26}$$

Since we cannot observe the error term ϵ_{ijt} in $\hat{U}_{ijt}$, we focus on the expected consumer surplus. In our model, U_{ijt} is linear in income and ϵ_{ijt} follows an i.i.d. type I extreme value distribution. In this case, following Small and Rosen (1981), the expected consumer surplus has a closed form representation as

$$E(CS_{it}) = \frac{1}{\gamma_{it}}\Big[\ln\sum_{j=1}^{J_t}\exp(\hat{V}_{ijt}) + C\Big], \tag{1.27}$$

where C is unknown constant. Since $\hat{V}_{ijt}$ depends on unobserved household characteristics, $u_{it}^{\gamma}, u_{it}^{k}, k = 1,\ldots,K$, we can only compute the expected welfare effects with unobserved household characteristics integrated out. The same simulation method used in the estimation is used to calculate the expected values. More specifically, the expected difference in consumer surplus for household i in trip t before and after the implementation of Proposition 12 becomes,

$$\Delta E(CS_{it}) = \frac{1}{R}\sum_{r=1}^{R}\Bigg[\frac{1}{exp(\overline{\gamma}+\sigma_{\gamma}u_{it}^{\gamma(r)})}\Big[\ln\sum_{j=1}^{J_t}\exp(\hat{V}_{ijt}^{new}(p_{jt}^{new}, u_{it}^{(r)})) - \ln\sum_{j=1}^{J_t}\exp(\hat{V}_{ijt}(p_{jt}, u_{it}^{(r)}))\Big]\Bigg]. \tag{1.28}$$

The estimation results of expression (1.28) are presented in Table 1.13. The mean welfare loss due to Proposition 12 amounts to 5.86 cents per dozen eggs per household per trip. Referring back to Table 1.8, we can see that the average purchase per trip was 14.83 eggs, which gives the loss in the expected consumer surplus of 7.24 cents per dozen eggs per household. Again, using the CEF data indicating that Californians consume 12 billion eggs annually, and the U.S, Census data showing 13 million households living in the state, gives the consumption of 76.9 dozen eggs per household. Multiplying the expected loss in consumer surplus per dozen eggs per household by the annual egg consumption per household gives the loss in consumer surplus of $5.57 per household per year and then multiplied by the number of households in the state gives the aggregate annual welfare loss for the state of California due to Proposition 12 in the amount of 72.4 million dollars.

In comparison to two related previous studies, our welfare estimates are lower. For example, Allender and Richards 2010 found that the California's aggregate loss in consumer surplus due to the ban of any type of cages would be $106 million and Norwood and Lusk (2011) predicted a $1.87 billion loss in consumer surplus nation-wide, which would be the equivalent of $193.5 million for the state of California.[17] We believe the welfare loss in our study is more precise because our estimates are based on the partial equilibrium framework where the intersection of the estimated demand and the regulation induced shift in supply generated new equilibrium prices, whereas neither of these studies model the supply side of the market.

In addition to average welfare effects, we are also interested in the distributional aspects of the proposed policy. The format of Table 1.13 is identical to that of Table 1.10 where we presented the marginal willingness to pay results. The comparison of these two tables show that one is the mirror image of the other in the sense that higher marginal willingness to pay for cage-free eggs leads to the lower welfare loss for any particular socio-economic group of households. For example, the expected average loss in consumer surplus for the age group younger than 34 is 5.23 cents per dozen, whereas for the group older than 65 is 7.27 cents per dozen per household. Notice also that even within the same group of households the loss in consumer surplus varies considerably. For example, for households in the lower 5% of the income distribution over 100 thousand dollars, the loss in consumer surplus is 4.7 cents per dozen eggs per trip, whereas for the upper 5% in the same income bracket, there is actually a welfare gain of 0.46 cents per dozen eggs.

1.7.3 Robustness

In this section we test the robustness of our results with respect to any potential remaining endogeneity in prices problem. First, we replace the Hausman-Nevo instrument with more traditional cost shifters. The idea behind cost shifters is that they usually correlate with retail prices but do not directly influence demand. Following Kotschedoff and Pachali (2020), we use average weekly wholesale egg prices and feed prices as natural candidates for instruments. For whole sale egg prices we used daily (USDA-AMS Poultry Report) California shell egg marketer's benchmark price for negotiated egg sales of USDA Grade AA, size large eggs. The laying hens feed prices expressed in $ per pound were approximated by the 60:40 weighted average of daily (USDA-AMS Grain Report) Iowa corn and soybean

[17] The U.S. census data shows 126,220,000 households lived in the U.S. in 2017, hence California's share of households is about 10.3%.

meal prices. Both estimated coefficients in the control function are significant indicating that they are relevant instruments for the retail price, see alternative model #1 in Table A.1 in the Appendix. However, as seen from Table A.2 in the demand estimation based on this approach (alternative #1), the marginal utility of money coefficient is not statistically significant which makes this approach unusable for counterfactual analyses.

Next, we combine the cost shifters with the Hausman-Nevo instrument that was used in the main model. The control function estimates given in Table A.1 (alternative #2) show that both Hausman-Nevo instrument and cost-shifters are highly significant satisfying the relevance condition for instruments. This approach shows very small differences in the demand function estimates and welfare results. For example, as seen from Table A.3, the post-regulation price of cage free eggs would be 8 cents per dozen eggs higher ($5.20 versus $5.12) yielding a reduction in producer surplus that is 1.67 percentage points lower than in the base model. On the other hand, the WTP would be 0.05 cents higher (5.94 vs. 5.89 cents) and the loss in consumer surplus 1.12 cents per dozen eggs higher than in our preferred specification.

Finally, we wanted to see whether our results are robust with respect to the definition of the Hausman-Nevo instrument. So, instead of defining p_{jt}^{IV} as the average price of product j in one of the randomly selected regions in California, we define it as the average price of product j in all regions other that the one in which trip t took place. Again, as seen from Table A.1 (alternative #3), this instrument is highly relevant and as seen from the mixed logit demand estimation in Table A.2 the results are very similar to our preferred model. The comparison of counterfactual results across different specifications in Table A.3 show very small differences relative to our preferred model.

Notice that in alternative specifications #2 and #3 the results show simultaneously higher WTP for cage-free eggs estimates and higher loss in consumer surplus due to regulation banning cage eggs. To explain this, notice that in the partial equilibrium setting, there are two factors affecting the changes in the expected consumer surplus: the gain, as all eggs are now cage-free and the loss, due to higher prices. As it turns out, the average WTP is slightly higher in both alternative models but the price increase is even higher, hence the resulting greater loss in CS? In summary, our main conclusions are unaffected by our robustness checks. Our preferred model results are nestled between two alternative specifications that give negligibly smaller reduction in producer surplus and a bit larger loss in consumer surplus.

1.8 Conclusions

The controversy surrounding the Californian Proposition 12 is growing louder as its implementation approaches. It is interesting that California's egg farmers support cage-free transition but with the originally imposed deadline of 2025, which was the date agreed upon by the Humane Society of the United States (HSUS). According to CEF's website, despite the commitments to go cage-free by the nation's food, retail, hospitality, food-service and food manufacturing businesses, HSUS has written Proposition 12 to require full compliance with cage-free production by the end of 2021 and, in doing so, is reneging on its own agreement with the industry. The politics behind this initiative is unknown to the authors, but it is worth reiterating that the Proposition 12 passed with more than 60% of the popular vote despite a substantial welfare loss to the consumers who voted favourably for its passage. Explaining this puzzle is high on the list of our next research topics.

The main findings in our paper are likely to be controversial. First we find that the willingness to pay for cage-free eggs is rather low but still within the meaningful range of the estimates found elsewhere. In fact, our WTP estimates for cage-free eggs are close to the low premiums found in the studies that used prices or purchase record data such as Allender and Richards (2010) and Vukina and Nestic (2020). Second, our estimates of welfare losses to consumers are also smaller than what has been previously found in the literature, e.g., Norwood and Lusk (2011) and Allender and Richards (2010). We think our results are more reliable compared to the existing studies in the field because our post-regulation equilibrium prices are obtained in the partial equilibrium framework where both demand and supply were allowed to adjust simultaneously. Finally, our pre-ban producer surplus estimates, but not the post-ban reduction, could sound high from an egg producer's perspective but taking into consideration the fact that they are inclusive of fixed costs and also measured at the retail level make them quite plausible.

The egg industry presents itself as an ideal case for studying the welfare implications of a regulatory proposal within the partial equilibrium framework because the spill-over effects on other industries are likely to be quite small. Of course, like in many other studies that rely on the retail data, the complication arises from the fact that the relationship between retailers and upstream suppliers has to be adequately modeled. Our model reflects the situation where each retailer behaves as a vertically integrated firm with respect to its own private labels and acquires brand name products at competitive prices. Implicit in this model is the zero price-cost margin assumption at the production level, hence the entire margin is created by the retail sector. In absence of brand loyalty for eggs, the assumption

that egg producers have no market power and sell their eggs to retailers at marginal cost seems plausible. A more complicated model (see e.g. the hybrid model in Villas-Boas (2007)) would be one where each retailer behaves as a vertically integrated firm with respect to its own private labels but plays the vertical Nash-Bertrand game in national brands. That model could be also estimated (of course, not easily and with some additional data requirements), but in our case, would complicate things tremendously and add relatively little to the story, given the structure of the egg industry, which is characterized by the preponderance of private labels.

Table 1.1: Table Egg Layers and Egg Production in the United States and California

		2015	2016	2017	2018	2019
Total table egg layers[a]	US	275,968	307,253	311,160	318,667	323,631
	CA	11,713	11,193	14,064	13,954	12,871
	%	4.24	3.64	4.52	4.38	3.98
Total table egg production[b]	US	83,147	88,394	92,112	95,275	99,089
	Eggs per layer	301.29	287.69	296.03	298.98	306.18
	CA[c]	3,529	3,220	4,163	4,171	3,940
Percentage of cage-free[d]	US	8.60	12.30	16.60	18.40	23.40

[a] Average number of table egg layers in flocks 30,000 and above on hand during the month of November each year, in 1,000 birds.
[b] Annual number of table eggs produced, in millions.
[c] Estimated based on egg per layer ratio in the U.S. multiplied by the number of table egg layers in California.
[d] Calculated as the number of cage-free table egg layers divided by the number of all table egg layers in the United States.
Note: Source: USDA Annual Chicken and Eggs Report (2015-2019), Monthly USDA Cage-Free Shell Egg Report.

Table 1.2: Top 15 US Grocery Retailers[a] and Table Egg Producers in 2017

	Grocery retailers			Table egg producers		
Rank	Company[b]	Sales[c]	Cum. share[d]	Company	Layers[d]	Cum. share
1	Wal-Mart Inc.	307.83	38.93	Cal-Main Foods	40.10	12.54
2	The Kroger Co.	115.34	53.51	Rose Acre Farms	26.00	20.67
3	AB Acquisition LLC	60.49	61.16	Hillandale Farms	16.73	25.91
4	Ahold Delhaize USA	42.95	66.59	Versova Holdings	16.49	31.06
5	Publix Super Markets Inc.	34.00	70.89	Daybreak Foods	12.80	35.07
6	H-E-B Grocery Co.	23.00	73.80	Rembrandt Enterprises	12.50	38.98
7	Meijer Inc.	16.50	75.89	Michael Foods	12.18	42.79
8	Wakefern Food Corp.	16.00	77.91	Center Fresh Group	9.70	45.82
9	Whole Food Market	15.72	79.90	Midwest Poultry Services L.P.	9.50	48.79
10	Aldi US Inc.	13.01	81.50	Prairie Star Farms	9.40	51.73
11	Southeastern Grocers LLC	11.82	83.04	Herbruck's Poultry Ranch	8.40	54.36
12	Trader Joe's Co.	10.29	84.30	Weaver Brothers	8.00	56.86
13	Hy-Vee Inc.	9.80	85.58	Hickman's Egg Ranch	7.35	59.16
14	Giant Eagle Inc.	9.50	86.78	Fremont Farms of Iowa	7.30	61.44
15	Wegmans Food Markets Inc.	8.30	87.83	Sparboe Farms	6.10	63.35
	Total sales of top-50 grocery retailers		790.77	Total number of table eggs layers in U.S.		319.72
	Top 4-firms concentration ratio		66.59%			31.06%
	Top 8-firms concentration ratio		77.94%			45.82%

Note: Source: Egg Industry Magazine, February 2018 and Progressive Grocer Super 50 2017

[a] Wholesale membership club such as Costco, Sam's Club, and BJ's Wholesale Club are not included.

[b] Top banners of each company are: **Walmart**: Walmart Supercenter, Walmart Neighborhood Market; **The Kroger Co.**: Kroger, Harris Teeter, Ralphs; **AB Acquisition LLC:** Safeway, Albertsons, Vons; **Ahold Delhaize USA:** Food Lion, Stop & Shop, Hannaford; **Publix Super Markets Inc.:** Publix, Publix Sabor, Publix GreenWise; **H-E-B Grocery Co.:** H-E-B, H-E-B Plus, H-E-B Central Market; **Meijer Inc.:** Meijer; **Wakefern Food Corp:** ShopRite, PriceRite Marketplace, The Fresh Grocer; **Whole Food Market:** Whole Foods Market, 365 by Whole Foods Market; **Aldi US Inc.:** Aldi Food Store; **Southeastern Grocers LLC.:** Winn-Dixie, Bi-Lo, Harveys; **Trader Joe's Co.:** Trader Joe's; **Hy-Vee Inc.:** Hy-Vee; **Giant Eagle Inc.:** Giant Eagle, Giant Eagle Market District; **Wegmans Food Markets Inc.:** Wegmans.

[c] In billion dollars.

[d] Retail companies' cumulative shares are relative to top-50 retailers' sales.

[e] In million layers

Table 1.3: Fresh Eggs Retail Sector in California – Retail Scanner data in 2016[a]

Retailers	Banners	# of stores	Sales (in $ mil.)[b]	%	million 12-egg cartons	%
A	A	128	23.92	7.64	8.81	7.73
B			78.38	25.03	21.72	19.05
	B1	238	77.07	24.61	21.33	18.70
	B2	4	1.31	0.42	0.40	0.35
C	C	204	45.31	14.47	15.64	13.72
D	D	93	15.16	4.84	5.27	4.62
E			53.86	17.20	18.02	15.80
	E1	199	46.85	14.96	15.92	13.96
	E2	26	7.01	2.24	2.11	1.85
F	F	50	14.87	4.75	7.45	6.53
G			44.79	14.30	23.62	20.71
	G1	95	34.06	10.88	18.06	15.83
	G2	22	10.73	3.43	5.57	4.88
H	H	58	12.02	3.84	3.52	3.09
Other[c]	Other	1,573	24.86	7.94	9.97	8.75
Total		2,690	313.16	100.00	114.05	100.00

[a] Company and banner names suppressed for confidentiality reasons.
[b] All numbers are based on 249 eggs products (UPC's).
[c] "Other" category includes 2 drug stores, 1 gas station, and 3 discount shops.

Table 1.4: Sales of Private Label and National Brand Eggs in California – Retail Scanner Data in 2016[a]

brand (private)	No. of carton	%	No. of carton	%	brand (national)
Private brands (B1)	17,891,838	15.69	8,798,238	7.71	Eggland's Best
Private brands (G1)	17,761,054	15.57	1,675,927	1.47	The Happy Egg Co.
Private brands (E1)	13,482,938	11.82	946,145	0.83	Horizon Organic
Private brands (C)	12,092,000	10.60	847,525	0.74	Alfresco Farms
Private brands (A)	7,457,492	6.54	762,742	0.67	Barnstar Family Farms
Private brands (F)	7,019,272	6.15	740,230	0.65	Land O Lake
Private brands (Other)	6,226,994	5.46	730,936	0.64	Rock Island
Private brands (G2)	5,343,107	4.68	678,691	0.60	Judy's Family Farm
Private brands (D)	4,221,273	3.70	354,157	0.31	Nulaid
Private brands (H)	2,261,395	1.98	327,782	0.29	Nest Fresh
Private brands (E2)	1,626,749	1.43	313,250	0.27	Farmers Gem
Private brands (Other)	903,283	0.79	243,781	0.21	Clover Organic Farms
Private brands (B2)	352,219	0.31	131,882	0.12	Dutch Farms
Private brands (Other)	348,451	0.31	124,251	0.11	Crystal
Private brands (Other)	159	0.00	121,437	0.11	California Ranch Fresh
			261,918	0.23	Other small brands
Private brand total	96,988,221	85.04	17,058,891	14.96	National brand total
Total	114,047,112				

[a] Numbers are based on 249 egg UPC's.

Table 1.5: Average Household Consumption of Fresh Eggs in California – Home Scanner Data 2015-2017

		All eggs	Cage-free eggs	% of cage-free
Average per household[a]		112.77	11.70	10.37
Household	male head	94.86	9.42	9.93
	female head	90.56	11.04	12.19
	married	127.74	12.62	9.88
Education[b]	high school or under	119.57	6.38	5.34
	college or advanced	111.79	12.46	11.15
Income	less than $25,000	102.59	8.96	8.73
	25,000—50,000	103.81	5.75	5.54
	50,000—100,000	116.39	11.62	9.98
	greater than $100,000	121.06	19.03	15.72
Age[c]	under 34 years	88.03	13.23	15.03
	35-64 years	116.21	12.22	10.51
	over 65 years	116.45	9.04	7.76

[a] The total number of households in the panel is 7,119.

[b] The household's education is that of the head; in case of a married couple it reflects the education level of the more educated spouse.

[c] The household's age is that of the head, in case of a married couple it represents the spousal average age.

Table 1.6: Regional Retail Competition in California: Retail Scanner Data - Cleaned Choice Set

	Number of stores by retail company							
region	A	B	C	D	E	F	G	H
1		47		22		44	4	
2		26				3		9
3		146		3		20	6	54
4		10		34	2	4		
5	11	16	15	5	31	4	2	2
6	12			30	14	10	8	
7	27		23		24		24	
8	26		114		85		52	
9	31		44		28		5	
10	25		22		53		13	

Note: Regions are based on Census 2020 Regional Classification (map included in Appendix). Region 1: Butte, Colusa, El Dorado, Glenn, Lassen, Modoc, Nevada, Placer, Plumas, Sacramento, Shasta, Sierra, Siskiyou, Sutter, Tehama, Yolo, Yuba county; Region 2: Del Norte, Humboldt, Lake, Mendocino, Napa, Sonoma, Trinity county; Region 3: Alameda, Contra Costa, Marin, San Francisco, San Mateo, Santa Clara, Solano county; Region 4: Alpine, Amador, Calaveras, Madera, Mariposa, Merced, Mono, San Joaquin, Stanislaus, Tuolumne; Region 5: Monterey, San Benito, San Luis Obispo, Santa Barbara, Santa Cruz, Ventura county; Region 6: Fresno, Inyo, Kern, Kings, Tulare county; Region 7: Riverside, San Bernardino county; Region 8: Los Angeles county; Region 9: Orange county; Region 10: Imperial, San Diego county.

Table 1.7: Summary Statistics of Product Characteristics and Prices[a]: Retail Scanner Data – Cleaned Choice Set

	# of UPC	mean	sd	min	max
brown	170	0.41	0.49	0	1
private	170	0.56	0.50	0	1
omega3	170	0.07	0.26	0	1
cage-free	170	0.36	0.48	0	1
organic	170	0.19	0.39	0	1
aa	170	0.57	0.50	0	1
xl	170	0.19	0.40	0	1
tc	170	16.28	13.17	6	60
price conventional	109	3.20	1.29	0.70	9.86
price cage-free	61	5.25	1.61	1.81	11.90
price total	170	3.94	1.72	0.70	11.90

Note: brown: 1=brown, 0=white; private: 1=private label, 0=national brand; omega3: 1=omega3-enriched, 0=regular; free: 1=cage-free, 0=conventional; organic: 1=organic; 0=conventioanl; aa: 1=grade AA, 0: grade A or lower; xl: 1=size extra-large, 0=large or smaller; tc: total count per carton.

[a] Prices are in $ per-dozen eggs, averaged across 1,560 markets (156 weeks and 10 regions).

Table 1.8: Summary Statistics of Product[a] and Demographic Characteristics[b]: Home Scanner Data - Cleaned Trips Data

	# of trips	mean	sd	min	max
brown	26,478	0.13	0.33	0	1
private	26,478	0.83	0.38	0	1
omega3	26,478	0.09	0.28	0	1
cage-free	26,478	0.13	0.34	0	1
organic	26,478	0.04	0.19	0	1
aa	26,478	0.79	0.41	0	1
xl	26,478	0.09	0.29	0	1
tc	26,478	14.83	5.68	6	60
quantity	26,478	1.11	0.32	1	2
price conventional	22,921	2.62	1.25	0.002	7.49
price cage-free	3,557	4.53	1.35	0.1	9.98
price total	26,478	2.88	1.42	0.002	9.98
male	250,540	0.15	0.36	0	1
female	250,540	0.24	0.43	0	1
married	250,540	0.60	0.49	0	1
college	250,540	0.88	0.33	0	1
age: 34 and less (young)	250,540	0.06	0.24	0	1
age: 35-64	250,540	0.67	0.47	0	1
age: 65+ (old)	250,540	0.27	0.44	0	1
income(0): less than $25,000	250,540	0.11	0.31	0	1
income(1): $25,000-$50,000	250,540	0.23	0.42	0	1
income(2): $50,000-$100,000	250,540	0.39	0.49	0	1
income(3): $100,000+	250,540	0.28	0.45	0	1
hhsize	250,540	2.41	1.28	1	9

Note: male: 1=male head of household, 0=otherwise; female: 1=female head, 0=otherwise; married: 1=household with married couple, 0=otherwise; college: 1=college or advance degree by head or at least one spouse if married, 0=otherwise; age of head or spousal average if married; income: annual household income; hhsize: number of persons in household.

[a] Product characteristics are based on 26,478 trips that involves egg purchases, averaged across 26,478 trips.

[b] Demographic characteristics are based on total 250,540 trips made by 4,374 household, including both egg purchases and outside option purchases.

Table 1.9: Price Elasticities of Selected Widely Available UPCs

Demand elasticity of:	with respect to price of:									
UPC	311	305	327	193	303	201	195	243	227	259
311	**-2.188**	0.351	0.254	0.137	0.146	0.334	0.159	0.318	0.454	0.249
305	0.535	**-2.012**	0.263	0.575	0.576	0.764	0.165	0.324	0.461	0.257
327	0.536	0.363	**-2.691**	0.144	0.152	0.344	0.163	0.322	0.457	0.254
193	0.543	0.839	0.270	**-2.979**	0.604	0.781	0.172	0.329	0.465	0.266
303	0.537	0.837	0.266	0.604	**-2.872**	0.779	0.171	0.328	0.463	0.264
201	0.492	0.805	0.236	0.572	0.570	**-1.618**	0.166	0.332	0.473	0.261
195	0.438	0.284	0.204	0.112	0.119	0.303	**-2.153**	0.315	0.454	0.238
243	0.389	0.248	0.176	0.095	0.101	0.269	0.135	**-1.686**	0.431	0.217
227	0.390	0.249	0.177	0.096	0.102	0.271	0.135	0.298	**-1.485**	0.219
259	0.428	0.276	0.198	0.108	0.115	0.297	0.147	0.312	0.451	**-1.997**

Note: Own-price elasticities are in bold font in the diagonal. Shaded UPCs are cage-free products. UPC description: 311-conventional, private, grade AA, large, 12 count white egg; 305- conventional, private, grade A, large, 12 count white egg; 327- conventional, private, grade AA, extra large, 12 count white egg; 193- conventional, national-branded, grade A, large, omega3-enriched, 12 count white egg; 303- conventional, private, grade A, extra large, 12 count white egg; 303- conventional, national-branded, grade A, extra large, omega3-enriched, 12 count white egg; 195- cage-free, national-branded, grade A, large, omega3-enriched, 12 count brown egg; 243- cage-free, national-branded, grade A, large, 12 count brown egg; 227- cage-free, national-branded, grade A, large, 12 count brown egg; 120- cage-free, private, grade AA, large, 12 count brown egg.

Table 1.10: Distribution of Marginal WTP for Cage-Free Eggs (in cents/package)

	Consumer group	mean	std	5%	25%	50%	75%	95%
	Average	5.89	0.06	5.80	5.85	5.89	5.93	5.99
head	male	5.41	0.15	5.16	5.31	5.42	5.52	5.66
	female	6.27	0.13	6.06	6.18	6.27	6.35	6.48
	married	5.84	0.07	5.73	5.80	5.84	5.88	5.95
educ	high school or less	3.79	0.08	3.13	3.18	3.22	3.26	3.31
	college or advanced	6.67	0.05	6.59	6.63	6.67	6.71	6.76
	age: 34 or less (young)	10.81	0.24	10.42	10.64	10.82	10.98	11.20
age	age: 35-64	5.98	0.06	5.89	5.94	5.98	6.02	6.07
	age: 65+ (old)	3.22	0.05	3.13	3.19	3.22	3.26	3.31
	income(0): less than $25,000	4.67	0.17	4.41	4.56	4.68	4.78	4.96
income	income(1): $25,000-$50,000	3.79	0.08	3.66	3.74	3.79	3.84	3.92
	income(2): $50,000-$100,000	5.30	0.07	5.18	5.25	5.30	5.35	5.42
	income(3): $100,000+	9.03	0.11	8.85	8.96	9.04	9.10	9.22

Note: Standard errors and quantiles are based on 1,000 bootstrap samples.

Table 1.11: Prices, Marginal Costs, and Price-Cost Margins[a] by Banners and UPCs (in $/dozen)

		A	B	C	D	E	F	G	H
	price	2.70	2.80	2.64	2.78	2.68	2.39	2.21	2.65
335	mc	2.26	2.52	1.94	2.24	2.15	1.79	1.80	2.10
	margin	0.16	0.10	0.27	0.20	0.20	0.25	0.19	0.21
	price	3.03	3.16	2.73	3.05	3.65	2.48	2.35	2.93
311	mc	2.76	2.87	2.01	2.59	3.09	1.86	1.95	2.44
	margin	0.09	0.09	0.26	0.15	0.15	0.25	0.17	0.17
	price	2.17	2.80	2.62		2.24	2.68		
305	mc	1.96	2.63	1.92	NA	1.84	2.05	NA	NA
	margin	0.10	0.06	0.27		0.18	0.23		
	price	3.14	3.55	3.22	3.46	3.19	2.52	1.79	3.86
327	mc	2.90	3.30	2.39	3.04	2.67	1.79	0.69	3.29
	margin	0.08	0.07	0.26	0.12	0.16	0.29	0.61	0.15
	price	4.16	4.68	4.00	4.55	4.16	3.63	3.86	4.42
193#	mc	3.51	3.43	2.39	3.65	3.12	1.91	2.53	3.46
	margin	0.16	0.27	0.40	0.20	0.25	0.47	0.34	0.22
	price	4.48	4.97	4.40	4.80	4.47	3.99	3.41	4.88
201#	mc	3.89	3.66	2.73	3.98	3.35	2.21	2.30	3.90
	margin	0.13	0.26	0.38	0.17	0.25	0.45	0.33	0.20
	price	4.77	5.32	4.61	5.02	4.83	4.02	3.39	4.96
195#	mc	3.77	3.87	2.77	3.98	3.57	2.15	2.35	3.79
	margin	0.21	0.27	0.40	0.21	0.26	0.46	0.31	0.24
	price	5.25	5.44	4.97	4.84	5.17			5.21
243#	mc	3.07	3.18	3.28	3.27	3.00	NA	NA	3.12
	margin	0.42	0.42	0.34	0.32	0.42			0.40
	price	5.59	5.33			5.48			6.15
255	mc	4.81	4.49	NA	NA	4.39	NA	NA	4.83
	margin	0.14	0.16			0.20			0.21
	price	5.49	4.26			3.99			5.46
259	mc	4.75	3.48	NA	NA	3.14	NA	NA	4.31
	margin	0.14	0.18			0.21			0.21

[a] Margins are calculated within each markets for each UPC as $\frac{p_{jt}-c_{jt}}{p_{jt}}$ and averaged across all markets.
Note: Shaded UPCs are cage-free. UPCs with # are national brand products. UPC description: 335-conventional, private, grade AA, large, 18 count white egg; 311-conventional, private, grade AA, large, 12 count white egg; 305- conventional, private, grade A, large, 12 count white egg; 327- conventional, private, grade AA, extra large, 12 count white egg; 193- conventional, national-branded, grade A, large, omega3-enriched, 12 count white egg; 201- conventional, national-branded, grade A, extra large, omega3-enriched, 12 count white egg; 195- cage-free, national-branded, grade A, large, omega3-enriched, 12 count brown egg; 243- cage-free, national-branded, grade A, large, 12 count brown egg; 255- cage-free, private, grade A, large, 12 count white egg; 259- cage-free, private, grade AA, large, 12 count white egg.

Table 1.12: Proposition 12 Changes in Equilibrium Price and Producer Surplus

	before			after			
	$/dozen	std.err	market share	$/dozen	std.err	market share	% Δ
			price				
Conventional	3.10	1.30	87.56			0.00	65.27%
Cage-free	5.30	1.25	13.44	5.12	1.83	100.00	-3.41%
Omega-3	5.82	124	9.31	5.79	2.15	11.01	-0.52%
Organic	5.95	1.26	4.19	6.12	2.05	4.02	2.86%
Producer Surplus (average of all firms and all market)							
Per dozen eggs	0.140	0.093		0.094	0.071		-32.71%
Industry level		131,539,700			108,331,097		-17.64%

Table 1.13: Proposition 12 Change in Expected Consumer Surplus (per household, per trip, in cents/dozen)

	Consumer group	mean	std.	5%	25%	50%	75%	95%
	Average	-5.86	2.04	-9.44	-7.04	-5.73	-4.43	-2.84
head	male	-7.92	3.57	-14.57	-10.03	-7.44	-5.47	-2.87
	female	-4.00	3.07	-9.03	-5.86	-3.97	-2.24	1.17
	married	-5.30	2.40	-9.25	-6.86	-5.26	-3.74	-1.41
educ	high school or less	-6.63	5.10	-14.45	-9.79	-6.96	-3.92	2.32
	college or advanced	-5.68	2.06	-9.20	-6.86	-5.56	-4.31	-2.52
	age: 34 or less (young)	-5.23	2.28	-9.05	-6.56	-5.15	-3.77	-1.66
age	age: 35-64	-6.23	4.75	-14.88	-9.17	-5.70	-3.01	0.71
	age: 65+ (old)	-7.27	3.11	-12.54	-9.07	-7.05	-5.32	-2.69
	income(0): less than $25,000	-7.07	3.04	-12.35	-8.86	-6.73	-4.97	-2.80
income	income(1): $25,000-$50,000	-7.68	3.12	-13.17	-9.52	-7.32	-5.60	-3.00
	income(2): $50,000-$100,000	-5.39	3.47	-11.49	-7.53	-5.21	-3.02	-0.27
	income(3): $100,000+	-4.70	2.97	-9.38	-6.59	-4.96	-2.87	0.46

Note: Standard errors and quantiles are based on 1,000 bootstrap samples.

CHAPTER

2

ESTIMATING PARENTAL DEMAND FOR CHILDREN'S SCREEN TIME IN A MODEL OF FAMILY LABOR SUPPLY

2.1 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 vessels such as watching TV or videos (like YouTube), playing video games, text messaging, social media, video-chat, web browsing and editing photos. Excessive screen time is considered as one of the crucial risk factors that can potentially hamper the early developmental processes in children. 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 Census report[1], children ages 5 to 8 spend nearly 3 hours per

[1]https://www.commonsensemedia.org/research/the-common-sense-census-media-use-by-kids-age-zero-to-eight-2017

day using digital devices and screen time grows fast as 95% of the family have a mobile device and nearly 80% of the family have a tablet. As the concerns of too much screen time for children grew, medical associations such as World Health Organization (WHO), American Academy of Pediatrics (AAP), and Canadian Pediatric Society (CAP) all came up with guidelines on the recommended time and rules on screen device exposure for children.

The situation got increasingly worse with 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 screens to keep frustrated and restless kids entertained and engaged. But remaining limits frequently vaporized as computers, tablets and phones became the centerpiece of school and social life. According to Qustodio, a company that tracks the usage of electronic devices by children ages 4 to 15, children screen time has doubled by May 2020 as compared with the same period a year earlier. 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. Similar trends were found in Britain and Spain (Ritchtel (2021a)).

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 (Danner (2008), Henderson (2007), and Parsons et al. (2005), Mark and Janssen (2008), and Sugiyama et al. (2007) among many; see also Tremblay et al. (2011) for the systematic review of this body of literature). However, considerably less attention in the literature has been devoted to investigating the relationship between children's exposure to screen time and families' socio-economic 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. 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 be contradicting 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. Into the first group of high time-intensive efforts, we classify activities like taking a child to after-school soccer practice or a violin lesson. In the second group of low time-intensive activities we classify children watching TV, playing com-

puter games or surfing the internet. Obviously, the demand on parents' time is significantly higher in the first group of activities than in the second. Invoking the standard labor-leisure microeconomic model, the optimal parental allocation of the 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 away from violin lessons and towards the video games. This line of reasoning jives perfectly with Linder (1970) who predicts that rising "productivity" decreases the demand for commodities whose consumption is expensive in time or inexpensive in money (Baumol (1973), p. 629). Therefore, we should see lower income parents spending more time driving their kids to soccer practices and violin lessons than higher income parents, yet the extant empirical literature recorded exactly the opposite, i.e., that children from lower-income, less educated, and single-parent families spend more time with screen devices than their more affluent counterparts. Explaining this apparent puzzle becomes the main motivation for this research.

The economic literature on parental time with children found that mothers with college education or greater spend about 4.5 hours more per week in child care than mothers with high school diplomas or less. This robust relationship holds for both nonworking and working mothers and working fathers (Guryan et al. (2008)). This positive education (as well as income) gradient for child care is also surprising given that the opportunity cost of time is higher for both high 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 looks like fundamentally different from leisure and home production; see Guryan et al. (2008), pp. 36-38) and references thereof for the competing explanations of this result.

It is often the case where parental time in household production is substituted or outsourced. Cortés and Tessada (2011) find that the increase in low-skilled immigrants increases both working hours and the probability of working for women at the top quartile of the wage distribution. They also show that these women decrease the time spent and increase the expenditure spent in household production. This result is in line of what Linder (1970) predicted. Indeed, it is true that market-supplied child cares such as nanny or daycare, or a support from the retired grandparent or other adult family member affect the mother's decision on her time allocation regarding labor supply and child upbringing. However, these are not modeled in this paper, since our main interest is to establish the link between the demand for the screen time of children and its price.

The focus of our 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 the money and time budget constraints, we derive Marshallian demand functions for two types of child upbringing activities and after the Slutsky decomposition show that the empirically observed result corresponds to the case where the screen time exhibits Giffen good like characteristics. Using two different data sets – National Longitudinal Survey of Youth 1979 (NLSY) data, and Adolescent Brain Cognitive Development (ABCD) data – we estimate the wage equation based on the Heckman's two-step correction procedure and then empirically decompose the total effect of an increase in wage rate on the parental demand for children's upbring activities into the substitution effect and income effect relying on the approach by Ashenfelter and Heckman (1974). For the case of low time intensive child upbringing activities such as exposing kids to screen time, in line with our theoretical predictions, we found that the substitution effect is positive and the income effect is negative and that negative income effect dominates the positive substitution effect. Hence our results shows that the empirical findings in the public health and psychology literature can be reconciled with the theoretical predictions of the Beckerian model.

2.2 A Theoretical Model

Following in the footsteps of Becker (1965) time allocation model, we formulate the utility maximization problem of parents. Here, the entire family (household) makes decision collectively as one agent. 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:

$$\begin{aligned} &\max_{(Z,C)} U = U(Z,C) \\ &\text{s.t.} \quad p_Z Z + p_c C = M + wL \\ &\qquad\quad t_z Z + t_C C + L = T \end{aligned} \tag{2.1}$$

By substituting the time constraint into the budget constraint we can re-write the problem with only one constraint:

$$\begin{aligned} &\max_{(Z,C)} U = U(Z,C) \\ &\quad \text{s.t.} \quad (p_Z + w\,t_Z)Z + (p_C + w\,t_C)C = M + w\,T \end{aligned} \tag{2.2}$$

where M is a non-labor income, w is a wage rate, T is the household's total disposable time and $(p_Z + w\,t_Z)$ and $(p_C + w\,t_C)$ as "full prices" of Z and C consisting of time prices $w\,t_Z$ and $w\,t_C$ and market prices p_z and p_C and related goods. We solve the system of first order conditions to obtain the Marshallian demands for Z and C:

$$\begin{aligned} Z^M &= Z^M(p_Z, p_C, w, t_Z, t_C, M, T) \\ C^M &= C^M(p_Z, p_C, w, t_Z, t_C, M, T) \end{aligned} \tag{2.3}$$

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

$$\begin{aligned} &\min_{(Z,C)} M = (p_Z + w\,t_Z)Z + (p_C + w\,t_C)C - w\,T \\ &\quad \text{s.t.} \quad U(Z,C) = u^0 \end{aligned} \tag{2.4}$$

leading to Hicksian demands for Z and C:

$$\begin{aligned} Z^h &= Z^h(p_Z, p_C, w, t_Z, t_C, u^0) \\ C^h &= C^h(p_Z, p_C, w, t_Z, t_C, u^0) \end{aligned} \tag{2.5}$$

and the associated indirect expenditure function:

$$e^*(p_Z, p_C, t_Z, t_C, w, u^0, T) = M^* = (p_Z + w\,t_Z)Z^h + (p_C + w\,t_C)C^h - w\,T. \tag{2.6}$$

Using the fundamental identity for Z,

$$Z^h(p_Z, p_C, w, t_Z, t_C, u^0) = Z^M(p_Z, p_C, w, t_Z, t_C, e^*(p_1, p_2, w, t_1, t_2, u^0, T)) \tag{2.7}$$

and differentiating with respect to the wage rate, we obtain the cross-price Slutsky equation:

$$\frac{\partial Z^M}{\partial w} = \frac{\partial Z^h}{\partial w} + (T - t_Z Z^h - t_C C^h)\frac{\partial Z^M}{\partial M}. \tag{2.8}$$

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 $(T - t_Z Z^h - t_C C^h)\frac{\partial Z_1^M}{\partial y}$, 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:

$$\frac{\pi_Z}{\pi_C} = \frac{p_Z + w\,t_Z}{p_C + w\,t_C} = \frac{p_Z}{p_C} \cdot \frac{1 + w\,t_Z/p_Z}{1 + w\,t_C/p_C}.$$

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 has to be negative, i.e.:

$$\frac{d}{d\,w}\left(\frac{p_Z}{p_C} \cdot \frac{1 + w\,t_Z/p_Z}{1 + w\,t_C/p_C}\right) = \frac{p_Z}{p_C} \frac{1}{\left[1 + w(t_C/p_C)\right]^2}\left[\frac{t_Z}{p_Z} - \frac{t_C}{p_C}\right] < 0. \tag{2.9}$$

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

$$\frac{\partial Z^h}{\partial\, w} > 0 \quad \text{if and only if} \quad \frac{t_Z}{p_Z} < \frac{t_C}{p_C}. \tag{2.10}$$

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, we need to sort out where our types of child upbringing activities belong. If Z is driving the kid 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.

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/income on child upbringing. If time consuming child upbringing activities are not inferior goods, households would want more of them as their income rises. They could be able to spend more money on those activities even if rising wages increase their opportunity cost of time. Also, assuming that income effect of a rise in wages is likely to be substantial and child upbringing activities not likely to be inferior, it appears that that demand for high quality child upbringing activities is likely to grow as households wealth grow. However, as pointed out by Baumol (1973), there are two important caveats to above reasoning. First, there are two constraints in the above model. The binding one is the time constraint and not the money constraint in the sense that if individual has more time, she can earn more money but she is prevented by the 24-hour limit to her day. It follows that additional time will purchase more income but additional income does not 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 like in this model) could be inferior goods and hence the demand for them will not rise with income.

To analyze all possible cases, we label the various parts of the Slutsky equation (8) as follows:

$$\underbrace{\frac{\partial Z_1^M}{\partial w}}_{C} = \underbrace{\frac{\partial Z_1^h}{\partial w}}_{A} + \underbrace{(T - t_Z Z^h - t_C C^h)\frac{\partial Z_1^M}{\partial M}}_{B} \tag{2.11}$$

and summarize the results in Table 2.1. Among six possible cases presented in Table 2.1, half of them represent positive ($A > 0$) and half of them negative substitution effects ($A < 0$). Since we are interested in signing the total effect of the wage change on parents decision to let their children play video games, the relevant 3 cases are those in the shaded portion of the Table 2.1 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 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

Table 2.1: Signing the elements of Slutsky equation

Case #	A	B	Absolute value	C
1	+	+		+
2	+	-	$\|A\| > \|B\|$	+
3	+	-	$\|A\| < \|B\|$	-
4	-	-		-
5	-	+	$\|A\| > \|B\|$	-
6	-	+	$\|A\| < \|B\|$	+

of other good 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 and that negative effect swamps the substitution effect such that the overall sign of the Marshallian cross-price effect turns out negative. The result in row 3 of Table 2.1 reminds us of the case of a Giffen good in the classical demand analysis. Because the sign of the income effect cannot be determined theoretically, it remains an empirical question. The Giffen good case represents the cornerstone of the empirical analysis that follows.

2.3 Data Sets

Our empirical analyses have been carried out using two data sets: National Longitudinal Survey of Youth 79 and National Longitudinal Survey of Youth 79 - Child and Youth (together as NLSY) and Adolescent Brain Cognitive Development (ABCD) data. The NLSY data is richer in terms of relevant content variables (questions) but ABCD data is about a decade newer. The use of two data sets provides an automatic robustness check for the results and lends additional credibility to empirical findings. Table 2.2 shows the summary statistics of screen times and other demographic variables from these two data sets.

National Longitudinal Survey of Youth 79 (NLSY79) was conducted by the National Bureau of Labor Statistics. NLSY data is a survey from a nationally representative sample of youth (girls and boys) in the United States 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 we only use observations from 2006 to 2014 where the age of children ranges from 10 to 14 years old. During this period, there are 1,703 observations (child-mother pairs) without

missing values. These observations are collected from 1,057 children and 698 mothers, indicating the fact that some mothers appear with more than one child.

ABCD data is very recent data, with the first wave started in 2016-2017, from the National Institute of Mental Health. ABCD has rich information on children's cognitive ability, physical and mental health as well as their family background. In this study we use only the data from the third wave (2018-2019) with the age of children ranging from 10 to 14 years. Unlike NLSY, ABCD collects responses from children, although some survey question, like family income, etc., are completed by parents. The 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 data are from longitudinal studies, we treat them as cross-sectional. In the NLSY interviews the respondents often skipped interview rounds, such that almost 90% of the mother-child pairs have recorded responses in fewer than three waves. ABCD is also an annual panel data, but we excluded the first two waves of the survey from our analysis because of the very detailed definition of children's screen times that lead to implausible results (see footnote 2) and the lack of some critical questions (variables).

A closer inspection of the entries in Table 1 indicate that the two data sets are similar in some respects but also somewhat different in 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 hours of watching television and hours of playing video games, whereas in the ABCD, children are asked to report total combined screen times (i.e., not separated by the type of screen activity).[2] In both cases we had to prune the data sets from some unreasonable screen time responses. In the NLSY data, the responses with the daily screen time greater 8 hours during the week and greater than 12 hours during weekends were deemed unreasonably high and hence dropped from the sample, leading to the final number of observations of 1,348 from 901 children. The same approach was used for the ABCD data leaving us with 3,986 observations.

[2]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 kids 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. I 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.

Since ABCD is more recent data, children from ABCD are born five to ten years later than those in 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 data sets. Mothers from NLSY are older than those from ABCD by about 7 years on average. Weekly family income and the mother's wage rate are both greater in 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 data sets are also different in how they provide information about siblings. In both data sets, we have the information on the number of children in the family. The number of children in the household is greater in NLSY (3.05) than than in the ABCD (2.52). In the NLSY data we have the age of the youngest child in the family whereas in the ABCD similar information is provided by number of younger sibling of the child responding to the survey. The percentage of a single-parent families is greater in NLSY (30%) than in the ABCD (20%).

Finally, there are differences in definitions of mothers' working status and job-related variables. ABCD asks whether mother is working full time, half time, or not working at all, and her annual income. For this reason we take the number of hours worked as 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 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 and the wage rate is a weighted average of wage rates from all jobs weighted by the hours worked. The variable tenure reflects the longest duration of employment (in weeks) among all reported jobs. This variable is not available in the ABCD.

2.4 Estimation and Testing

To establish the link to the previous research we start by estimating a simple model that mimics the empirical models in the existing literature. The estimation results are presented in Table 2.3. In line with what the previous literature has found, our results also indicate a negative and statistically significant relationship between family income and children's screen time. In the NLSY data set, a $1,000 increase of weekly family income leads to a decrease of 0.11 hours of weekday screen time and 0.07 hours of a weekend screen time. The results with the ABCD data set show comparable decreases of 0.10 and 0.15 hours respectively.

The rest of the estimated coefficients show that both age and sex of the child are important determinants of the screen time exposure. The results show that older children and boys spend more time in front of the screens. On the other hand, the age of the mother is insignificant in all specifications but mothers' education achievement is an important determinant of the children's screen time exposure. In all specifications, the coefficients are negative indicating the children of more educated mothers will spend less time in front of the screens but only in the ABCD model, education coefficients (both weekdays and weekends) are statistically significant.

The remaining two estimated parameters are quite interesting. First, the family structure appears to be important in the sense that children coming from a single-parent families tend the 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 translates 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.

2.4.1 An Econometric Model

The main objectives of the subsequent empirical analysis is to test whether (a) the substitution effect of the change in wages on screen time types of child upbringing activities is positive, (b) the screen time activities are inferiors 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.

Our approach is based on Ashenfelter and Heckman (1974) who proposed an estimation strategy for disentangling the income and substitution effects in 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

$$dZ^M = \frac{\partial Z^M}{\partial w} dw + \frac{\partial Z^M}{\partial M} dM. \tag{2.12}$$

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

$$dZ^M = \left[\frac{\partial Z^h}{\partial w} + H \frac{\partial Z^M}{\partial M} \right] dw + \frac{\partial Z^M}{\partial M} dM \tag{2.13}$$

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

$$dZ^M = \frac{\partial Z^h}{\partial w} dw + \frac{\partial Z^M}{\partial M}[H\,dw + dM] \tag{2.14}$$

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

$$\Delta Z_k = \frac{\partial Z^h}{\partial w} \Delta w_k + \frac{\partial Z^M}{\partial y}[H_k \Delta w_k + \Delta M_k] + \epsilon_k \tag{2.15}$$

To test the sign of the substitution effect and income effect of an increase in wage on the parental demand for screen time, we estimate the following equation:

$$\Delta Z_k = \beta_1 \Delta w_k + \beta_2 F_k + \epsilon_k, \tag{2.16}$$

where H is the hours of worked per week and y is the exogenous income per week, which is defined as all of family income other than the mother's labor income. $H\Delta w + \Delta y$ is denoted as F.

We propose an estimation model where households are headed by mothers who either work outside the home earning the prevailing market wages or stay at home. We proceed by first estimating the wage equation and then use the estimated parameters of the wage equation to generate in-sample wage predictions. These forecasted wages are subsequently used as a generated regressor in (2.16). The distinction between employed and unemployed mothers is critical because unemployed workers not only have lower incomes but also lower opportunity costs and thus lower relative prices of time and other earnings-intensive commodities (Becker (1965), p.434). 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. In order to estimate the wage equation we use two-step correction procedure used in Heckman (1979). In the first step the probability of mothers' participation in the labor force is 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. ABCD data does not have information on the size of the labor market and the age of the youngest child so 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 a younger sibling of the child being surveyed. The estimation results for the selection equation are presented in Table 2.4.

As seen from Table 2.4, most of the estimated probit model coefficients are intuitively correct. Clearly, children are deterrents to mothers' 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 NLSY model). Similarly, more younger siblings has a negative sign on the probability of employment (in 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, we also found that the mother is more likely to work if she is a single parent and that the size of the market is negatively related to employment. The first results could be explained by the economic pressure that the household faces where single parents must work to secure 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.

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, the tenure on the current job and the inverse Mill's ratio (IMR) calculated from the selection equation that controls for the selection bias. The tenure and the market size are not available in the ABCD data. The results are presented in Table 2.5. All obtained results are economically meaningful and most are statistically significant. The results show that hourly wages of working mothers increase with years of education, the number of hours worked, the tenure on the job, and decrease with the number of children she has. This last results 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 the selection bias was present and without the correction, the estimates would have been biased downward.

2.4.2 Hypotheses Testing

The estimation of equation (2.16) provides the basis for the empirical testing of the proposed hypotheses. We experiment three different measurements of the dependent variable screen time, ΔZ_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 2.5) 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 this setup, β_1 and β_2 are the coefficients of interest measuring the substitution effect and the income effect respectively. Based on our spelled out hypotheses (recall the summary of all relevant cases in Table 2.1.), the correspondence between equations (2.15) and (2.16) is straightforward and given by:

$$\beta_1 = \frac{\partial Z^h}{\partial w} > 0, \quad \beta_2 = \frac{\partial Z^M}{\partial y} < 0 \tag{2.17}$$

The results are summarized in Table 2.6. First, the sign of the substitution is always positive and three out of six coefficients are statistically significant. Recall from the theory part 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 the screen time, as wage increases, the household will increase its consumption of 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. All coefficients and their standard errors are obtained as empirical distributions based on 500 bootstraps.

Finally, we want to test test the hypothesis that the parental demand for children's exposure to screen time has the characteristics of a Giffen good. Based on the estimated substitution and income effects, we generate the total price effect of a change in wage rate on the screen time demand as $\hat{\beta}_1\Delta w_k + \hat{\beta}_2(H_k\Delta w_k + \Delta M_k)$. The mean values and the 5% confidence intervals of the total price effect are also generated from 500 bootstraps. As we can see from the bottom part of Table 2.6, in five version of the model the total price effect is negative and falls inside the 5% confidence interval confirming 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.

2.4.3 Counterfactual Experiment

From the estimated model, we can also predict the changes in the screen time when maternal wage rate or her exogenous income are changed. Suppose a mother k's wage rate increase by a certain percent. Under the assumption that this individual wage increase does not affect the average wage level (since Δw_k is defined as the deviation from the mean), and every other things stays the same, we can compute new ΔZ_k as:

$$\Delta Z_k^{new} = \hat{\beta}_1 \Delta w_k^{new} + \hat{\beta}_2 F_k, \tag{2.18}$$

which can be translated back to Z_k^{new}. For this simulation, we generate 500 bootstraps and for each sampled individual, Z_k^{new} are calculated under 10%, 50%, and 100% increase in maternal wage, w_k. Since we assumed individual wage increase does not affect the average wage level, $\overline{Z}$ and $\overline{w}$ from the main estimation are used to calculate the variables that are defined as the deviation from the mean (ΔZ and Δw). Changes in screen time with respect to an increase in exogenous income is similarly computed.

In table 2.7, predicted changes in weekday, weekend, and total screen time are presented with respect to different level of increase in wage, and in exogenous income of mothers. Results from changes in weekday screen time are not relevant since the substitution effect and the income effect are not statistically significant in both data. Same is true for the total screen time changes in ABCD data. Based on the simulation using NLSY data, weekday screen time will decrease by 0.6%, 2.71%, and 5.35% if the wage is increased by 10%, 50% and 100%, respectively. The same percentage increases in mother's exogenous income would lead to a decrease in screen time by 0.23%, 1.43%, and 2.93%. The predicted percentage increase of weekend screen time are mostly smaller when ABCD data is used. For total screen time, which is the sum of daily weekday screen time and daily weekend screen time, the percentage change mostly showed similar trend and similar size to that of weekend screen time in both data.

2.5 Conclusion

The excessive exposure of children to screen time has worried public health and psychology professionals as well as many parents for quite some time. The situation got increasingly worse with the Covid-19 pandemic. When the outbreak hit, many parents were willing to relax restrictions on screens to keep their frustrated and restless children entertained and engaged. Tracking data on the usage of electronic devices by children ages 4 to 15 showed that children screen time has doubled by May 2020 as compared with the same period a year earlier. 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. Less attention has been devoted to investigating the relationship between children's exposure to screen time and families' socio-economic background and structure. Some examples in the latter group found significant correlations between children's screen time exposure and parents' income and education, family structure, and residence 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 be contradicting the standard economic model of 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 the computer games. The optimal parental allocation of the 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 away from violin lessons and towards the video games. Therefore, we 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 the children's screen time as the result of a parent's optimal labor-leisure choice. We start by presenting a model that can explain the apparent contradiction between the existing empirical results and the economic theory. Based on a simple model of parental utility maximization subject to the money and time budget constraints, we derive Marshallian parental demand functions for two types of child upbringing activities and after the Slutsky decomposition show that the empirically observed result corresponds to the case where

the screen time exhibits Giffen good like characteristics. In our empirical work we use two datasets: National Longitudinal Survey of Youth 1979 (NLSY), and Adolescent Brain Cognitive Development (ABCD). We propose an estimation model where households are headed by mothers who either work outside the home earning the prevailing market wages or stay at home. In line with this approach, we estimate the wage equation based on the Heckman's two-step correction procedure. Using thereby forecasted wages, we empirically decompose the total effect of an increase in wage rate on the parental demand for children's upbringing activities into the substitution effect and income effect relying on the approach by Ashenfelter and Heckman (1974). For the case of low time intensive child upbringing activities such as exposing kids to screen time, in line with our theoretical predictions, we fund that the substitution effect is positive and the income effect is negative. Moreover, relying on the bootstrapped confidence intervals we found that the negative income effect (signaling that parents perceive children's screen time as inferior good) dominates the positive substitution effect causing the sign of the total wage effect to turn negative. Hence our results shows 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 notable limitation of our approach is that, as mentioned in the introduction, our model does not allow for a market supplied child care such as nanny and daycare, nor the support from the family member. In reality, this is frequent case for working mothers yet ignored for the simplicity. Another deficiency to the problem of children's exposure to screen time becomes apparent with the prolonged lock-downs 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 disconnect. But doing so becomes really complicated because screen devices are now vessels 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 the beneficial impacts from developmental and social costs. Consequently, the parental task to police children screen time exposure becomes almost impossible because if they are doing schoolwork that bores them, children can easily switch to playing a video game, without parents' awareness or permission. As a result, the parental decision regarding optimal consumption of children's screen time is too complicated to even contemplate let alone to systematically model.

Table 2.2: Summary Statistics For Two Data Sets

	NLSY			ABCD		
variable	Mean	Std.Dev.	Range	Mean	Std.Dev	Range
screen time (weekday)	3.57	1.91	0-7.5	2.22	1.54	0-7.75
screen time (weekend)	3.77	2.26	0-11.5	3.34	2.26	0-11
age:child	12.44	1.29	10-14	11.94	0.65	10-14
age:mother	47.27	2.87	42-56	40.15	5.82	25-64
child:male	0.46	0.50	0-1	0.50	0.50	0-1
family income	1.89	1.92	0-11.46	2.38	1.43	0.05-4.97
mother's education	14.45	2.77	6-20	17.31	2.35	1-21
single parent	0.30	0.46	0-1	0.20	0.40	0-1
# of child	3.05	1.48	1-11	2.52	1.24	1-11
age of youngest child	10.72	2.48	0-14			
# of younger sibling				0.84	1.08	0-5
mother working	0.82	0.39	0-1	0.76	0.43	0-1
wage	16.31	18.00	0-290.69	26.17	28.18	0-240.38
hours	34.94	26.62	0-80	26.13	16.59	0-40
tenure	363.42	396.31	0-1969			
years covered		2006-2014			2018-2019	
N		1,348			3,986	

Notes: screen times: in hours; male: 1=male; 0=female; income: weekly household income in thousand dollars; education: years of mother's education; single: 1=single parent; 0=two parents; mother working: 1=working; 0=not working; wage: hourly rate in dollars; hours: weekly working hours; tenure: in weeks on the current job.

Table 2.3: A Simple Model of Children's Screen Time Exposure: OLS Regression Results

	NLSY		ABCD	
	weekdays	weekend	weekdays	weekend
age:child	0.1001**	0.0587	0.1982***	0.2252***
	(0.0400)	(0.0476)	(0.0378)	(0.0550)
age:mother	0.0064	0.0184	0.0042	0.0096
	(0.0182)	(0.0216)	(0.0045)	(0.0066)
child:male	0.8386***	0.9181***	0.1624***	0.4143***
	(0.1017)	(0.1211)	(0.0483)	(0.0705)
family income	-0.1057***	-0.0681*	-0.0989***	-0.1491***
	(0.0314)	(0.0374)	(0.0213)	(0.0311)
educ.:mother	-0.0287	-0.0162	-0.0482***	-0.0392***
	(0.0213)	(0.0253)	(0.0122)	(0.0178)
single parent	0.0290	0.1785	0.2790***	0.3140***
	(0.0213)	(0.1465)	(0.0666)	(0.0972)
number of children	-0.0361	-0.0797*	-0.0419***	-0.1301***
	(0.0358)	(0.0426)	(0.0199)	(0.0290)
(intercept)	2.37**	1.8377	0.7047***	1.3373***
	(09526)	(1.1337)	(0.4891)	(0.7134)
N	1,348	1,348	3,965	3,965

Notes: Standard errors in parentheses.

Family weekly income is in thousands of dollars.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.4: Probit estimates of mothers' labor force participation

	NLSY	ABCD
age:youngest	0.0577***	
	(0.0185)	
# of younger sibling		-0.1569 ***
		(0.0248)
# of children	-0.0467*	-0.1187***
	(0.0280)	(0.0192)
single parent	0.1172	0.1543**
	(0.0957)	(0.0603)
education:mother	0.0909***	0.1231***
	(0.0169)	(0.0102)
age:mother	-0.0330**	-0.0023
	(0.0160)	(0.0046)
market size		
medium	-0.6698**	
	(0.3477)	
large	-0.9833***	
	(0.3460)	
(intercept)	1.5137**	-0.8622***
	(0.8085)	(0.2264)
N	1,348	3,965

Notes: 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.5: Wage equation estimates for working mothers

	NLSY	ABCD
educ	2.5092***	4.9956***
	(0.3205)	(0.4176)
age:mother	-0.0817	0.8140***
	(0.1777)	(0.0873)
hours	0.0291	0.3143***
	(0.0219)	(0.0509)
# of child	-1.1641***	-1.1311***
	(0.4486)	(0.6471)
market size		
medium	-5.0525	
	(3.1157)	
large	-5.0689	
	(3.7037)	
tenure	0.0102***	
	(0.0013)	
IMR	25.8361***	8.1313***
	(8.8364)	(6.4885)
(intercept)	-15.7689	-99.2708***
	(9.7150)	(9.7549)
N	1,103	3,029

Notes: Definition of market size is the same as in Table 4.
Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.6: Substitution, income and total effect of an increase in wage on screen time demand

		weekdays	weekend	total
NLSY	$\hat{\beta}_1$	0.0034	0.0141**	0.0175*
		(0.0066)	(0.0076)	(0.0132)
	$\hat{\beta}_2$	-0.0001***	-0.0001***	-0.0002***
		(0.0000)	(0.0000)	(0.0001)
	$\hat{\beta}_1\Delta w_k + \hat{\beta}_2(H_k\Delta w_k + \Delta M_k)$	-0.0134	-0.0103	-0.0247
		[-0.0279,-0.0008]	[-0.0214,0.0008]	[-0.0484,-0.0011]
ABCD	$\hat{\beta}_1$	0.0000	0.0031*	0.0031
		(0.0016)	(0.0022)	(0.0000)
	$\hat{\beta}_2$	-0.0002***	-0.0002***	-0.0004***
		(0.0000)	(0.0000)	(0.0000)
	$\hat{\beta}_1\Delta w_k + \hat{\beta}_2(H_k\Delta w_k + \Delta M_k)$	-0.0417	-0.0545	-0.0962
		[-0.0486,-0.0349]	[-0.0633,-0.0457]	[-0.1118,-0.0807]

Note: Standard error are in parentheses. 95% intervals in square-bracket for the total effect.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.7: Changes in screen time with respect to changes in wage and exogenous income

		screentime	changes in wage			changes in exo.income		
		mean	+10%	+50%	+100%	+10%	+50%	+100%
NLSY	weekday	3.57	-0.04	+0.12	+0.33	-0.24	-1.51	-3.09
	weekend	3.77	-0.60	-2.71	-5.35	-0.23	-1.43	-2.93
	total	7.35	-0.49	-1.99	-5.17	-0.23	-1.46	-3.00
ABCD	weekday	2.22	-0.03	-0.06	-0.11	-0.52	-1.27	-2.22
	weekend	3.34	-0.91	-1.53	-2.31	-0.35	-0.85	-1.48
	total	5.54	-0.69	-1.32	-2.10	-0.42	-1.02	-1.78

Note: Changes in wage and exogenous income are percentage increase and changes in screen time are in terms of percentage change. Weekday and weekend screen time are in hour/day and total screen time is the sum of those two.

CHAPTER

3

UNDERSTANDING MATERNAL DECISIONS ON CHILDREN'S SCREEN TIME AND ITS DYNAMIC EFFECTS ON CHILDREN'S OBESITY

3.1 Introduction

Childhood obesity remains the largest health threat for children and adolescents in the United States and several other developed countries. Obese and overweight elementary school children in the United States nearly quadrupled between 1965 and 2000, affecting more than 13.7 million children and adolescents (Ogden et al. (2002)). Moreover, an increasing amount of evidence suggests that the epidemic of childhood obesity holds several long-term health consequences on mortality and morbidity (Hales et al. (2017)). Around 55% of total obese children suffer from obesity during their adolescence; of these, nearly 80% of obese adolescents remain obese in adulthood as well, and around 70% will remain

obese over age 30 (Dietz (1998)). Given the tremendous social cost associated with childhood obesity, identifying the leading causes and effective intervention in this context is critical.

Countless medical, sociological, and economic studies have been dedicated to the investigation of causes of childhood obesity and possible mitigation of the same. Traditional factors that are known to cause childhood obesity are the increased consumption of energy-dense food as a result of a decline in real food price (Powell (2009); Auld and Powell (2009); Sturm and Datar (2005)) and mass media advertising of fast foods (Harris et al. (2009); Buijzen et al. (2008)). More recently, increased levels of stress (Miller and Lumeng (2018); Koch et al. (2008)), depression (Puder and Munsch (2010); Gundersen et al. (2011)), and sleep deprivation (Nielsen et al. (2011); Hart et al. (2011)) have been found to exacerbate this epidemic. Additionally, the sedentary lifestyle of children due to increased screen time has also been considered a primary cause of the same, now more than ever.

Screen time of children surged due to virtual schooling and relaxed restrictions set by parents, particularly during the COVID-19 pandemic. According to Qustodio, a company that tracks children's usage of electronic devices, screen time for children had doubled by May 2020 in comparison with the same period the previous year (Ritchtel (2021b)). As matter of fact, the rate of Body Mass Index (BMI) increase almost doubled during the pandemic period, as Center of Disease Control reported (Lange et al. (2021)).

Many previous studies have found a positive correlation between the amount of screen time and obesity among children[1]. The literature is generally dominated by cross-sectional studies, each outlining remarkably mixed effects on obesity, in terms of both size and significance. The causal effect of screen time (mostly watching television) on children's obesity was first recognized and investigated back in the 1980s. Dietz and Gortmaker (1985) was one of the first scholars to investigate the causal relationship between television and children's obesity, employing two rounds of cross-sectional to find a small yet significant association between the two studied variables. Similarly, Gortmaker (1996) established a positive correlation between the hours of television viewed and the probability of getting overweight among adolescents. However, with well-established evidence, it is acknowledged that obesity is based on the imbalance between energy intake and energy expenditure over time. Thus, cross-sectional data is insufficient to adequately capture the dynamics of obesity. Recognizing this limitation of the cross-sectional approach, Hancox et al. (2004) conducted a longitudinal study using a birth cohort of 1,000 children in New Zealand between 1972

[1]Furthner et al. (2018); Tsujiguchi et al. (2018); Herman et al. (2014); Godakanda et al. (2018); Shang et al. (2015) among many; see Fang et al. (2019) for the systemic review.

and 1973. The study found that weekday television hours are positively correlated with higher future body mass index (BMI). Furthermore, Danner (2008), and Boone et al. (2007) also used longitudinal survey data in the US, finding similar results in terms of signs and magnitude of the effect.

Another popular strategy to investigate the adverse effects of screen time on the health outcomes of children is to observe experimental interventions with regard to television viewing hours. Authoring one of the first of such studies, Robinson (1999) keenly observes a randomized controlled school-based trial conducted from September 1996 to April 1997 in the US. A 6-month classroom curriculum was offered to 198 children from the 4th- and 5th-grade so that they may reduce screen time. A statistically significant decrease was observed in the overall body mass index, as compared to the controlled group. Other studies also reported similar results with varying intervention programs to limit the screen time of children, according to the systematic review of Buchanan et al. (2016). However, as noted by Nieto and Suhrcke (2021), most experimental studies lack data regarding the long-term effects and are generally based on very small sample sizes. The population-level effect of screen time can greatly vary from the previous findings of small-scale experiment studies, whose external validity and generalizability are not guaranteed.

Nieto and Suhrcke (2021) offer one of the closest studies to this paper in terms of academic resemblance. The researchers employ a nationwide natural experiment paired with a nationally representative survey data from the UK to investigate the causal relationship of screen time with children's obesity and mental health. In the study, the exogenous variation in the timing of the transition from analog to digital television in the UK was scrutinized, via enforced stages between 2008 and 2012. Throughout this transition, there was a rise in the number of television channels available (5 to 40). This resulted in an increase in the hours of television viewing by 12.55% per children relative to the total TV viewing time over the same period of 2008-2012. Combining a nationally representative longitudinal survey data with an event study model, the researchers found that one additional hour of television viewing in a week resulted in an increase in test scores that correspond with their mental health difficulties by 3.53% and raise their BMI by 1.04%. Further, Nieto and Suhrcke (2021) provide evidence on the plausible mechanisms of screen time with relation to children's obesity by noting how the number of sports played by children had decreased by 0.03 from one extra hour per week during a year, using the same method and exogenous variation.

Nevertheless, extant literature, including the abovementioned study, fails to critically address how an increase in screen-based activities leads to the deterioration of children's health. There exist multiple channels by which obesity in this context is affected or induced

by screen time, with each mechanism impacting the other. While it is true that the most obvious of these is the decrease in the level of energy expenditure (physical activities) due to screen time, thereby resulting in obesity, researchers have established other mechanisms as well. Thus, the increased screen time affects other co-factors that lead to a rise in the probability of getting overweight. For instance, having a meal while watching television raises the Body Mass Index (BMI) of children by extending the duration of food intake (Liang et al. (2009)). Furthermore, advertising of energy-dense food promoted in media is also responsible for childhood obesity (Chou et al. (2008);Story and French (2004)). Often, gaming and video-watching lead to delayed bedtimes and deprivation of sleep (Barlett et al. (2012)). Conversely, obesity may lead to a higher screen time, as obese children avoid participating in vigorous physical activities. Finally, screen time can be addictive; screen time exposure leads to even more screen time (Kuss and Griffiths (2017)).

The various types of evidence outlined above suggest that identifying mechanisms within the relationship between screen-based activities and related co-factors that affect children's obesity is key to precisely estimating the causal bonds therein. Failing to account for these co-factors would lead to a biased result. In line with this reasoning, instead of focusing on a single factor that affects childhood obesity, Chang and Nayga (2009) focus on the interrelations between television viewing and fast-food consumption using data from the National Health Interview Survey in Taiwan. He found that the two activities are positively correlated and contribute to the increased risk of obesity. Xue et al. (2011) also investigates the role of caregivers in determining child obesity by jointly estimating a caregiver's labor force participation choices, involvement in children's outdoor activity, and household food expenditures. The authors did not find the role of caregivers with specific relation to labor force participation and household food expenditure as significant variables that impact children's BMI; furthermore, only a weak correlation was found between child BMI and caregiver participation in outdoor activity. Due to the nature of obesity as a result of an accumulated energy imbalance between calorie intake and expenditure over a period, these co-factors can have a lagged effect on obesity. Thus far, however, no study has suggested a dynamic and unifying framework that incorporates these multiple channels and their potential lagged effects. It is this gap in the literature that the current study intends to address.

This paper presents a unifying framework that can account for the dynamic effects of screen time, in addition to the unobserved individual heterogeneity. This is formulated as the time and money allocation decisions of a mother with regards to a variety of child-rearing activities, namely screen time, preparing healthy food, participating in the labor

force, and producing her children's health. While most of the studies on this topic are based on purely reduced forms, the model in this paper approximates an optimal decision rule derived from a mother's utility maximization and time/money allocation problem.

The current study builds off of existing literature to seek a causal inference regarding children's screen-based activities and their obesity. Moreover, to the best of my knowledge, this is the first to estimate the total marginal effect of screen time on children's obesity in a short-run time frame (1-2 years). The findings of this study also contribute to the body of literature on the mechanism of maternal labor supply in the context of children's obesity. Similar to the suggestion posited by Cawley and Liu (2012), increased hours for maternal labor have been associated with a decreased amount of time for grocery shopping, preparing home-cooked meals, and the time spent by the mother with her children. Crepinsek and Burstein (2004) also confirmed the effect of high take-out food prevalence due to maternal employment on the obesity of children.

From the simulation of the estimated model using 2017-2019 Adolescent Brain Cognitive Development data, I found that the percentage of children who are overweight or obese will increase from 32.6% to 36.4% in two years, if they spend one additional hour on watching screen daily. Such a result may be interpreted as the total marginal effect of screen time on children's obesity. If the model were to be estimated separately without allowing for correlations between decisions and outcomes, or for individual unobserved heterogeneity, this percentage is shown to be biased in an downward direction as a result of failure to account for unobserved indirect effects of screen time on obesity. Additionally, restricting the daily screen usage time has been effectively correlated with a decreased likelihood of a mother working in full-time employment.

This finding illustrates the trade-off a mother faces in her day-to-day life: on one hand, if the mother participates in the labor market and earns a wage, then it is likely that she would have to allow or even encourage more screen time usage for her children, thus leading to a higher chance of her children developing obesity. However, if she elects to stay at home, she may use her extra time to attend to the health needs of her children, although this may ultimately decrease her income.

With several more intervention programs being introduced to reduce sedentary behavior such as television viewing and playing video games as a remedy to the obesity epidemic, counterfactual simulations under scenarios of different interventions on children's screen time have been conducted, including meeting the daily screen time limit for children suggested by American Academy of Pediatrics(AAP), which is less than two hours per day. Another scenario mimics the recent Chinese ban on minors playing video games

during weekdays. This ban finds such games accountable for children's nearsightedness and addiction. The results of this study may offer policy implications such as this ban. However, in both cases, the study finds that even if it successfully decreases the likelihood of getting obese or overweight for children, an intervention to restrict screen time without any proper substitute activity may lead to notable a decrease in mothers' participation in the labor force.

This paper is structured as follows: Section 3.2 discusses a model concerning the theoretical motivation of the maternal decision and its various specifications. Section 3.3 describes the data used while Section 3.4 explains details regarding empirical estimation such as identification strategies and unobserved heterogeneity. Section 3.5 presents and discusses the results of the estimation and the counterfactual simulation results. Lastly, section 3.6 provides the conclusion of the study.

3.2 Model

3.2.1 Theoretical Motivation

Most prior studies make use of a reduced-form equation to investigate the relationship between obesity and screen time. The most widely used dependent variable across these studies is the Body Mass Index (BMI) of the child (which measures the adiposity of the child) in conjunction with covariates such as screen time, a measure for the caloric intake of the child, maternal labor supply, and other demographic variables corresponding with the child – all on the right-hand side. The amount of screen time in the context of this study is endogenous in several ways. First, there may be an issue of reverse causality. While longer screen time and sedentary behavior could increase the risk of obesity, obese children may also avoid engaging in vigorous physical activities, remain indoors, play video games, or watch videos. Furthermore, screen time can be correlated to omitted confounding factors, which may be unobservable as variables. For example, each parent has a unique parenting style. Certain parents are more concerned about the body shape of their children than others, and thus, remain stricter in enforcing rules on screen time and pay further attention to their daily level of activities. While some studies such as Nieto and Suhrcke (2021) employ other sources of exogenous variations such as a natural experiment, most prior studies deal with the problem of endogeneity from the approach of unobserved heterogeneity by controlling for as many covariates as possible. However, as Auld and Grootendorst (2011) indicated, it is highly challenging to identify an adequate instrument for obesity

research, as most of the personal or household characteristics are likely to be ruled out from the candidate, and the proportion of variation explained by observable characteristics of individuals is mostly less than 10%.

Despite correctly identifying the effect of screen time and modeling unobserved heterogeneity, the dynamic and complex effect of screen time on children's health is generally lumped together in a single coefficient. Higher screen time is not only associated with increased probability of obesity due to reduced energy expenditure, but also with frequent snacking behavior (Liang et al. (2009)), a preference over energy-dense food (Coon and Tucker (2002); Story and French (2004)), and sleep deprivation, altogether contributing to an increased risk of being overweight or obese. Additionally, due to the addictive aspect of screen time, any level of screen time can further lead to even higher levels in the future. Finally, mothers with children who spend excessive amounts of time using screen devices may experience great concern regarding their children's health and body shape. These mothers may attempt to spend more time staying home and preparing a healthy diet for their children, thereby decreasing their work hours. Without a model based on economic theory, such complex paths cannot be explored. Yet, most studies continue to rely on reduced-form models.

Several reasons underpin the scarcity of studies that use a structural model to investigate the effects of screen time on obesity among children. One of these is that most behavioral models and estimation strategies in obesity research are more focused on adult obesity, where a rational behavioral framework appears to fail to account for the prevalence of obesity. If obesity is considered a result of the rational behavior of an individual, then in equilibrium, that individual would possess (or be close to) their desired level of weight. However, individuals across the world spend vast amounts of money on weight loss and the diet industry (Ruhm (2012))[2].

Nevertheless, it is recommended that childhood obesity studies refrain from following the frameworks offered by adult obesity studies. Firstly, it is clearly unreasonable to assume that children make rational decisions regarding their screen time and their intake of calories by calculating and discounting their potential utilities. Moreover, children are constrained by their caregiver's action and their environment. It is important to consider that most families have parents that set rules about screen times and that meals are prepared based on the economic conditions of the parents. Across previous studies, most of the explanatory

[2]To overcome this issue, more sophisticated decision-making processes have been developed such as hyperbolic/quasi-hyperbolic discounting model (Laibson (1997)) and dual decision model between deliberative and affective system responses (Ruhm (2008))

variables included in reduced-form regression which were correlated with the probability of child obesity were variables that were primarily associated with their parents and family - family income, parental education, residence area, etc.

Of these variables, the labor status of the mother is a well-established factor that affects child obesity. Theoretically, however, the precise direction of the effect of maternal labor on children's obesity remains ambiguous. Working mothers have less time to prepare home-made food and are more likely to serve their children with take-out food or prepared meals (Cawley and Liu (2012)). These mothers are most likely to adhere to childcare, wherein children are generally provided with high-calorie and nutritionally poor food (Geoffroy et al. (2013)). Furthermore, unsupervised children tend to stay indoors and remain sedentary, which may result in the chances of these children snacking more during this time. Conversely, the income of labor allows mothers to provide fresh and healthier food, thereby providing much-needed balance to the child's diet. However, this effect may be spurious if mothers who work are less attentive to their children's health and nutrition requirements. Previous empirical studies have definitively established a positive correlation between mothers' labor status and children's obesity. A seminal work by Anderson (2011) directly estimates that an additional 10 hours per week of maternal labor results in a 1-1.5% increase in the probability of a child developing obesity. Follow-up studies have mostly confirmed this finding (Morrissey et al. (2011); Fertig et al. (2009); Chia (2008); Courtemanche (2008); Ruhm (2008)). Considering these results, it is more reasonable to model the demand for regulating the screen time of children as a caregiver decision, as opposed to a decision to be taken by the child.

This paper presents a theoretical framework to estimate a mother's dynamic time and money allocation decisions with relation to various child-rearing activities, namely screen time, preparing healthy food, participating in the labor force, and protecting her children's health. This model can identify the dynamic effect of children's screen time on their obesity, as well as the effects of other co-factors such as quality of food served to children and maternal labor supply. Despite the body of literature dedicated to modeling a collective decision of household members, in the context of child upbringing, the role of the mother is generally understood to be more prominent than that of the father. Consistent evidence establishes that paternal influence, in terms of labor supply and time spent with a child, is nearly irrelevant to childhood development and fathers represented only 17% of all parent participation (Davison et al. (2016)). Therefore, I am of the assumption that a child does not deviate from maternal decisions. There may be concerns regarding supervision and maternal decisions not being strictly enforced, i.e., children breaking the screen time rule

and eating snacks while they are unsupervised. Although imperfect, the test scores on children's impulsiveness are included in the findings to control for such deviations from maternal decisions.

Certain papers by You and Davis (2010) and Xue et al. (2011) have examined the screen usage time of children as a consequence of parents' rational decisions. The former study has modeled parents' food expenditure and time allocation for the health production of children's obesity as part of a two-stage Stackelberg game structure, wherein the parents are regarded as the leaders and the associated child is the follower. Xue et al. (2011) has also studied the impacts of a primary caregiver's time allocation and food expenditure choices on child obesity. In both studies, parents consume and produce children's health (measured in terms of BMI), and maximize their utility, which is in line with the Beckarian model.

The uniqueness of this study in juxtaposition with previous literature is its relevance in its provision of the insight that screen time is fundamentally different from other child-rearing activities that a mother can make decisions about while caring for her child. Oh and Vukina (2021) argue that child-rearing activities can be divided into two groups, based on how time-intensive (demanding of parents' time) they are. The first group requires high time-intensive activities such as taking a child to after-school soccer practice or a violin lesson. The second group requires low time-intensive activities like letting their child watch TV, play computer games, or surf the internet.

Researchers and health organizations such as the World Health Organization (WHO), American Academy of Pediatrics (AAP), and Canadian Pediatric Society (CAP) prescribes certain guidelines for the recommended time and rules concerning screen device exposure for children, confirming the potential negative impact the excess screen time may have on their health. Thus, a mother who maximizes her utility, which is a function of her child's health, by allocating her time and budget to protect her child's health, faces a trade-off due to limited disposable time. On one hand, if she spends most of her time participating in the labor market to earn income, she would have lesser time to spare for preparing home-cooked meals for her child. In this case, she would be forced to choose less time-intensive child-rearing activities like allowing the child to spend time in front of a screen device, thereby potentially weakening the child's health. On the other hand, a mother could spend most of her disposable time preparing healthy meals and participating in more physically engaging activities (high time-intensive) with her children. However, in this scenario, the mother would have lesser time to work, and in turn, fewer resources that could be spent to improve the health of her child. In this sense, the screen time of children can be understood as a proportion of the mothers' leisure time. This trade-off experienced by the mother is

embedded in the theoretical model wherein she must make discrete choices about the allocation of her time for three different child-rearing activities: labor supply, preparing high-quality meals, and letting her child spend time with screen devices.

Another obstacle that impedes the estimation of the effect of screen time on children's weight within a dynamic structural framework lies in the fact that estimating a structural parameter is computationally burdensome due to the large dimension of choice sets, state spaces, and covariates. To overcome this problem rather than fully solving the system, the decision rule of mothers is approximated and jointly estimated with their child's health production function and her wage determination simultaneously, in line with the study by Bernal and Keane (2010).

3.2.2 Maternal Decision

To assess the effect of children's screen time on their weight, I first model a mother's dynamic decision to allocate her time and budget based on economic theory. In line with the seminal work of Grossman (1972), a mother produces a household good, her child's health (B), and gets utility from it. Also, she makes decisions on three different activities related to child upbringing: letting her child watch screen (x), preparing food for her child (n), and supplying resources from labor (ℓ).

The model is dynamic in the sense that her decisions are a function of previous decisions. As the medical literature stresses, obesity is not just affected by contemporaneous diet and level of physical activity, but a consequence of a stock of calorie intakes and expenditures over a period of time. Furthermore, there could be a possible habitual or addictive behavior on the demand for screen time and quality of nutrition, and a stickiness in supplying labor. To incorporate these, previous decisions of screen time, nutrition, and maternal labor supply enter the health production function, as well as the utility function of the mother. Besides the health production function and time and money constraints, she also faces wage equation (W) in determining the level of labor to supply. Wage is important in a mother's decision as it serves as the opportunity cost of time.

A timing of each decisions and outcomes are assumed such that first, a mother enters the beginning of the time period t with information set Ω_t, which includes the past history of decisions on screen time, nutrition and labor supply, and exogenous characteristics of the mother and child. Ω_t also includes previous obesity status, B_{t-1}, current period wage rate W_t, exogenous demographic characteristics R_t, and Z_t. Z_t is a vector of exogenous identification variables. She makes simultaneous decisions on the level of screen time for her child (x_t),

the quality of food for her child (n_t) and the level of labor market participation (ℓ_t). Also, at this point, the obesity status for time period t is also determined. At the end of each period, the mother's next period wage W_t is updated, based on labor supply decisions of period t and other determinants. This timing assumption also serves as one of identification strategies, which will be further discussed in next section.

I implicitly assume that a mother's demand for leisure is proportional to the child's screen time. The mother faces a trade-off where, on one side, she can participate in the labor market and earn income to be used in producing her child's good health, i.e. staying in the normal range of weight. At the same time, however, her disposable time is limited so she would have less time to spend preparing quality food and also may opt to let her child watch more screen devices, both of which could lead to adverse health issues in her child. The child's health is measured in terms of his/her weight status, and the level of screen time and the quality of nutrition goes into the health production function as the input.

I model a mother's decision on the level of labor supply as a discrete choice, either she work full-time ($\ell = 2$), part-time ($\ell = 1$), or does not work ($\ell = 0$)[3]. She also choose the daily hours of screen time she's allowing to her children, x_t, and the level of the quality of food she prepares for her children.

Formally, as described in the timing assumption, the mother solves an inter-temporal dynamic utility maximization problem, in which the contemporaneous utility subject to a budget constraint and time constraint is given as:

$$\begin{aligned} \max_{x_t, n_t, \ell_t} U_t = U(x_t, n_t, \ell_t | \Omega_t, R_t) + \mu(x_t, n_t, \ell_t)^k + \epsilon_t^{xn\ell} = \overline{U} + \epsilon_t^{xn\ell} \\ \text{s.t} \quad f^m(x_t, n_t, \ell_t) = W_t \ell_t + Y_t \\ f^t(x_t, n_t, \ell_t) + \ell_t = \overline{T} \end{aligned} \tag{3.1}$$

where $\epsilon_t^{xn\ell}$ is a decision-specific independently and identically distributed error that follows type 1 Extreme value distribution. $\mu(x_t, n_t, \ell_t)^k$ is an individual unobserved heterogeneity of type k, which will be explained in detail in section 3.4.1. $f^m(\cdot)$, and $f^t(\cdot)$ are functions for total money cost and time cost associated with the maternal decisions $\{x_t, n_t, \ell_t\}$. Y_t is an exogenous income of the mother and $\overline{T}$ is a total disposable time of the mother. Solving this dynamic problem would lead to a value function of choosing $\{x, n, \ell\}$:

$$V^{xn\ell}(x_{t-1}, n_{t-1}, \ell_{t-1}, B_{t-1}, W_{t-1}, \Omega_t, R_t, Z_t; x_t = x, n_t = n, \ell_t = \ell) \tag{3.2}$$

[3]Labor supply enters the model through two binary variables p_t and f_t, which stands for working part-time and working full-time, respectively.

Fully solving the mother's optimization problem in equation (3.1) requires calculation of a value function at every point in the state spaces, which makes estimation of structural parameters computationally burdensome, considering a large set of alternatives and state spaces. A full solution also inevitably requires additional assumptions. For instance, one needs to fully specify the process of how an individual forms expectation on the future utility. One can assume perfect foresight, or myopia, or a rational expectation. Additionally, fertility decision and the problem of multiple children are ignored in the structural model since it requires specification on how maternal time is allocated among them. This problem can be simply dealt with by adding the number of children in the model and their interaction term to other variables.

Following Yang et al. (2009), Bernal and Keane (2010), and Darden et al. (2021), instead of fully-solving the structural model, the value function (3.2) is approximated using second-order Taylor expansion as a function of its arguments. The approximated decision rule is in linear form of all the state variables, since the envelope theorem eliminates the derivatives of value function. Alternative-specific error term ($\epsilon_t^{xn\ell}$) is independent across each decision, which enables us to separate the joint decision rules into each single decision of screen time, quality of nutrition, and labor supply, and the correlation between those decisions are modelled through the unobserved heterogeneity. The approximated solution, which are a set of a maternal demand function for the level of screen time, the quality of nutrition, and the labor supply function, takes form of

$$\begin{aligned} x_t &= f^x(x_{t-1}, n_{t-1}, \ell_{t-1}, B_{t-1}, W_{t-1}, \Omega_t, R_t, Z_t) + \mu^x + \varepsilon_t^x \\ n_t &= f^n(x_{t-1}, n_{t-1}, \ell_{t-1}, B_{t-1}, W_{t-1}, \Omega_t, R_t, Z_t) + \mu^n + \varepsilon_t^x \\ \ln\left[\frac{\ell_t = \ell}{\ell_t = 0}\right] &= f^\ell(x_{t-1}, n_{t-1}, \ell_{t-1}, B_{t-1}, W_{t-1}, \Omega_t, R_t, Z_t) + \mu^\ell, \quad \ell = 1,2 \end{aligned} \tag{3.3}$$

Specifically, the demand for daily screen time for children is:

$$\begin{aligned} x_t =& \delta_0^x + \delta_1^x B_{t-1} + \delta_2^x x_{t-1} + \delta_3^x n_{t-1} + \delta_4^x p_{t-1} + \delta_5^x f_{t-1} + \delta_6^x \text{age} + \delta_7^x \text{age}^2 \\ &+ \delta_8^x \text{age}^C + \delta_9^x \text{gender} + \delta_{10}^x \text{father} + \delta_{11}^{\text{Nsib}} + \delta_{12}^x \text{Nyounger} + \delta_{13}^x \text{black} + \delta_{14}^x \text{hispanic} \\ &+ \delta_{15}^x \text{educ} + \delta_{16}^x \text{condition} + \delta_{17}^x \text{school} + \delta_{18}^x \text{famincome} + \delta_{19}^x \text{sleep} \\ &+ \delta_{20}^x \text{impulse} + \delta_{21}^x \text{stress} + \delta_{22}^x \text{depression} + \delta_{23}^x Z_t^x + \mu^x + \varepsilon_t^x \end{aligned} \tag{3.4}$$

The level of screen time depends on the child's obesity level since there could be a correlation between the obesity and screen time such that if the child is overweight or obese,

he/she could avoid engaging in vigorous activities and prefer more sedentary activities, such as watching videos or playing games. The coefficient δ_2^x captures the possible influence of the lagged screen time on current screen time. The child's daily screen time is also a function of past nutrition quality and maternal labor supply. A set of factors, which captures the opportunity cost of time the mother faces during her non-wage-earning times (the age of mother, the square of the age of mother, the presence of the child's biological father, the number of sibling, the number of younger sibling, race, years of education, whether the child has chronic health condition, and whether the child goes to middle school) also have an impact on children's screen time. Other demographic variables, such as age and gender of the child, family income, and the test scores of impulsiveness of the child (as to control for the degree of the child's deviation from maternal decisions), are included in the regression. As discussed in the earlier section, a binary variable for whether the child gets enough sleep, the stress level of the child, and whether the child suffers from the depression are also assumed to be correlated with the level of screen time of the child. Z_t^x, which is a subset of Z_t, is a vector of exogenous variables for the exclusion restriction and μ^x is the unobserved heterogeneity of the mother-child pair. The error term ε_t^x follows iid standard Normal distribution.

Next, I specify the demand for the quality of nutrition the mother prepares for her children as:

$$\begin{aligned} n_t =& \delta_0^n + \delta_1^n B_{t-1} + \delta_2^n x_{t-1} + \delta_3^n n_{t-1} + \delta_4^n p_{t-1} + \delta_5^n f_{t-1} + \delta_6^n \text{age} + \delta_7^n \text{age}^2 + \delta_8^n \text{age}^C \\ &+ \delta_9^n \text{gender} + \delta_{10}^n \text{father} + \delta_{11}^n \text{Nsib} + \delta_{12}^n \text{Nyounger} + \delta_{13}^n \text{black} + \delta_{14}^n \text{hispanic} + \delta_{15}^n \text{educ} \\ &+ \delta_{16}^n \text{condition} + \delta_{17}^n \text{school} + \delta_{18}^n \text{famincome} + \delta_{19}^n \text{impulse} + \delta_{20}^n Z_t^N + \mu^n + \epsilon_t^n \end{aligned} \tag{3.5}$$

where Z_t^n is the vector of exogenous, identifying variables and μ^n captures permanent, unobserved heterogeneity for each individual family that affects nutritional decisions of the mother. I assume that the quality of meal is positively correlated with maternal time spent on cooking and grocery shopping, so higher quality means higher time input. This leads to where the opportunity cost of time serves as the price of this decision, and it is, again, captured by factors such as the mother's age, maternal education, and so on. The effect of the number of children (as the number of siblings) and the number of younger siblings is undetermined a priori because these can affect the mother's decision in both directions; if the mother has many children, and especially if they are young, then she would not have enough time to consciously provide nutrition to them. However, it is also possible that the

marginal effort of preparing a quality meal decreases with the number of children to serve. It could also be the case that the mother focuses more effort on feeding younger children. The error term is assumed to be iid and follows standard Normal distribution.

The last decision the mother makes is her level of labor supply. She could choose to either work full-time, part-time, or not to work at all. The multinomial logit probability of working full-time and part-time compared to not working is that:

$$\begin{aligned}\ln\left[\frac{Pr(\ell_t=\ell)}{Pr(\ell_t=0)}\right]=&\delta_0^\ell+\delta_1^\ell B_{t-1}+\delta_2^\ell x_{t-1}+\delta_3^\ell n_{t-1}+\delta_4^\ell p_{t-1}+\delta_5^\ell f_{t-1}+\delta_6^\ell E_{t-1}+\delta_7^\ell \text{age}+\delta_8^\ell \text{age}^2\\&+\delta_9^\ell \text{age}^C+\delta_{10}^\ell \text{gender}+\delta_{11}^\ell \text{father}+\delta_{12}^\ell \text{Nsib}+\delta_{13}^\ell \text{Nyounger}+\delta_{14}^\ell \text{black}\\&+\delta_{15}^\ell \text{hispanic}+\delta_{16}^\ell \text{educ}+\delta_{17}^\ell \text{condition}+\delta_{18}^\ell \text{school}+\delta_{19}^\ell \text{famincome}\\&+\mu^\ell;\quad \ell=1,2\end{aligned} \tag{3.6}$$

Her decision on labor supply is a function of the determinants of her opportunity costs of time, and the family income. Also, the current labor supply depends on the previous labor supply to capture any adjustment costs, as well as her cumulative work experience and her decision on the screen time and the nutrition of her child. The presence of a father could affect a mother's decision to work in the opposite direction, such that the mother does not have to work if her partner earns enough money to cover the living expenses. Conversely, it could be the case that she has paternal support for the care of her children and continues her career. Finally, the coefficients for her child's obesity status and obese-related chronic health condition capture the mother's hesitance to work due to the adverse health concern for her child. Again, the unobserved heterogeneity that affects maternal labor supply decisions is included.

Simultaneously with these decisions, the health, which is the obesity status, is produced for period t such that the logit probability of the child getting overweight or obese in log odd is:

$$\begin{aligned}\ln\left[\frac{Pr(B_t=1)}{Pr(B_t=0)}\right]=&\beta_0+\beta_1 B_{t-1}+\beta_2 x_{t-1}+\beta_3 n_{t-1}+\beta_4 p_{t-1}+\beta_5 f_{t-1}+\beta_6 \text{gender}+\beta_7 \text{age}^C\\&+\beta_8 \text{famincome}+\beta_9 \text{father}+\beta_{10} \text{school}+\beta_{11} \text{Nsib}+\beta_{12} \text{black}\\&+\beta_{13} \text{hispanic}+\beta_{14} \text{educ}+\beta_{15} \text{condition}+\beta_{16} \text{stress}+\beta_{17} \text{depression}\\&+\beta_{18} \text{sleep}+\beta_{19} \text{breastfeed}+\beta_{20} Z_t^B+\mu^b\end{aligned} \tag{3.7}$$

Here, B_t and B_{t-1} are binary variables indicating overweight or obesity in period t and $t-1$.

Past health and maternal choices determine the children's health in the subsequent period through a health production function, to account for contemporaneous and lagged effect of the environment around the child. Other demographic variables of child and family environment such as age, gender, race, family income, presence of a biological father in the household, and whether the child has obesity-related chronic health conditions were also controlled. Whether the child goes to middle school or elementary school is included to capture different physical activity levels and physical education curriculum in the school environment. As discussed before, correlations between sleep deprivation, breastfeeding history, and the level of stress and depression can be captured in this specification. Z_t^B is included for the exclusion restriction and μ^b controls for permanent, unobserved heterogeneity that affect the odds of the child getting overweight or obese, such as genetics. Finally, after the mother makes the decisions and the health of children is produced, the wage equation is updated at the end of each period. For wage, I implicitly divided wage equation into two parts: a base wage part which is comprised as those factors (that were mentioned previously) which captures the opportunity cost of time of the mother, and the additional part that is related to maternal employment history. The base wage is a function of the mother's age and the squared mother's age, to capture movement along the life-cycle wage path, and age of child, number of siblings the child has, the number of younger siblings the child has, to capture her trade-off between child-rearing and potential inefficiency in her work due to taking care of young and/or multiple children. Similarly, the health condition of the child could lead to potential decreased work efficiency and/or frequent absences due to hospital visits, etc, and thus affects base wage.

Even though wage is not observed for an unemployed mother, the opportunity cost of time should be different across unemployed mothers, depending on their characteristics such as education and the number of children. By including base wage variables in a mother's decision model, they can capture different opportunity costs vary across mothers.

The observed log of wage at the end of period t, W_{t+1} is given as:

$$\begin{aligned}\ln W_{t+1} = {} & \alpha_0 + \alpha_1 f_t + \alpha_2 p_{t-1} + \alpha_3 f_{t-1} + \alpha_4 E_t + \alpha_5 \text{age}^C + \alpha_6 \text{age} + \alpha_7 \text{age}^2 + \alpha_8 \text{Nsib} \\ & + \alpha_9 \text{Nyounger} + \alpha_{10} \text{condition} + \alpha_{11} \text{hispanic} + \alpha_{12} \text{black} + \alpha_{13} \text{educ} \\ & + \alpha_{14} \text{father} + \alpha_{15} Z_t^W + \mu^w + \varepsilon_t^w\end{aligned} \tag{3.8}$$

where p_{t-1} and f_{t-1} are binary indicators for working full-time and part-time in the previous period and E_t is the cumulative work experience variable, $E_t = \sum_{g=0}^{t} \ell_g$. For current period employment, p_t is excluded from the model to avoid perfect multicollinearity since

wage is only observed for either part-time or full-time working mother. μ^w is unobserved, permanent heterogeneity of the mother-child pair. Identifying, exogenous variables Z_t^W that shifts the demand side of the labor market are included for the exclusion restriction, along with the unobserved heterogeneity. The idiosyncratic error ε_t is assumed to be i.i.d. $\varepsilon_t^w \sim N(0,1)$.

3.3 Data

The estimation of the model is carried out using Adolescent Brain Cognitive Development (ABCD) data from the National Institute of Mental Health. ABCD data is very recent, longitudinal data, with the first wave starting in 2016-2017. Using 21 study sites around the United States, data was collected on brain maturation in the context of social, emotional, and cognitive, as well as various health and environmental outcomes of the children. The ages of the sample children in ABCD range between 9 and 12 years in the first wave of interviews. ABCD data consists of surveys and interviews with children and their caregivers, Magnetic Resonance Imaging (MRI) images of children's brains, and task-based experiment results. The surveys and interviews with the sample children and their caregivers documented their medical, socioeconomic, and demographic information of the parents and family. This information includes family income and education, size of the household, marital status of parents, labor force participation, physical and mental health condition and medical history, and test score on parents' social abilities. It also includes behavioral information of the child and their caregivers, such as number of hours of screen time, daily nutrition and food, hours of sleep, substance use, physical activities, and various test scores on the child's impulsiveness, pro-social behavior, cognitive development, etc. Since the main object of ABCD are the children, their family are not given individual identification and siblings are not identified in this data.

Table 3.1 presents the empirical distribution of sample participation in ABCD data. In its initial wave, a total of 11,878 children and their caregivers were interviewed, and the latest release is the third wave. A total of 6,415 children and their parents completed all three waves of interviews, which is about half of the initial samples.

The exclusion criteria and the resulting number of children is illustrated in Table 3.2. First, as described in the previous section, this study focuses on maternal behavior. Thus, those who indicated that the primary care giver (and thus the interviewee) is not a biological mother are dropped from the sample. A total of 246 child-mother pairs have missing

information on the decision on screen time, food, and labor supply, as well as weight status. Finally, an additional 921 samples of pairs are excluded since their core exogenous variable and identifying variables are missing. The final number of samples is 4,223 mother-child pairs.

The weight status of the children is measured using Body Mass Index (BMI), which is a commonly used to measure adiposity. Children's weight status is different from the adult BMI category, since children's body composition varies by their age and gender. According to the Center for Disease Control and Prevention (CDC), overweight is defined as an age- and gender-specific BMI greater than the 85% percentile and less than the 95% percentile, while obesity is greater than the 95% percentile. In this study, a dichotomous variable B_t equals 1 if the child's age- and gender-specific BMI is greater than the 85% percentile, i.e. if the child is overweight or obese.

As the measure for the decision on the level of screen time, children in the sample were asked for the number of hours they spend on different screen-based activities on typical weekdays, such as watching television, videos, playing games, using Social Network Service (SNS), video chatting, and surfing the internet. Daily weekday screen time is then constructed as a sum of all screen time across different media.

The quality of nutrition is measured based on nutritional survey questions on their daily food intake. They were asked a series of questions as to whether they eat (or do not eat) a certain food to the desired amount. These nutritional survey questions are converted to a nutritional index that ranges from 0 to 9, depending on the number of positive answers from the mother to each of the nine questions[4]. These nine questions are whether their children eat: vegetables six or more times per week, red meats and meat products less than 4 times per week, fish 1 or more time per week, poultry 2 or more times per week, fast food or fried food less than 1 time per week, butter or margarine is used less than 1 Tablespoon per day, pastries or sweets less than 5 times per week, olive oil is used as the primary oil, soft drinks less than 3 per week.

Maternal labor decision is a categorical variable in which 0 indicates she does not work for money, 1 for part-time working and 2 for full-time working. Her hourly wage rate is her weekly income (annual income divided by 52 weeks) divided by her weekly working hours: 20 hours for part-time employees and 40 hours for full-time employees, following the argument from Keane and Moffitt (1998) that weekly hours are very concentrated at 20 and 40 per week, and much of the deviations are likely due to the measurement error.

[4]Originally, the survey asked a total of 13 questions but 4 of them were excluded since they were not comparable to the questions from Wave 3.

Finally, cumulative work experience variable is defined as the sum of annual working hours, $E_t = \sum_{g=0}^{t} 1000 \cdot p_g$, based on annual working hours of 1,000 hours for the part-time employees and 2,000 hours for the full-time employees. Notice that since work force participation decision in Wave 1 is available, the cumulative work experience is counted from the Wave 1.

Table 3.3 presents the summary statistics of the endogenous variables, the predetermined variables and the exogenous variables in the model. Exogenous variables included in the models are mainly the mother's demographic characteristics that capture her base wage level, which proxies for her opportunity cost of time. They are: mother's age, the square of mother's age, race, whether the child is living with his/her biological father, number of children[5](as a number of siblings of the child), number of younger siblings (younger than the sample child), and years of education. Also, whether the child has an obesity-related chronic condition is included such as asthma, diabetes, hypertension and heart problems. Binary variables for whether the child is in middle school or elementary school, whether the child sleeps more than 7 hours and whether the child has an obesity-related, chronic, health condition are also included.

One benefit of employing ABCD data is that it has a variety of test scores on children's psychology and emotions. Five test scores for UPPS-P Impulsive Behavior Scale[6] are included for the child's impulsiveness, which control for the child's deviation from their mother's decisions. As numerous studies emphasize the role of stress and depression in obesity, a measure for the level of stress is constructed as the number of negative life events[7] occurring in the past year such as the death or illness of family, parents' separation, moving to a new school, or financial stress in the family, etc. For depression, a binary indicator variable indicates whether a child has symptoms, or is diagnosed depression was used. Finally, relevant exogenous variables were included in each equation for the identification purpose. Detailed description can be found in section 3.4.2. The average daily screen time, as shown in Table 3.3, is 4.60 hours for all sample, whereas 5.01 hours for boys and 4.15

[5]The fertility decision, and the mother's own education decision were ignored so variables related to these are treated as exogenous.

[6]Negative urgency: tendency to act rashly under extreme negative emotions; Lack of premeditation: tendency to act without thinking; Sensational seeking: tendency to seek out novel and thrilling experiences; Lack of perseverance: inability to remain focused on a task; Positive urgency: tendency to act rashly under extreme positive emotions.

[7]death, serious injury of family member or close friend, saw crime or accident, lost close friend, parent arrested, went to jail or having trouble with the law, parent lost job, parent have negative financial changes, parent argues more often or separated, family member have drug/alcohol problem, moved to new place, went to new school, had new step-parent

hours for girls. On average, boys and girls are almost equally likely to be overweight or obesity. Noticeable difference between gender is that the test scores for impulsiveness are all higher in boys that in girls.

3.4 Estimation and Empirical Specification

3.4.1 Unobservable heterogeneity

It is important to account for individual heterogeneity, which can sometimes be unobserved. Unobservable heterogeneity in each equation in the model are highly likely to be correlated. For instance, some mothers care more about their children's body weight and the overall health, and therefore their children could be less likely to be overweight or obese. At the same time, these parents could be strict on their children's screen time, more cautious on what their children eat, and are more attentive to their daily level of activities. Thus, handling this heterogeneity could be a remedy to a potential selection bias as discussed before.

I take a semi-parametric approach by decomposing error structure into a permanent part (μ), which does not have any distributional assumption, and idiosyncratic error terms in each equation, which is assumed to follow parametric distribution. This approach is often called Discrete Factor Random Effect (DFRE) method. DFRE method does not require restrictive distributional assumptions on the unobserved heterogeneity, which could sometimes lead to an over-parameterization problem. Mroz (1999) finds that when the true errors across the equations in the model are not distributed in joint normal, the DFRE outperforms maximum likelihood method with the parametric distributional assumptions using a Monte Carlo simulation[8].

Instead, the DFRE method allows the distribution of unobserved heterogeneity to be approximated by a discrete step-wise function (Heckman and Singer (1984)). Suppose the empirical distribution of unobserved heterogeneity has three mass points. The DFRE method implies that a mother-child pair belongs to one of these three "type" that jointly characterize their heterogeneity in each equation. For example, if type-1 group of mothers have higher aversion to overweight or obese children, this group would have a negative unobserved heterogeneity term, $\mu_1^b < 0$, in health production function and positive for the nutrition decision, $\mu_1^n > 0$. There are a total K number of mass points in the distribution,

[8]When the true errors are joint normally distributed, the DFRE estimation are also comparable to the estimates that are from the correct distribution

where K is determined empirically. I choose K to be three because increasing K does not improve the model fit, following "Upward-testing" approach discussed in Mroz (1999). This method has been used in a wide variety of empirical applications (Yang et al. (2009); Cronin (2019); Darden et al. (2021)).

This approach saves us from the need for numerical or stochastic integration in the estimation procedure, which can sometimes be computationally burdensome and time-consuming. Instead, only summation of the discrete mass points of support is required. In addition to the computational convenience and minimization of possible estimation bias, the DFRE method fits more to the data structure used in this study. Compared to the regular fixed effect, which is a typical way to deal with this type of unobserved heterogeneity in the panel data, there is no need for estimation of $N-1$ additional parameters, where N is the number of individuals in the data. ABCD data is fairly recent data and individuals are followed for a short period of time. Considering N being around 5,000, the DFRE approach would minimize potential estimation bias arising from the structure of the data.

All unobserved heterogeneity mass points, $\mu_k = \{\mu_k^b, \mu_k^x, \mu_k^n, \mu_k^p, \mu_k^f, \mu_k^w\}, k = 1,\ldots,3$, along with the probability of an individual falls into each type, $\eta_k, k = 1,\ldots,3$ are estimated in the model jointly with other parameters in the equations. I maximize the likelihood function with respect to parameters in the behavioral decisions, health production functions and wage equation, and the distribution of unobserved heterogeneity. The likelihood function is given as

$$
\begin{aligned}
L = \prod_{i=1}^{I}\prod_{t=1}^{T}\Bigg[\sum_{k=1}^{K}\eta_k\Bigg\{\prod_{b=0}^{1} Pr(B_{it}=b|\mu_k^b)^{1(B_{it}=b)}\cdot\phi(x_{it}-\hat{x}_{it}|\mu_k^x) \\
\cdot\phi(n_{it}-\hat{n}_{it}|\mu_k^n)\cdot Pr(\ell_{it}=0|\mu_k^p,\mu_k^f)^{1(\ell_{it}=0)} \\
\cdot\prod_{\ell=1}^{2}\Big[Pr(\ell_{it}=\ell|\mu_k^p,\mu_k^f)\cdot\phi(\ln W_{it}-(\ln\hat{W}_{it}|\mu_k^w))\Big]^{1(\ell_{it}=\ell)}\Bigg\}\Bigg]
\end{aligned}
\tag{3.9}
$$

where unobserved μ is integrated out based on its discrete empirical distribution and $\phi(\cdot)$ is pdf of a normal distribution.

3.4.2 Identification

According to the arguments of Bhargava and Sargan (1983) and Arellano and Bond (1991), the estimation of dynamic system of equations using panel data requires exogeneity for a subset of explanatory variable conditioned on individual unobserved heterogeneity. In

theory, the mother's joint decision rule for labor supply, screen time, and nutrition should be a function of all the state variables in the structural model. On the other hand, wage determination and the health production process only depend on a subset of those state variables. Thus, the structural framework described above delivers exclusion restriction to identify the parameters in the model. Table 3.4 depicts the exclusion restriction in each equation.

The two additional sources of identification in this model are the inclusion of theoretically relevant, exogenous variables in each equation and the timing assumption. As seen in the bottom part of Table 3.4, identifying exogenous variables, which are elements of $\{Z_t^B, Z_t^X, Z_t^N, Z_t^\ell\} \in Z_t$, are included in each equation. The child's weight at the time of birth is a proxy for their initial health condition, which can affect obesity later on. The hours of physical activities while the child is in school also affects the likelihood of the child getting obese. These two variables do not have direct effects on other maternal decisions and wage formation, but it affects the health production of the child. The child with more social network service (SNS) accounts is likely to spend more time using screen devices. However, this does not affect other maternal decisions, health production function, and the mother's wage. From the demand side of the labor market, national average wage is somewhat likely to serve as a pressure-point when the firm determines the wage except for extreme urban or rural markets, due to the presence of union, regulations, etc. On the other hand, from the supply side, even if there's a discrepancy between the local wage of each individual and the national average wage, the individual would have to bear the cost of relocation so this will less likely affect labor supply decisions. Finally, some mothers who have better knowledge of dieting and who maintain a healthy weight are more likely to provide high quality nutrition to their children. Indicators that the mother or father of a child work at an occupation that is likely to be familiar with nutritional information(e.g., dietitian, nutritionist, health educator, working in the food-related industry, and healthcare providers) was used to proxy for this extra knowledge on nutrition.

Also, because of the timing assumption, parameters in two different equations can be identified through variables from different time periods. For example, labor supply decision and wage equation process both depend on the cumulative work experience of a mother. However, current period labor supply decision depends on E_{t-1}, which is the experience up to the previous period. Meanwhile, wage equation is updated after the current period decision is made, thus becoming a function of E_t.

3.5 Results and Discussion

This section presents the estimation results of two models: the individual model, where each equation is estimated separately without the unobserved heterogeneity parameter; and the preferred model (main model) wherein all equations are allowed to be correlated and estimated jointly, in addition to the unobserved heterogeneity.

3.5.1 Parameter estimation

Table 3.5-3.9 presents parameter estimations for health production, maternal decisions, and wage equation. Although the interpretation of the total effects of screen time on child obesity is challenging to carry out, the signs of such parameters shall remain useful. First, in the health production function of children's obesity (as presented in Table 5), most of the coefficients have expected signs across both models. For instance, both current and previous high amounts of screen time are associated with a higher probability of a child developing obesity. This finding is in line with many previous studies, including Hancox and Poulton (2005), and Chang and Nayga (2009). On the other hand, children with higher-quality diets have a lower tendency to be outside of the healthy weight range. Furthermore, children with full-time working mothers are more likely to be overweight or obese, in line with the previous results of a study by von Hinke Kessler Scholder (2008), who found that while the full-time employment of mothers of seven-year-old children was associated with an increased risk of obesity among their children, this association was absent among part-time working mothers.

Furthermore, obesity in children is far more prevalent in families with lower incomes, families with a black or Hispanic ethnicity, and among single-mother families.Income is found to be one potential contributor that is presumed to be relevant, although there has been no consistent evidence that family income is associated with children's obesity (Cawley (2010)). Finally, and consistent with previous findings, the amount of sleep is negatively correlated (Van Cauter and Knutson (2008), Hart et al. (2011), Nielsen et al. (2011)), and depression is positively correlated (Reeves et al. (2008), Puder and Munsch (2010), Gundersen et al. (2011)), with obesity.

In Table 3.5, one may observe a significant efficiency gain in the main model as compared to the individual model. This is another advantage of the estimating system that considers equations jointly that has been noted in other works of similar literature as well (Bernal and Keane (2010)), because a residual in one equation conveys information about

the mother's unobserved characteristics, which are then correlated to the residual in other equations within the system.

From Table 3.6, we see that a mother's cumulative work experience and work history in the previous period is positively correlated with the maternal wages. Furthermore, the table shows that education tends to increase earnings and, that on average, black and Hispanic mothers tend to earn less.

In the context of screen time (See Table 3.7), children who are obese or overweight tend to have a higher exposure to screen time, confirming the possible reverse causality problem that has been identified in previous studies based on a reduced-form model of obesity on screen time. Additionally, the coefficient of the previous period of screen time is positive and statistically significant, implying that screen time decisions of mothers have habitual characteristics. In fact, television viewing, surfing the internet, and video gaming are consistently found to be addictive among children and adolescents (Fisher (1994), Chiu et al. (2004)). Furthermore, higher nutrition quality is negatively correlated with screen time of children, and mothers who work full-time are more likely to have children that engage in longer durations of screen time. Mothers of boys, older children, black and Hispanic mothers, and those with low family income tend to let their children spend more time in front of screens. If a child is raised by a single mother, it follows that a mother will have less financial support to raise her children. Thus, she would sacrifice more of her parental time to earn a wage. This encourages mothers to allow heavy periods of screen usage time, so that their own time may be used for resting, leisure, household chores, and so on.

As presented in Table 3.8, several factors are associated with the provision of a healthy and balanced diet for children, which demands both time and money. Mothers with overweight or obese children are more likely to provide healthier nutrition to their children, which is somewhat counter-intuitive. This can be explained by their concern regarding their children's obesity and the conscious desire to provide them with a healthy diet. Furthermore, mothers who are employed for longer work hours and who permit heavier screen usage time among their children tend to provide lower quality meals. This is consistent with the finding from Chang and Nayga (2009), which notes a significant positive correlation between television viewing time and fast-food consumption. Taveras et al. (2006) also found that for each extra hour for television and video watched per day, the odds ratio for consuming fast food per week was 1.60. While higher-income mothers are more likely to provide high-quality meals, mothers caring for a greater number of children tend to provide lower-quality meals.

The final factor examined in the study is the labor status of the mother. Mothers with

greater cumulative work experience tend to work more. Also, mothers who allow their children to watch online videos and frequently use smartphones tend to work more. Among mothers, education is positively correlated with the tendency to work. The more children the mother has, the less likely she is to work a full-time job. Additionally, if the mother rears younger child, she is more likely to work.

In addition to the parameters in the health production function, wage equation, and approximated maternal decision rules, a set of parameters representing the unobserved heterogeneity and the probability of individuals belonging to a certain type has been presented in Table 3.10. According to the table, mothers in Type 3 are more likely to raise a child within a healthy weight range ($\mu_3^b = -0.021$), restrict their children's screen time ($\mu_3^x = -0.050$), and provide higher quality nutrition ($\mu_3^n = 0.048$). These mothers are also less likely to work full-time ($\mu_3^f = -0.012$) and earn a higher wage rate ($\mu_3^w = 0.060$). This serves as further evidence in support of the findings of Chang and Nayga (2009) and Taveras et al. (2006); children's screen time is correlated with their diet, and with maternal labor decisions. These results demonstrate the importance of accounting for unobserved heterogeneity.

3.5.2 Simulation

Considering the dynamics and complexity of the jointly estimated model, the effect of children's screen time on their obesity can best be viewed through simulation. Formally, I endowed each child-mother pair in the sample with a complete set of idiosyncratic error draws and a set of draws from their unobserved heterogeneity "type" distributions[9]. Using these draws, I simulated forward the maternal decisions, the health outcomes of children, and the wages of the mother by updating relevant state-spaces. Another benefit to simulations is that the method is convenient for interpreting biases that stem from endogeneity and unobserved heterogeneity.

In terms of the simulation horizon, it is important to note that the data used in the main estimation is one period deep as the decision rule for x_t, n_t, and ℓ_t requires x_{t-1}, n_{t-1}, and ℓ_{t-1}. Similarly, the health production function, which is updated at the end of period t, considers not only x_t, n_w, ℓ_t, but also those maternal decisions one period before, $x_{t-1}, n_{t-1}, \ell_{t-1}$. Thus, two cycles of maternal decisions can be simulated (period $t-1$ and t).

The simulation procedure of a scenario of interest begins with imposing a policy in the maternal decision of period $t-2$. This is followed by a step where the decisions and

[9]The number of draws used in the simulation is 500.

outcomes of preceding period $t-1$ are simulated conditioning on x_{t-2}, along with other exogenous variables. Moving forward to period t, maternal decisions are simulated according to the simulated decisions of period $t-1$, and the health and wage are also updated similarly.

Table 3.11 depicts a model fit of the simulation without imposing any behavioral changes. This is established as the baseline scenario. Based on the comparison between the simulated fraction of mothers who choose heavy screen time, high quality of nutrition, part-time and full-time employment, their children's overweight or obesity, and the mean of the log wage with that of the sample, the simulation predicts decisions and outcomes in close approximation to the original data.

Total marginal effect of screen time

The natural scenario relevant to the main interest of this paper would be one where every child is assigned an additional hour of daily screen time, followed by a comparison with the baseline result, which does not impose any behavioral change. The outcome can be interpreted as the total marginal effect of screen time, which can be found in Table 3.12. As can be observed, if children spend one additional hour in front of the screen per day, the percentage of children who are either overweight or obese after two years will increase from 32.6% to 36.4%.

Although findings from previous studies are mixed in terms of signs, magnitude, and significance of the effect, this result is comparable to papers that outline a positive correlation between children's screen time and their obesity. Cleland et al. (2018) argue that one extra hour per day of television viewing is associated with a BMI increase of 0.41kg/m^2 among a cohort of children between ages 7 and 15 in Australia. Similarly, Danner (2008) found that children who watched four hours per day have a 0.42kg/m^2 higher BMI than those who watched only one hour per day. If the BMI of sample children in this study had gone up to 0.41-0.42kg/m^2, it would be translated into a rise in the percentage of children who are overweight or obese by approximately 35%. However, as suggested at the outset of this study, extant literature addresses the correlation of screen time and children's obesity, without focusing explicitly on the causal relation. Additionally, Nieto and Suhrcke (2021) predicted that one additional hour increase in a week leads to a 1.03% increase in children's baseline BMI. In case this data had been applied to the sample children in this study, it would correspond with 42% of children who are overweight or obese. The results provided by their study are somewhat greater than that of the present study; such a difference may

be attributed to the variation in the time range of the two data sets utilized. While Nieto and Suhrcke (2021) used data from 2008-2012, the present study employs data from 2017-2019. Considering the rapid increase in the percentage of children who are overweight and obese, the baseline BMI of sample children may have been lower in the study by Nieto and Suhrcke (2021).

Furthermore, by comparing main model and individual model result in Table 3.12, one may observe that the effect for the preferred (main) model is greater than that of the individual model. This difference implies a downwards bias in the findings of the previous study. This bias may have occurred because, as emphasized in the introduction, screen time not only affects children's obesity directly but also causes indirect effects such as unhealthier diets and less sleep, which altogether consequently affect children's obesity. These indirect effects cannot be captured in the individual model, while in the preferred model, the unobserved heterogeneity among individuals takes account for this potential "spill-over" effects.

The screen time of children also affects other maternal decisions such as nutrition and labor supply. If the child is allowed to have one additional screen time per day, it will slightly increase the percentage of mothers working full-time, from 56.7% to 57.2%. Based on this statistic, it can be inferred that mothers who permit their children more screen time tend to use their spare time to work rather than preparing healthier meals. This result also concurs with the findings of Cawley and Liu (2012), who posit that an increased maternal labor supply is associated with less time for preparing home-cooked meals, and less time to spend with their children.

Daily screen time restriction

One of the most interesting counterfactual simulations to be explored would be the impact of daily screen time restrictions on the health of children and maternal labor supply. In this section, I consider two counterfactual scenarios that limit children's daily screen time: 1) all children are allowed to have two hours (or less) screen time for each weekday, and 2) a complete ban of screen usage during weekdays.

The American Academy of Pediatrics (AAP) has been recommending 2 hours or less as the desired level of daily screen time for children (Strasburger et al. (2013)). For this scenario, while children who watch screens less than two hours per day maintain their duration of screen time as is, those who exceed the recommendation are forced to have screen time only two hours per day. The second scenario is a close mimic of China's ban

on minors' game-playing hours. In effect since September 2021, the Chinese government has banned minors from playing video games on weekdays. In this scenario, every mother chooses zero screen time across all periods (Liao (2021)).

The results from both scenarios are also presented in Table 3.12. Compared to the percentage of children who are overweight or obese in the sample (32.6%), upon restricting children's screen time, the size of this group drops to 30.3% if AAP recommendation is met (2 hours or less per day), and 28.1% if for the total restriction. Further, upon a comparison of each result with the corresponding findings in the individual model, we observe that the effect of reducing screen time on children's health is greater in the preferred model. This is due to the spillover effect that screen time has on other factors such as diet and sleep, while the positive effect of screen time reduction impacts obesity of children both directly and indirectly.

It is important to note that in both the above scenarios, the percentage of mothers who work full-time decreases from 56.7% to 54.1% in case children's screen time is restricted to less than two hours, and 53.5% if restricted to zero hours. However, the reduction in the individual model is not as significant; implying that models, such as the one employed herein, that allow correlations between different factors associated with children's health production and maternal decisions are certainly useful is certainly useful as they reveal the overlooked consequences of policies and intervention programs to limit children's screen time. As screen time is restricted, mothers are tasked with the responsibility of caring for their children during those additional hours. This result ultimately suggests that there are indeed "no free lunches". Limiting children's screen time decreases their chances of developing obesity - yet, at the same time, mothers must bear the costs of decreased time allocated to labor, and subsequently, their income.

Restriction on Maternal Labor Supply

To further investigate the relationship between maternal labor supply, children's screen time, and their health, the last two simulation scenarios impose behaviors on maternal labor supply, where either none of the mothers work at all, or all work full-time. While these scenarios may appear unrealistic, they are certainly comparable to real-life situations. For instance, if children are living with one of their close non-working family members such as retired grandparents who take care of them, this context would closely resemble the scenario where none of the mothers work. Similarly, in the case of a single mother, they likely work a certain amount of time, potentially a full-time job, to afford the living expenses

for her family.

The results from these simulations are presented in Table 13 as well. As maternal labor supply decreases with all no-work, the percentage of children who are overweight or obese decreases from 32.6% of the baseline result to 31.9%, with a 0.783-hour decrease in children's screen time. On the other hand, if all mothers are forced to work full-time, children tend to watch 0.53 more hours per day, and the percentage of children who are overweight or obese increases to 33.6%. This result is in line with what has been found from Anderson et al. (2003), Morrissey et al. (2011), and Fertig et al. (2009) such that the level of maternal labor supply is positively correlated with children's BMI.

3.6 Conclusion

This research puts forward a theoretical framework to investigate the relationship of children's screen time exposure on their obesity as a resource allocation problem for the mother of the children. In this study, a dynamic model of maternal decision on the level of screen time for her child, quality of nutrition, the level of labor supply for the mother, the health production function for the obesity of her child, and wage equation are jointly estimated, and the errors that dictate the mother's behavior and the resulting outcomes are allowed to be flexibly correlated.

I find that, based on simulated results, the percentage of children who are overweight or obese will increase from 32.6% to 36.4% in two years, if their daily screen time increase by one hour. Furthermore, and relevant to the guideline of AAP on screen time usage for children, and to recent Chinese ban of video games during weekdays for minors, the study finds that the percentage of children overweight or obese is likely to decrease from 32.6% to 30.3% and to 28.1% if their daily screen time is restricted to less than two hours, and to zero hours, respectively. On the other hand, in both scenarios, the percentage of mothers who work full-time decreases from 56.7% to 54.1% in case children's screen time is restricted to less than two hours, and to 53.5% if restricted to zero hours.

This study illustrates the trade-off mothers face in everyday life; a mother could participate in the labor market, and during her time off, she could choose less time-intensive child-rearing activity; i.e., letting her children spend time in front of screen devices. At the same time, however, this could lead to adverse effects on her child's health. If she chooses to stay at home, she could use her extra time preparing high quality meals for her children and may choose to not allow her children to use screen devices alone, but this would ultimately

decrease her income.

Furthermore, the results of this study give us a lesson which can serve as a policy implication; even if the screen time of children is found to cause children's obesity, restricting screen time could lead to a decrease in mothers in the labor force , so long as there is no proper, substitute, child-care activity which is less time-intensive than the use of screen devices.

One notable limitation of this study is that the model suggested here cannot incorporate recent growing trends regarding screen time and maternal employment, especially in the post-pandemic era. The model does not allow for a situation when a mother works from home and lets her children watch screens. Another problem is that screen devices have become essential for school life, as well as, social life of children. It is getting hard to disentangle beneficial impacts of those educational media which increase access to rich learning sources and the developmental and social cost of screen devices. Finally, schools and governments are now developing childhood obesity intervention programs using screen devices. Games that educate children on healthy diet and nutrition, and inspire children to be more active, are gaining more and more evidence of effectiveness (Almonani et al. (2014); Kalarchian et al. (2021); Lu et al. (2012); see Lu et al. (2013) for the systemic review). These would all require a more complicated model.

Table 3.1: Empirical distribution of sample participation in ABCD data

Wave 1	Wave 2	Wave 3	Number of individuals	Percent of sample
X	X	X	6,415	54.01
X	X		4,783	40.26
X		X	137	1.15
Total unique individual			11,878	100

Table 3.2: Working dataset construction

# of obs.	Exclusion criteria
6,415	All three waves completed
5,390	Interviewed by other than the biological mother
5,335	Missing BMI
5,311	Missing labor force participation
5,206	Missing screen time
5,144	Missing wage conditional on working
4,672	Missing core exogenous variables[1]
4,223	Missing exogenous variables for identification[2]

[1] family income, education, number of sibling, number of younger sibling, and the duration of breastfeeding

[2] birth weight, national average wage by occupation, and industry conditional on working

Table 3.3: Descriptive statistics by level of screen time of children

		Total N=4,223	Boy N=2,206	Girl N=2,017
Endogenous variables				
Bt	1(obese or overweight), period t	0.32	0.33	0.30
xt	daily screen time, period t	4.60	5.01	4.15
nt	nutrition quality index, period t	4.94	4.89	4.98
pt	1(work part-time), period t	0.20	0.21	0.19
ft	1(work full-time), period t	0.55	0.55	0.56
lnWt	log hourly wage, period t	3.15	3.14	3.15
Et	cumulative work experience up to t	1.87	1.86	1.88
Predetermined variables				
B(t-1)	1(obese or overweight), period t-1	0.30	0.32	0.29
x(t-1)	daily screen time, period t-1	3.60	3.85	3.32
n(t-1)	nutrition quality index, period t-1	5.09	5.07	5.12
p(t-1)	1(work part-time), period t-1	0.21	0.21	0.20
f(t-1)	1(work full-time), period t-1	0.53	0.52	0.53
Exogenous variables				
age	age of mother (divided by 10)	4.17	4.03	4.22
age^2	age of mother, squared (divided by 10)	17.75	16.67	18.11
age_child	age of child	11.96	11.97	11.95
male	1(the child is male)	0.52	1.00	0.00
father	1(the child living with biological father)	0.67	0.52	0.73
Nsib	number of sibling	1.50	1.38	1.56
Nyounger	number of younger sibling	0.61	0.51	0.66
black	1(mother's race is black)	0.03	0.06	0.01
hispanic	1(mother's race is hispanic)	0.15	0.20	0.12
educ	years of education of mother	17.05	16.18	17.43
condition	1(child have obesity-related chronic condition)	0.28	0.29	0.27
school	1(the child goes to middle school)	0.85	0.85	0.85
famincome	combined family total income (in $1000)	0.12	0.09	0.13
sleep	1(child sleeps more than 7 hours per day)	0.95	0.91	0.97
Impulse$_{nu}$[1]	Impulsivity test score of child (negative urgency)	7.66	7.81	7.49
Impulse$_{lpl}$	Impulsivity test score of child (lack of premeditation)	7.68	7.91	7.41
Impulse$_{ss}$	Impulsivity test score of child (sensational seeking)	9.48	9.80	9.13
Impulse$_{pu}$	Impulsivity test score of child (positive urgency)	7.31	7.60	6.99
Impulse$_{lpe}$	Impulsivity test score of child (lack of perseverance)	6.82	6.90	6.72
stress	number of bad life event happened in the past year	1.55	1.91	1.41
depression	1(child has sympton, or diagnosed to have depression)	0.10	0.14	0.08
Naccount	Number of social media account the child has	2.28	3.65	1.61
breastfeed	Duration of breastfeed (in months)	8.00	6.18	8.77
birthweight	Weight of child at the time of birth (in oz)	6.98	6.96	6.99
activity	Hours of physical activity in school	6.89	7.32	6.43
avewage	Occupation and industry specific average hourly wage (in $)	30.33	27.73	31.44
knowledge	1(parents have food or health related occupation)	0.17	0.18	0.16

[1] Higher score translates into high level of impulsiveness in all five types of test scores.

Table 3.4: Exclusion restrictions in the model

variable	x_t	n_t	ℓ_t	B_t	$\ln W_t$
B_{t-1}	X	X	X	X	
x_{t-1}	X	X	X	X	
n_{t-1}	X	X	X	X	
p_{t-1}	X	X	X	X	X
f_{t-1}	X	X	X	X	X
E_{t-1}			X		
x_t				X	
n_t				X	
p_t				X	
f_t				X	X
E_t					X
age^C	X	X	X	X	X
age	X	X	X		X
age^2	X	X	X		X
gender	X	X	X	X	
famincome	X	X	X	X	
father	X	X	X	X	X
school	X	X	X	X	
Nsib	X	X	X	X	X
Nyounger	X	X	X		X
black	X	X	X	X	X
hispanic	X	X	X	X	X
educ	X	X	X	X	X
sleep	X			X	
condition	X	X	X	X	X
stress	X	X		X	
depression	X	X		X	
Impulse$_{nu}$	X	X			
Impulse$_{lpl}$	X	X			
Impulse$_{ss}$	X	X			
Impulse$_{pu}$	X	X			
Impulse$_{lpe}$	X	X			
breastfeed		X		X	
Z_t^B: birthweight				X	
Z_t^B: activity				X	
Z_t^X: Naccount	X				
Z_t^N: knowledge		X			
Z_t^W: avewage					X

Table 3.5: Parameter Estimation result for health production function

	main model		individual model	
	Coeff.	Std.Err.	Coeff.	Std.Err.
const.	-0.007***	(0.002)	-2.115**	(0.846)
B_{t-1}	3.503***	(0.017)	4.291***	(0.078)
x_{t-1}	0.034***	(0.004)	0.042***	(0.012)
n_{t-1}	-0.030***	(0.016)	-0.045*	(0.027)
p_{t-1}	-0.052***	(0.001)	0.044	(0.113)
f_{t-1}	0.091***	(0.002)	0.037	(0.095)
male	0.045***	(0.001)	0.019	(0.077)
age^C	-0.086***	(0.018)	0.008	(0.070)
income	-0.060***	(0.000)	-1.138*	(0.688)
father	-0.284***	(0.000)	-0.299***	(0.093)
school	-0.049***	(0.001)	-0.230**	(0.116)
Nsib	0.021***	(0.005)	0.014	(0.032)
black	0.046***	(0.000)	0.202	(0.219)
hispanic	0.269***	(0.002)	0.205*	(0.110)
educ	-0.092***	(0.011)	-0.024	(0.019)
condition	0.145***	(0.002)	0.069	(0.084)
stress	0.031***	(0.012)	0.001	(0.025)
depression	0.036***	(0.000)	0.115	(0.125)
sleep	-0.091***	(0.002)	-0.138	(0.119)
breastfeed	-0.015	(0.038)	-0.011**	(0.005)
bweight	0.093***	(0.011)	0.094	(0.026)
activity	-0.006	(0.006)	-0.006**	(0.003)

Table 3.6: Parameter Estimation Results for wage equation

	main model		individual model	
	Coeff.	Std. Err.	Coeff.	Std.Err.
Const.	-3.272***	0.524	-3.447***	0.074
f_t	-0.016	0.040	-0.029	0.055
p_{t-1}	0.512***	0.047	0.724***	0.017
f_{t-1}	0.912***	0.048	1.106***	0.051
E_t	0.222***	0.022	0.378***	0.092
age	1.080***	0.237	1.199***	0.312
age^2	-0.106***	0.028	-0.120	1.334
age^C	0.047***	0.018	0.040	0.892
father	0.019	0.028	0.199	0.151
Nsib	-0.056***	0.012	0.006	0.105
Nyounger	0.012	0.018	-0.017	0.039
black	-0.211***	0.068	-0.241***	0.002
hispanic	-0.032	0.035	-0.119***	0.011
educ	0.120***	0.006	0.139***	1.287
condition	0.005	0.026	0.290***	0.031
avewage	0.012***	0.001	0.012	2.248

Table 3.7: Parameter Estimation Result for maternal decision: screen time

	main model		individual model	
	Coeff.	Std.Err.	Coeff.	Std.Err.
const.	0.284***	(0.010)	4.845***	(0.885)
B_{t-1}	0.247***	(0.009)	0.230***	(0.077)
x_{t-1}	0.466***	(0.017)	0.451***	(0.012)
n_{t-1}-	0.600***	(0.019)	-0.029	(0.024)
p_{t-1}	-0.103***	(0.003)	-0.092	(0.101)
f_{t-1}	0.144***	(0.006)	0.225***	(0.086)
age	0.040	(0.068)	-0.067***	(0.012)
age^2	0.000	(2.595)	0.001***	(0.000)
age^C	0.349***	(0.046)	0.015	(0.070)
male	0.652***	(0.014)	0.718***	(0.070)
father	-0.398***	(0.002)	-0.255***	(0.087)
Nsib	0.065***	(0.006)	0.045	(0.034)
Nyounger	-0.149***	(0.004)	-0.136***	(0.050)
black	0.829***	(0.009)	1.106***	(0.209)
hispanic	0.314***	(0.001)	0.170*	(0.103)
educ	-0.142***	(0.052)	-0.149***	(0.018)
condition	-0.024***	(0.006)	-0.032	(0.077)
school	-0.080***	(0.006)	0.263**	(0.104)
income	-0.467***	(0.011)	-3.537***	(0.609)
sleep	-0.831***	(0.016)	-0.712***	(0.114)
Impulse$_{nu}$	0.032	(0.023)	0.033*	(0.017)
Impulse$_{lpl}$	0.063**	(0.032)	0.057***	(0.018)
Impulse$_{ss}$	-0.025	(0.029)	-0.027*	(0.014)
Impulse$_{pu}$	0.077*	(0.046)	0.065***	(0.016)
Impulse$_{lpe}$	0.064***	(0.024)	0.049***	(0.018)
stress	0.069***	(0.020)	0.064***	(0.023)
depression	0.476***	(0.009)	0.377***	(0.117)
Naccount	0.198***	(0.031)	0.205***	(0.010)

Table 3.8: Parameter Estimation Results for maternal decision: quality of nutrition

	main model		individual model	
	Coeff.	Std. Err.	Coeff.	Std.Err.
const.	0.096***	(0.004)	1.377***	(0.363)
B_{t-1}	0.006***	(0.002)	0.011	(0.032)
x_{t-1}	-0.021***	(0.008)	-0.018***	(0.005)
n_{t-1}	0.524***	(0.019)	0.517***	(0.010)
p_{t-1}	-0.087***	(0.002)	-0.064	(0.042)
f_{t-1}	-0.094***	(0.002)	-0.080**	(0.036)
age	0.061	(0.087)	0.061***	(0.005)
age^2	-0.001	(3.013)	-0.001***	(0.000)
age^C	0.136***	(0.040)	0.040	(0.029)
male	-0.059***	(0.002)	-0.059**	(0.029)
father	0.013***	(0.003)	0.000	(0.036)
Nsib	-0.023***	(0.005)	-0.025***	(0.014)
Nyounger	0.018***	(0.002)	0.021	(0.021)
black	0.125***	(0.002)	0.190**	(0.087)
hispanic	0.222***	(0.004)	0.181***	(0.043)
educ	0.025***	(0.061)	0.009	(0.007)
condition	-0.003***	(0.001)	-0.006	(0.032)
school	-0.218***	(0.004)	-0.112***	(0.043)
income	0.003***	(0.001)	0.181	(0.252)
Impulse$_{nu}$	-0.004	(0.030)	-0.006	(0.007)
Impulse$_{lpl}$	-0.012	(0.029)	-0.013*	(0.008)
Impulse$_{ss}$	0.003	(0.034)	0.004	(0.006)
Impulse$_{pu}$	0.004	(0.033)	0.001	(0.006)
Impulse$_{lpe}$	0.005	(0.029)	0.001	(0.008)
knowledge	0.048***	(0.001)	0.047	(0.038)

Table 3.9: Parameter Estimation Results for maternal decision: labor supply

	main model		individual model	
	Coeff.	Std. Err.	Coeff.	Std.Err.
part-time employment				
Const.	-7.625***	0.002	-7.481***	2.662
B_{t-1}	0.223	0.151	0.164	0.132
x_{t-1}	0.221***	0.001	0.267*	0.153
n_{t-1}	0.155***	0.001	0.006	0.119
p_{t-1}	2.053***	0.011	2.525***	0.197
f_{t-1}	-0.033***	0.002	-0.174	0.344
E_{t-1}	0.525***	0.014	0.493***	0.095
age	1.881***	0.008	1.858	1.158
age^2	-0.219***	0.031	-0.203	0.138
age^C	0.176	0.124	0.132	0.107
male	0.251	0.206	0.020	0.117
father	0.019	0.002	0.028	0.161
Nsib	0.120***	0.023	0.004	0.054
Nyounger	-0.265***	0.004	-0.117	0.082
black	-0.801***	0.001	-0.741*	0.423
hispanic	-0.597***	0.004	-0.346	0.179
educ	0.124***	0.030	0.084***	0.031
condition	-0.198***	0.004	0.085	0.130
school	-0.206***	0.002	-0.285	0.184
famincome	0.954***	0.000	1.031	0.992
full-time employment				
Const.	-9.999***	0.004	-9.705***	2.746
B_{t-1}	0.505	0.403	0.315**	0.138
x_{t-1}	0.225***	0.002	0.383**	0.157
n_{t-1}	-0.017***	0.006	-0.198	0.126
p_{t-1}	0.752***	0.006	0.790***	0.205
f_{t-1}	1.603***	0.002	1.490***	0.279
E_{t-1}	1.374***	0.021	1.175***	0.085
age	1.941***	0.013	1.877	1.195
age^2	-0.245***	0.047	-0.221	0.143
age^C	0.474***	0.047	0.197*	0.113
male	-0.287***	0.003	-0.165	0.124
father	-0.503	0.401	-0.514***	0.159
Nsib	-0.136***	0.019	0.010	0.061
Nyounger	-0.425***	0.007	-0.301***	0.093
black	0.381***	0.001	0.146	0.354
hispanic	-0.023***	0.005	-0.143	0.179
educ	0.146***	0.049	0.118***	0.032
condition	-0.046***	0.001	0.133	0.139
school	-0.311***	0.001	0.069	0.200
famincome	0.548***	0.000	0.668	1.091

Table 3.10: Estimation result of Unobserved heterogeneity parameters

	μ_2	μ_3
Factor loadings		
Overweight or obese, μ^b	0.007*	-0.021***
	(0.004)	(0.000)
Heavy screen time, μ^x	0.002*	-0.051***
	(0.001)	(0.000)
High quality nutrition, μ^n	-0.038	0.048***
	(0.040)	(0.001)
Part-time working, μ^p	-0.002	0.025
	(0.080)	(0.100)
Full-time working, μ^f	0.015*	-0.012***
	(0.008)	(0.000)
Log-wage, μ^w	-0.005	0.060***
	(0.400)	(0.000)
Probability		
${\psi_2}^1$		0.094
		(0.100)
ψ_3		-0.066
		(0.090)

[1] $\eta_2 = \frac{exp(\psi_2)}{1+exp(\psi_2)+exp(\psi_3)}; \eta_3 = \frac{exp(\psi_3)}{1+exp(\psi_2)+exp(\psi_3)}; \eta_1 = 1-\eta_2-\eta_3$

Table 3.11: Model Fit of Simulation

	Sample	Simulated	CI
period t-1			
Overweight or obese, B_{t-1}	0.316	0.316	[0.305,0.327]
screen time, x_{t-1}	3.968	3.966	[3.938,3.995]
nutrition, n_{t-1}	5.244	5.242	[5.211,5.274]
part-time, p_{t-1}	0.198	0.207	[0.198,0.217]
full-time, f_{t-1}	0.544	0.533	[0.526,0.539]
log(wage), $ln W_{t-1}$	3.120	3.116	[3.082,3.150]
period t			
Overweight or obese, B_t	0.324	0.324	[0.312,0.336]
screen time, x_t	5.239	5.233	[5.200,5.267]
nutrition, n_t	4.631	4.631	[4.601,4.661]
part-time, p_t	0.201	0.208	[0.198,0.218]
full-time, f_t	0.565	0.567	[0.559,0.575]
log(wage), $ln W_t$	3.169	3.119	[3.084,3.155]

Table 3.12: Counterfactual Simulation Results

	B_t	x_t	n_t	p_t	f_t	lnW_t
Baseline	0.326	5.220	4.629	0.206	0.567	3.130
Additional one hour of daily screen time						
main model	0.364		4.487	0.202	0.572	3.129
individual model	0.338		4.534	0.218	0.569	3.119
AAP Recommendation (2 hours/day)						
main model	0.303		4.749	0.220	0.541	3.133
individual model	0.312		4.647	0.219	0.565	3.118
Zero screen time						
main model	0.281		4.762	0.220	0.535	3.133
individual model	0.301		4.785	0.215	0.560	3.119
All mothers not working						
main model	0.319	4.437	4.733			2.576
individual model	0.315	4.144	4.769			2.384
All mothers working full-time						
main model	0.336	5.751	4.586			3.319
individual model	0.322	5.544	4.643			3.331

REFERENCES

Allender, W. J. and Richards, T. J. (2010). Consumer impact of animal welfare regulation in the California poultry industry. *Journal of Agricultural and Resource Economics*, 35(3):424–442.

Almonani, E., Husain, W., San, O. Y., Almomani, A., and Al-Betar, M. (2014). Mobile game approach to prevent childhood obesity using persuasive technology. In *2014 International Conference on Computer and Information Sciences (ICCOINS)*, pages 1–5. IEEE.

Anderson, P. M. (2011). Maternal Employment. In Cawley, J., editor, *The Oxford Handbook of the Social Science of Obesity*, pages 313–328. Oxford University Press.

Anderson, P. M., Butcher, K. F., and Levine, P. B. (2003). Maternal employment and overweight children. *Journal of Health Economics*, 22(3):477–504.

Arellano, M. and Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies*, 58(2):277.

Ashenfelter, O. and Heckman, J. (1974). The Estimation of Income and Substitution Effects in a Model of Family Labor Supply. *Econometrica*, 42(1):73.

Auld, C. M. and Powell, L. M. (2009). Economics of Food Energy Density and Adolescent Body Weight. *Economica*, 76(304):719–740.

Auld, M. C. and Grootendorst, P. (2011). Challenges for Causal Inference in Obesity Research. In *The Oxford Handbook of the Social Science of Obesity*, pages 243–248. Oxford University Press.

Barlett, N. D., Gentile, D. A., Barlett, C. P., Eisenmann, J. C., and Walsh, D. A. (2012). Sleep as a Mediator of Screen Time Effects on US Children's Health Outcomes. *Journal of Children and Media*, 6(1):37–50.

Baumol, W. J. (1973). Income and Substitution Effects in the Linder Theorem. *The Quarterly Journal of Economics*, 87(4):629.

Becker, G. S. (1965). A Theory of the Allocation of Time. *The Economic Journal*.

Bernal, R. and Keane, M. P. (2010). Quasi-structural estimation of a model of childcare choices and child cognitive ability production. *Journal of Econometrics*, 156(1):164–189.

Bhargava, A. and Sargan, J. D. (1983). Estimating Dynamic Random Effects Models from Panel Data Covering Short Time Periods. *Econometrica*, 51(6):1635.

Boone, J. E., Gordon-Larsen, P., Adair, L. S., and Popkin, B. M. (2007). Screen time and physical activity during adolescence: longitudinal effects on obesity in young adulthood. *International Journal of Behavioral Nutrition and Physical Activity*, 4(1):26.

Buchanan, L. R., Rooks-Peck, C. R., Finnie, R. K., Wethington, H. R., Jacob, V., Fulton, J. E., Johnson, D. B., Kahwati, L. C., Pratt, C. A., Ramirez, G., Mercer, S. L., and Glanz, K. (2016). Reducing Recreational Sedentary Screen Time. *American Journal of Preventive Medicine*, 50(3):402–415.

Buijzen, M., Schuurman, J., and Bomhof, E. (2008). Associations between children's television advertising exposure and their food consumption patterns: A household diary–survey study. *Appetite*, 50(2-3):231–239.

Carter, C. A., Schaefer, K. A., and Scheitrum, D. (2021). Piecemeal Farm Regulation and the U.S. Commerce Clause. *American Journal of Agricultural Economics*, 103(3):1141–1163.

Cawley, J. (2010). The Economics Of Childhood Obesity. *Health Affairs*, 29(3):364–371.

Cawley, J. and Liu, F. (2012). Maternal employment and childhood obesity: A search for mechanisms in time use data. *Economics & Human Biology*, 10(4):352–364.

Chang, H.-H. and Nayga, R. M. J. (2009). Television Viewing, Fast-food Consumption, and Children's Obesity. *Contemporary Economic Policy*, 27(3):293–307.

Chang, J. B., Lusk, J. L., and Norwood, F. B. (2010). The price of happy hens: A hedonic analysis of retail egg prices. *Journal of Agricultural and Resource Economics*, 35(3):406–423.

Chia, Y. F. (2008). Maternal labour supply and childhood obesity in Canada: Evidence from the NLSCY. *Canadian Journal of Economics*, 41(1):217–242.

Chiu, S.-I., Lee, J.-Z., and Huang, D.-H. (2004). Video Game Addiction in Children and Teenagers in Taiwan. *CyberPsychology & Behavior*, 7(5):571–581.

Choi, H. J., Wohlgenant, M. K., and Zheng, X. (2013). Household-level welfare effects of organic milk introduction. *American Journal of Agricultural Economics*, 95(4):1009–1028.

Chou, S., Rashad, I., and Grossman, M. (2008). Fast-Food Restaurant Advertising on Television and Its Influence on Childhood Obesity. *The Journal of Law and Economics*, 51(4):599–618.

Cleland, V. J., Patterson, K., Breslin, M., Schmidt, M. D., Dwyer, T., and Venn, A. J. (2018). Longitudinal associations between TV viewing and BMI not explained by the 'mindless eating' or 'physical activity displacement' hypotheses among adults. *BMC Public Health*, 18(1):797.

Coon, K. and Tucker, K. (2002). Television and children's consumption patterns. *Minerva Pediatr*, 54(5):423–436.

Cortés, P. and Tessada, J. (2011). Low-Skilled Immigration and the Labor Supply of Highly Skilled Women. *American Economic Journal: Applied Economics*, 3(3):88–123.

Courtemanche, C. (2008). Working Yourself to Death? The Relationship Between Work Hours and Obesity.

Crepinsek, M. K. and Burstein, N. R. (2004). Maternal Employment and Children's Nutrition: Volume 2: Other Nutrition-Related Outcomes. Technical report, Economic Research Service, U.S. Department of Agriculture, Washington, DC.

Cronin, C. J. (2019). Insurance-induced Moral Hazard: a Dynamic Model of Within-year Medical Care Decision Making Under Uncertainty. *International Economic Review*, 60(1):187–218.

Danner, F. W. (2008). A National Longitudinal Study of the Association Between Hours of TV Viewing and the Trajectory of BMI Growth Among US Children. *Journal of Pediatric Psychology*, 33(10):1100–1107.

Darden, M. E., Hotchkiss, J. L., and Pitts, M. M. (2021). The dynamics of the smoking wage penalty. *Journal of Health Economics*, 79:102485.

Davison, K. K., Gicevic, S., Aftosmes-Tobio, A., Ganter, C., Simon, C. L., Newlan, S., and Manganello, J. A. (2016). Fathers' Representation in Observational Studies on Parenting and Childhood Obesity: A Systematic Review and Content Analysis. *American Journal of Public Health*, 106(11):e14–e21.

Dietz, W. H. (1998). Health consequences of obesity in youth: childhood predictors of adult disease. *Pediatrics*, 101(Supplement 2):518–25.

Dietz, W. H. and Gortmaker, S. L. (1985). Do We Fatten Our Children at the Television Set? Obesity and Television Viewing in Children and Adolescents. *Pediatrics*, 75(5):807–812.

Dubé, J.-P. (2004). Multiple Discreteness and Product Differentiation: Demand for Carbonated Soft Drinks. *Marketing Science*, 23(1):66–81.

Duch, H., Fisher, E. M., Ensari, I., and Harrington, A. (2013). Screen time use in children under 3 years old: a systematic review of correlates. *International Journal of Behavioral Nutrition and Physical Activity*, 10(1):102.

Fang, K., Mu, M., Liu, K., and He, Y. (2019). Screen time and childhood overweight/obesity: A systematic review and meta-analysis. *Child: Care, Health and Development*, 45(5):744–753.

Fertig, A., Glomm, G., and Tchernis, R. (2009). The connection between maternal employment and childhood obesity: inspecting the mechanisms. *Review of Economics of the Household 2009 7:3*, 7(3):227–255.

Fisher, S. (1994). Identifying video game addiction in children and adolescents. *Addictive Behaviors*, 19(5):545–553.

Furthner, D., Ehrenmueller, M., Lanzersdorfer, R., Halmerbauer, G., Schmitt, K., and Biebl, A. (2018). Education, school type and screen time were associated with overweight and obesity in 2930 adolescents. *Acta Paediatrica*, 107(3):517–522.

Geoffroy, M. C., Power, C., Touchette, E., Dubois, L., Boivin, M., Séguin, J. R., Tremblay, R. E., and Côté, S. M. (2013). Childcare and Overweight or Obesity over 10 Years of Follow-Up. *The Journal of Pediatrics*, 162(4):753–758.

Godakanda, I., Abeysena, C., and Lokubalasooriya, A. (2018). Sedentary behavior during leisure time, physical activity and dietary habits as risk factors of overweight among school children aged 14–15 years: case control study. *BMC Research Notes 2018 11:1*, 11(1):1–6.

Gortmaker, S. L. (1996). Television Viewing as a Cause of Increasing Obesity Among Children in the United States, 1986-1990. *Archives of Pediatrics & Adolescent Medicine*, 150(4):356.

Greene, J. L. (2015). Update on the Highly-Pathogenic Avian Influenza Outbreak of 2014-2015. *Congressional Research Service*, pages 1–18.

Grossman, M. (1972). On the Concept of Health Capital and the Demand for Health. *The Journal of Political Economy*, 80(2):223–255.

Gundersen, C., Mahatmya, D., Garasky, S., and Lohman, B. (2011). Linking psychosocial stressors and childhood obesity. *Obesity Reviews*, 12(5):e54–e63.

Guryan, J., Hurst, E., and Kearney, M. (2008). Parental Education and Parental Time with Children. *Journal of Economic Perspectives*, 22(3):23–46.

Hales, C. M., Carroll, M. D., Fryar, C. D., and Ogden, C. L. (2017). Prevalence of obesity among adults and youth : United States, 2015–2016. Technical report, Center for Disease Control and Prevention.

Hancox, R. J., Milne, B. J., and Poulton, R. (2004). Association between child and adolescent television viewing and adult health: a longitudinal birth cohort study. *The Lancet*, 364(9430):257–262.

Hancox, R. J. and Poulton, R. (2005). Watching television is associated with childhood obesity: but is it clinically important? *International Journal of Obesity 2006 30:1*, 30(1):171–175.

Hardy, L. L., Baur, L. A., Garnett, S. P., Crawford, D., Campbell, K. J., Shrewsbury, V. A., Cowell, C. T., and Salmon, J. (2006). Family and home correlates of television viewing in 12-13 year old adolescents: The Nepean Study. *International Journal of Behavioral Nutrition and Physical Activity*.

Harris, J. L., Bargh, J. A., and Brownell, K. D. (2009). Priming Effects of Television Food Advertising on Eating Behavior. *Health Psychology*, 28(4):404–413.

Hart, C. N., Cairns, A., and Jelalian, E. (2011). Sleep and Obesity in Children and Adolescents. *Pediatric Clinics of North America*, 58(3):715–733.

Hausman, J. A. (1997). Valuation of New Goods under Perfect and Imperfect Competition. In Bresnahan, T. F. and Gordon, R. J., editors, *The Economics of New Goods*, chapter 5, pages 209–247. University of Chicago Press.

Heckman, J. and Singer, B. (1984). A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data. *Econometrica*.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, 47(1):153.

Hendel, I. (1999). Estimating Multiple-Discrete Choice Models: An Application to Computerization Returns. *Review of Economic Studies*, 66(2):423–446.

Henderson, V. R. (2007). Longitudinal Associations Between Television Viewing and Body Mass Index Among White and Black Girls. *Journal of Adolescent Health*, 41(6):544–550.

Herman, K. M., Sabiston, C. M., Mathieu, M. E., Tremblay, A., and Paradis, G. (2014). Sedentary behavior in a cohort of 8- to 10-year-old children at elevated risk of obesity. *Preventive Medicine*, 60:115–120.

Kalarchian, M. A., Hammer, J., and Kapuścińska, A. (2021). Fostering Innovation in Prevention and Treatment of Obesity in Youth: Digitally Mediated Physical Play as an Exemplar. *Obesity*, 29(3):475–477.

Keane, M. and Moffitt, R. (1998). A Structural Model of Multiple Welfare Program Participation and Labor Supply. *International Economic Review*, 39(3):553.

Koch, F. S., Sepa, A., and Ludvigsson, J. (2008). Psychological Stress and Obesity. *The Journal of Pediatrics*, 153(6):839–844.

Kotschedoff, M. J. and Pachali, M. J. (2020). Higher minimum quality standards and redistributive effects on consumer welfare. *Marketing Science*, 39(1):253–280.

Kuss, D. and Griffiths, M. (2017). Social Networking Sites and Addiction: Ten Lessons Learned. *International Journal of Environmental Research and Public Health*, 14(3):311.

LaFrance, J. T. and Hanemann, W. M. (1989). The Dual Structure of Incomplete Demand Systems. *American Journal of Agricultural Economics*, 71(2):262–274.

Laibson, D. (1997). Golden Eggs and Hyperbolic Discounting. *The Quarterly Journal of Economics*, 112(2):443–478.

Lange, S. J., Kompaniyets, L., Freedman, D. S., Kraus, E. M., Porter, R., Blanck, H. M., and Goodman, A. B. (2021). Longitudinal Trends in Body Mass Index Before and During the COVID-19 Pandemic Among Persons Aged 2–19 Years — United States, 2018–2020. *MMWR. Morbidity and Mortality Weekly Report*, 70(37):1278–1283.

Liang, T., Kuhle, S., and Veugelers, P. J. (2009). Nutrition and body weights of Canadian children watching television and eating while watching television. *Public Health Nutrition*, 12(12):2457–2463.

Liao, S. (2021). China restricts young people to playing video games three hours a week.

Linder, S. B. (1970). *The harried leisure class*. New York: Columbia University Press.

Lu, A. S., Kharrazi, H., Gharghabi, F., and Thompson, D. (2013). A Systematic Review of Health Videogames on Childhood Obesity Prevention and Intervention. *Games for Health Journal*, 2(3):131–141.

Lu, A. S., Thompson, D., Baranowski, J., Buday, R., and Baranowski, T. (2012). Story Immersion in a Health Videogame for Childhood Obesity Prevention. *Games for Health Journal*, 1(1):37–44.

Malone, T. and Lusk, J. L. (2016). Putting the chicken before the egg price: An ex post analysis of California's battery cage ban. *Journal of Agricultural and Resource Economics*, 41(3):518–532.

Mark, A. E. and Janssen, I. (2008). Relationship between screen time and metabolic syndrome in adolescents. *Journal of Public Health*, 30(2):153–160.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In *Frontiers in Econometrics*, pages 105–141.

McFadden, D. and Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, 15(5):447–470.

McMillan, R., McIsaac, M., and Janssen, I. (2015). Family structure as a predictor of screen time among youth. *PeerJ*, 3:e1048.

Miller, A. L. and Lumeng, J. C. (2018). Pathways of Association from Stress to Obesity in Early Childhood. *Obesity*, 26(7):1117–1124.

Morrissey, T. W., Dunifon, R. E., and Kalil, A. (2011). Maternal Employment, Work Schedules, and Children's Body Mass Index. *Child Development*, 82(1):66–81.

Mroz, T. A. (1999). Discrete factor approximations in simultaneous equation models: Estimating the impact of a dummy endogenous variable on a continuous outcome. *Journal of Econometrics*.

Mullally, C. and Lusk, J. L. (2018). The Impact of Farm Animal Housing Restrictions on Egg Prices, Consumer Welfare, and Production in California. *American Journal of Agricultural Economics*, 100(3):649–669.

Nevo, A. (2001). Measuring Market Power in the Ready-to-Eat Cereal Industry. *Econometrica*, 69(2):307–342.

Nielsen, L. S., Danielsen, K. V., and Sørensen, T. I. A. (2011). Short sleep duration as a possible cause of obesity: critical analysis of the epidemiological evidence. *Obesity Reviews*, 12(2):78–92.

Nieto, A. and Suhrcke, M. (2021). The effect of TV viewing on children's obesity risk and mental well-being: Evidence from the UK digital switchover. *Journal of Health Economics*, 80:102543.

Norwood, F. B. and Lusk, J. L. (2011). *Compassion, by the Pound*. Oxford University Press.

Ogden, C. L., Flegal, K. M., Carroll, M. D., and Johnson, C. L. (2002). Prevalence and Trends in Overweight Among US Children and Adolescents, 1999-2000. *JAMA*, 288(14):1728–1732.

Oh, S. E. and Vukina, T. (2021). Estimating Parental Demand for Children's Screen Time in a Model of Family Labor Supply.

Panzar, J. C. and Savage, I. (2011). Does a minimum quality standard always reduce the price of high quality products? *B.E. Journal of Economic Analysis and Policy*, 11(1).

Parsons, T. J., Power, C., and Manor, O. (2005). Physical activity, television viewing and body mass index: a cross-sectional analysis from childhood to adulthood in the 1958 British cohort. *International Journal of Obesity*, 29(10):1212–1221.

Powell, L. M. (2009). Fast food costs and adolescent body mass index: Evidence from panel data. *Journal of Health Economics*, 28(5):963–970.

Puder, J. J. and Munsch, S. (2010). Psychological correlates of childhood obesity. *International Journal of Obesity 2010 34:2*, 34(2):S37–S43.

Reeves, G. M., Postolache, T. T., and Snitker, S. (2008). Childhood Obesity and Depression: Connection between these Growing Problems in Growing Children. *International journal of child health and human development : IJCHD*, 1(2):103.

Ritchtel, M. (2021a). Children's Screen Time Has Soared in the Pandemic, Alarming Parents and Researchers - The New York Times.

Ritchtel, M. (2021b). Children's Screen Time Has Soared in the Pandemic, Alarming Parents and Researchers - The New York Times.

Robinson, T. N. (1999). Reducing Children's Television Viewing to Prevent Obesity. *JAMA*, 282(16):1561.

Ruhm, C. J. (2008). Maternal employment and adolescent development. *Labour Economics*, 15(5):958–983.

Ruhm, C. J. (2012). Understanding overeating and obesity. *Journal of Health Economics*, 31(6):781–796.

Shang, L., Wang, J. W., O'Loughlin, J., Tremblay, A., Mathieu, M. , Henderson, M., and Gray-Donald, K. (2015). Screen time is associated with dietary intake in overweight Canadian children. *Preventive Medicine Reports*, 2:265–269.

Small, K. A. and Rosen, H. S. (1981). Applied Welfare Economics with Discrete Choice Models. *Econometrica*, 49(1):105.

Story, M. and French, S. (2004). Food Advertising and Marketing Directed at Children and Adolescents in the US. *International Journal of Behavioral Nutrition and Physical Activity 2004 1:1*, 1(1):1–17.

Strasburger, V. C., Hogan, M. J., Mulligan, D. A., Ameenuddin, N., Christakis, D. A., Cross, C., Fagbuyi, D. B., Hill, D. L., Levine, A. E., McCarthy, C., Moreno, M. A., and Swanson, W. S. L. (2013). Children, Adolescents, and the Media. *Pediatrics*, 132(5):958–961.

Sturm, R. and Datar, A. (2005). Body mass index in elementary school children, metropolitan area food prices and food outlet density. *Public Health*, 119(12):1059–1068.

Sugiyama, T., Xie, D., Graham-Maar, R. C., Inoue, K., Kobayashi, Y., and Stettler, N. (2007). Dietary and Lifestyle Factors Associated with Blood Pressure among U.S. Adolescents. *Journal of Adolescent Health*, 40(2):166–172.

Sumner, D. a., Rosen-molina, J. T., Matthews, W. a., Mench, J. a., and Richter, K. R. (2008). Economic Effects of Proposed Restrictions on Egg-laying Hen Housing in California. Technical report, University of California Agricultural Issues Center.

Taveras, E. M., Sandora, T. J., Shih, M.-C., Ross-Degnan, D., Goldmann, D. A., and Gillman, M. W. (2006). The Association of Television and Video Viewing with Fast Food Intake by Preschool-Age Children*. *Obesity*, 14(11):2034–2041.

Train, K. E. (2003). *Discrete Choice Methods with Simulation*. Cambridge University Press, Cambridge.

Tremblay, M. S., LeBlanc, A. G., Kho, M. E., Saunders, T. J., Larouche, R., Colley, R. C., Goldfield, G., and Gorber, S. (2011). Systematic review of sedentary behaviour and health indicators in school-aged children and youth. *International Journal of Behavioral Nutrition and Physical Activity*, 8(1):98.

Tsujiguchi, H., Hori, D., Kambayashi, Y., Hamagishi, T., Asakura, H., Mitoma, J., Kitaoka, M., Anyenda, E. O., Nguyen, T. T. T., Yamada, Y., Hayashi, K., Konoshita, T., Sagara, T., Shibata, A., Sasaki, S., and Nakamura, H. (2018). Relationship between screen time and

nutrient intake in Japanese children and adolescents: a cross-sectional observational study. *Environmental Health and Preventive Medicine 2018 23:1*, 23(1):1–12.

Van Cauter, E. and Knutson, K. L. (2008). Sleep and the epidemic of obesity in children and adults. *European Journal of Endocrinology*, 159(suppl_1):S59–S66.

Villas-Boas, S. B. (2007). Vertical relationships between manufacturers and retailers: Inference with limited data. *Review of Economic Studies*, 74(2):625–652.

von Hinke Kessler Scholder, S. (2008). Maternal employment and overweight children: Does timing matter? *Health Economics*.

Vukina, T. and Nestic, D. (2020). Paying for animal welfare? A hedonic analysis of egg prices. *Agribusiness*, 36(4):613–630.

Wooldridge, J. M. (2015). Control Function Methods in Applied Econometrics. *Journal of Human Resources*, 50(2):420–445.

Xue, H., You, W., and Nayga, Rodolfo M., J. (2011). Childhood Obesity Risk and the Role of Primary Caregivers: A Triangular Semi-parametric Simultaneous Equations Approach. In *Agricultural and Applied Economics Association Conference*.

Yang, Z., Gilleskie, D. B., and Norton, E. C. (2009). Health insurance, medical care, and health outcomes: A model of elderly health dynamics. *Journal of Human Resources*.

You, W. and Davis, G. C. (2010). Household Food Expenditures, Parental Time Allocation, and Childhood Overweight: An Integrated Two-Stage Collective Model with an Empirical Application and Test. *American Journal of Agricultural Economics*, 92(3):859–872.

APPENDIX

APPENDIX

A

THE PRICE OF CAGE-FREE EGGS: SOCIAL COST OF PROPOSITION 12 IN CALIFORNIA

Table A.1: Control Function Estimation Results

	(1) main model		(2) alternative #1		(3) alternative #2		(4) alternative #3	
	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
brown	0.156***	0.0015	1.033***	0.0024	0.166***	0.0015	0.156***	0.0015
private	-0.126***	0.0012	-0.949***	0.0020	-0.133***	0.0012	-0.126***	0.0012
omega3	0.0211***	0.0013	-0.0632***	0.0022	0.0201***	0.0013	0.0208***	0.0013
free	-0.0215***	0.0016	-0.184***	0.0027	-0.0231***	0.0016	-0.0216***	0.0016
organic	0.127***	0.0016	0.926***	0.0027	0.133***	0.0016	0.127***	0.0016
aa	-0.0272***	0.0011	-0.343***	0.0019	-0.0308***	0.0011	-0.0268***	0.0011
xl	-0.0245***	0.0013	-0.0408***	0.0021	-0.0240***	0.0013	-0.0248***	0.0013
tc	0.0324***	0.0001	0.199***	0.0001	0.0340***	0.0001	0.0324***	0.0001
priceiv	0.844***	0.0004			0.836***	0.0004	0.844***	0.0004
b2	0.140***	0.0015	0.217***	0.0025	0.142***	0.0015	0.141***	0.0015
b3	-0.279***	0.0018	-0.430***	0.0030	-0.280***	0.0018	-0.279***	0.0018
b4	0.0640***	0.0071	0.187***	0.0120	0.0659***	0.0071	0.0643***	0.0071
b5	-0.0701***	0.0020	-0.139***	0.0033	-0.0692***	0.0020	-0.0698***	0.0020
b6	-0.0537***	0.0015	-0.00154	0.0026	-0.0523***	0.0015	-0.0533***	0.0015
b7	-0.771***	0.0031	-1.147***	0.0052	-0.774***	0.0031	-0.773***	0.0031
b8	-0.724***	0.0033	-0.925***	0.0055	-0.724***	0.0033	-0.723***	0.0033
b9	0.217***	0.0022	0.129***	0.0036	0.218***	0.0022	0.217***	0.0022
b10	-0.0186***	0.0029	0.0650***	0.0048	-0.0171***	0.0029	-0.0162***	0.0029
b11	-0.594***	0.0056	-1.099***	0.0095	-0.598***	0.0056	-0.597***	0.0056
wth2015	0.154***	0.0010	0.231***	0.0028	0.0357***	0.0017	0.154***	0.0010
feed			0.00322**	0.0010	0.00541***	0.0006		
wholesale			0.600***	0.0017	0.0988***	0.0010		
const.	0.266***	0.0020	0.900***	0.0108	0.0853***	0.0064	0.264***	0.0020
adj. R^2	0.915		0.762		0.916		0.915	
N	2,744,213		2,744,213		2,744,213		2,744,213	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2: Demand Estimation: Mixed Logit Model

		(1) main model		(2) alternative #1		(3) alternative #2		(4) alternative #3	
Variable	Parameter	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
price	$\overline{\gamma}$	1.5962***	0.5587	1.0969	2.8711	1.5980***	0.5635	1.5915***	0.5556
	σ_{γ}	1.2416*	0.6536	0.0719	1.9564	1.2337*	0.6608	1.2389*	0.6475
cage-free	$\overline{\beta}^{\text{free}}$	-4.1033***	0.1000	-9.2476***	0.0744	-1.7864***	0.0969	-6.3832***	0.0957
	σ^{free}	0.7276***	0.0940	1.2490***	0.1022	0.8185***	0.0991	0.2330***	0.0425
	$\theta^{\text{free x male}}$	-0.0656***	0.0328	-0.1887***	0.0220	0.0293	0.0346	-0.1605***	0.0300
	$\theta^{\text{free x female}}$	0.2068***	0.0541	0.2393***	0.0405	0.1669***	0.0493	0.2083***	0.0549
	$\theta^{\text{free x college}}$	3.6287***	0.1000	6.8087***	0.0744	0.9710***	0.0967	6.3221***	0.0957
	$\theta^{\text{free x young}}$	0.6552***	0.0519	1.0307***	0.0534	0.7154***	0.0516	0.6533***	0.0525
	$\theta^{\text{free x old}}$	-0.5835***	0.0238	-0.9112***	0.0069	-0.3305***	0.0309	-0.7321***	0.0188
	$\theta^{\text{free x income1}}$	-0.1617***	0.0257	-2.2265***	0.0008	-0.1779***	0.0208	-0.1100***	0.0276
	$\theta^{\text{free x income2}}$	0.1080***	0.0511	0.5962***	0.0383	0.3120***	0.0541	0.0267	0.0457
	$\theta^{\text{free x income3}}$	0.6355***	0.0789	1.2421***	0.0633	0.7652***	0.0756	0.5826***	0.0758
	$\theta^{\text{free x hhsize}}$	-0.1708	0.2428	-0.1182	0.1936	-0.1454	0.2406	-0.2030	0.2239
	$\theta^{\text{free x 2015}}$	-0.1801***	0.0186	0.2018***	0.0185	-0.2385***	0.0166	-0.1766***	0.0177
omega3	$\overline{\beta}^{\text{omega3}}$	-0.1294	0.0866	-0.7673***	0.0567	-0.1398	0.0869	-0.0973	0.0855
	σ_{omega3}	0.2899***	0.0456	0.6014***	0.0417	0.3149***	0.0486	0.1957***	0.0341
aa	$\overline{\beta}^{\text{aa}}$	-0.7662***	0.0838	-15.4383***	0.0000	-0.7666***	0.0837	-0.7707***	0.0831
	σ_{aa}	0.1676***	0.0218	0.0281***	0.0000	0.1696***	0.0219	0.0640***	0.0185
organic	$\overline{\beta}^{\text{organic}}$	-17.5697***	0.0000	-17.7002***	0.0000	-17.7006***	0.0000	-12.4421***	0.0000
	σ_{organic}	0.9079***	0.0000	0.9018***	0.0000	0.9016***	0.0000	0.2777***	0.0000
brown	$\overline{\beta}^{\text{brown}}$	-0.8036***	0.1026	1.8524***	0.1174	-0.7774***	0.1025	-0.7745***	0.1055
	σ_{brown}	0.2605***	0.0334	0.2502***	0.0303	0.2560***	0.0334	0.0752***	0.0279
private	$\overline{\beta}^{\text{private}}$	0.1217	0.1751	-3.8585***	0.1737	0.1141	0.1749	0.1313	0.1769
	σ_{private}	0.2661***	0.0399	3.2048***	0.1823	0.2653***	0.0400	0.0197***	0.0400
xl	$\overline{\beta}^{\text{xl}}$	-0.8070***	0.0948	-0.9555***	0.0993	-0.8086***	0.0947	-0.8959***	0.0937
	σ_{xl}	0.0552***	0.0210	0.2159***	0.0227	0.0720***	0.0213	0.5180***	0.0381
tc	$\overline{\beta}^{\text{tc}}$	0.0828	3.0475	0.5160	3.8287	0.0843	3.0444	0.0824	3.0531
	σ_{tc}	0.0002	0.8365	0.0008	0.8488	0.0002	0.8426	0.0012	0.8866
iv	η	0.6626***	0.2294	2.5510***	0.3097	0.6863***	0.2285	0.6638***	0.2298
banner	b2	-0.9481***	0.0735	-0.0381	0.1163	-0.9227***	0.0734	-0.9515***	0.0737
	b3	-3.9716***	0.0577	-3.0584***	0.0691	-3.9536***	0.0576	-3.9591***	0.0584
	b4	-0.2044***	0.0069	0.1570***	0.0114	-0.2085***	0.0069	-0.6290***	0.0076
	b5	-0.0441	0.0342	-0.4408***	0.0627	0.0215	0.0338	-0.1076***	0.0351
	b6	-0.7974***	0.0708	-0.1895*	0.1031	-0.7587***	0.0705	-0.7542***	0.0708
	b7	-3.1200***	0.0290	-5.1254***	0.0327	-3.1228***	0.0290	-3.0641***	0.0289
	b8	-0.7049***	0.0333	-2.4055***	0.0500	-0.7189***	0.0338	-0.7367***	0.0336
	b9	-0.2789***	0.0331	-0.0208	0.0571	-0.2129***	0.0326	-0.2418***	0.0329
	b10	-0.8382***	0.0217	-0.1416***	0.0316	-0.7993***	0.0217	-0.7441***	0.0210
	b11	-2.7373***	0.0153	-4.7497***	0.0181	-2.7190***	0.0153	-2.8045***	0.0152
season	Easter	0.7304***	0.0725	2.6998***	0.1250	0.7384***	0.0723	0.7506 ***	0.0727
	Christmas	0.0303	0.0354	0.0158	0.0542	0.0366	0.0355	0.0238	0.0356

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Comparison of Counterfactual Results Across Alternative Models

	(1) main model			(2) alternative #2			(3) alternative #3		
	before	after	%	before	after	%	before	after	%
price($/dozen): conventional	3.10		65.27%	3.10		69.34%	3.10		66.42%
price($/dozen): cage-free	5.30	5.12	-3.41%	5.30	5.20	-1.98%	5.30	5.15	-3.09%
PS ($/dozen)	0.14	0.09	-32.71%	0.15	0.11	-31.04%	0.14	0.10	-31.55%
Average WTP (cent/dozen)		5.89			5.94			5.91	
changes in CS (cent/dozen)		-5.86			-6.98			-6.26	

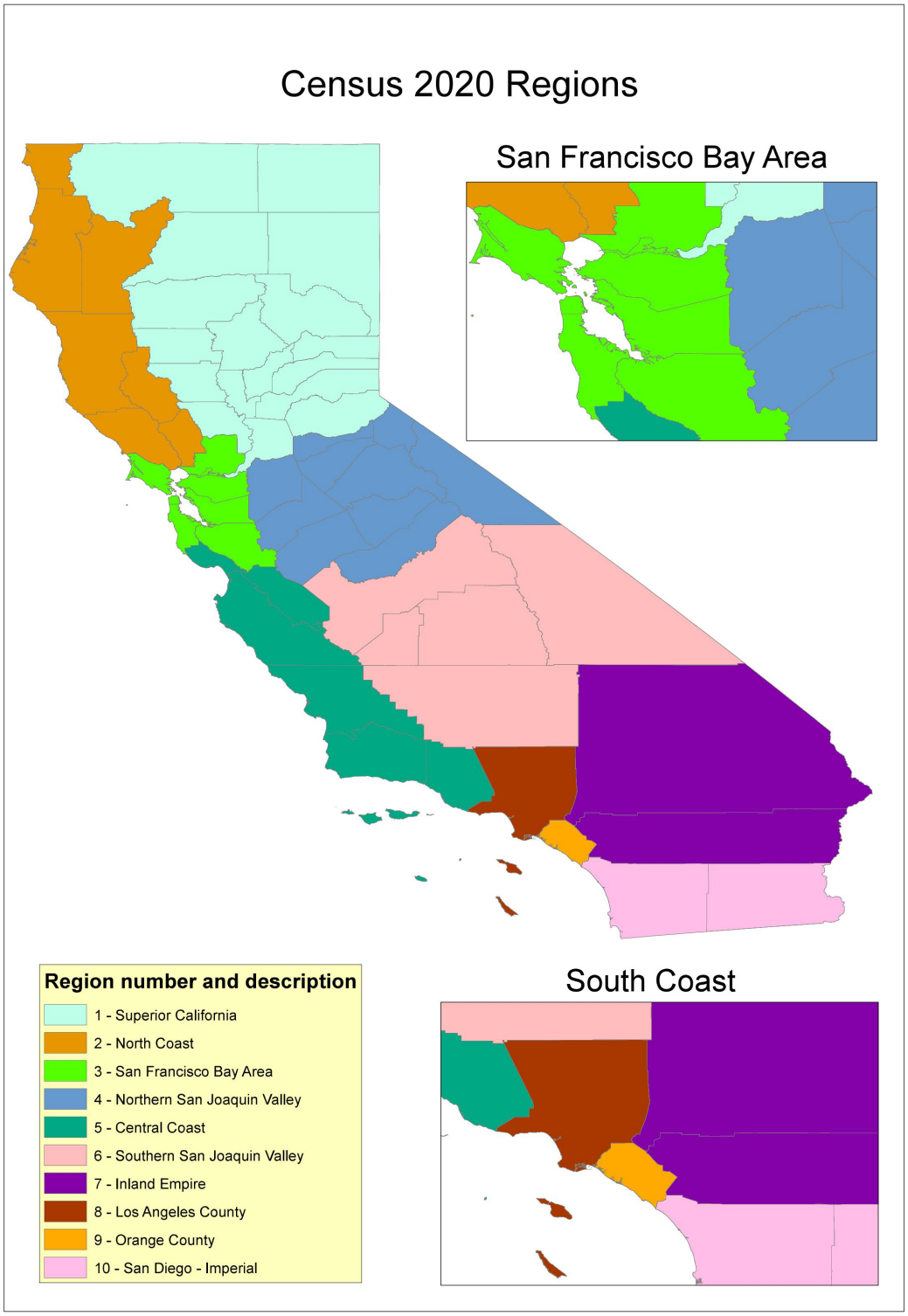

Figure A.1: Regions in California