# THREE ESSAYS IN HEALTH ECONOMICS

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DOCTOR OF PHILOSOPHY

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by
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## ABSTRACT

This dissertation consists of three essays in health economics. The first chapter, "The Built Environment and Obesity in Philadelphia: The Use of Satellite Imagery and Transfer Learning," investigates the relationship between the built environment and health outcomes, specifically obesity prevalence in Philadelphia. The built environment can affect obesity prevalence through the physical activity environment and the food environment. The main innovation of this paper is to use a pre-trained convolutional neural network (CNN) to extract data representing the features of the built environment from high-resolution satellite imagery. Because of the lack of information on the food environment in satellite images, I combined a proxy variable for food access together with the feature variables to represent the characteristics of the built environment. I then employed the Elastic Net model to test the relationship between the feature variables of the built environment and obesity prevalence in Philadelphia. The results show that the built environment is highly associated with obesity prevalence. This study also provides some evidence that the features of the built environment that have been extracted from satellite imagery can reduce the role of food access in estimating obesity, as well as that adding these features can explain more variance of obesity.

The second chapter, "Paid Maternity Leave and Child Health: Evidence from Urban China," uses the China Health and Nutrition Survey data to study whether the extension of paid maternity leave affects children's health outcomes in urban China. This paper uses the time variation of the implementation of a maternity leave policy across different provinces from 1987 to 1991 in China to estimate a two-way fixed-effects model. The results suggest that the expansion of paid maternity leave has no impact on children's health in urban China.

The last chapter, titled "The Association between Paid Maternity Leave and Mothers' Health and Labor Outcomes in Urban China," studies whether the extension of paid maternity leave in 1987-1991 would affect the labor and health outcomes of mothers in urban China by using the China Health and Nutrition Survey data. Based on the variation in the implementation time of a paid maternity leave policy across different provinces, this paper employs a two-way fixed-effects model to estimate the policy impact on mothers' health and labor outcomes in China. The findings indicate that extending the duration of paid maternity leave is associated with an increased likelihood of mothers remaining employed after childbirth. However, the study also reveals a negative relationship between the extension of paid maternity leave and mothers' wage rates.

## DEDICATION

To Dear Mom.

## ACKNOWLEDEMENTS

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# CHAPTER 1

# THE BUILT ENVIRONMENT AND OBESITY IN PHILADELPHIA: THE USE OF SATELLITE IMAGERY AND TRANSFER LEARNING

## 1.1 Introduction

Does one's place of residence impact their health? What is a good community design for health? This paper studies the relationship between built environments and health outcomes, specifically obesity prevalence in Philadelphia.

The built environment is broadly defined as the human-made space in which people live, work, and participate in recreational activities daily. It includes buildings, parks, roads, and lakes. The built environment affects obesity because it helps determine individuals' access to healthy food, health resources, and facilities that promote physical activity and healthy behaviors.

Based on previous studies, there are two main channels through which the built environment can affect obesity: the physical activity environment and the food environment. The physical activity environment affects individual and community health outcomes by defining barriers and opportunities to engage in healthy behaviors. Some features of the physical activity environment, such as land use diversity and street connectivity, have been associated with increased physical activity (Cervero & Kockelman, 1997; Frank et al., 2006; Xu et al., 2015). Mixed land use may promote more active living by allowing residents to live close to multiple destinations without relying on motor

vehicles (Brown et al., 2009). Areas with better connectivity can promote more walking by making more and shorter routes available (Doyle et al., 2007).

The food environment affects an individual's body weight by influencing dietary behavior and nutrient intake. The Centers for Disease Control and Prevention (CDC) defines the food environment as "the physical presence of food that affects a person's diet; a person's proximity to food store locations, the distribution of food stores, food service, and any physical entity by which food may be obtained; or a connected system that allows access to food." Limited access to healthy foods may negatively affect diet and lead to worse health outcomes (Caspi et al., 2012a; Cobb et al., 2015; Gamba et al., 2015).

An important consideration for built environment studies is how to measure the built environment. Measures of the physical activity environment contain the structural environment near the home and urban design characteristics that may affect physical activity, such as the distance to the nearest park, green spaces, walkability, access to recreational facilities, street connectivity, and land use (Arvidsson et al., 2013; Carroll-Scott et al., 2013; Ding et al., 2011; Dunton et al., 2009). Measures of the food environment include the availability of healthy food (e.g., access to supermarkets or large grocery stores), the availability of unhealthy food (e.g., convenience/ corner stores, fast food restaurants, or full-service restaurants), and the ratio of healthy food to unhealthy food (e.g., the Retail Food Environment Index[1]). This study uses satellite imagery and the Convolutional Neural Network (CNN) to extract data representing the features of the built environment from

[1] Retail Food Environment Index (RFEI) is a ratio of the total number of fast-food restaurants and convenience stores compared to grocery stores and produce vendors near a person's home (Babey et al., 2008).

Google Static Maps. Since satellite images cannot provide direct information about the food environment, a food access variable was added to the feature variables extracted from satellite images to represent the built environment. The food access variable was measured by the ratio of healthy food supply stores to the total number of food supply stores.

Once the food access variable was combined with the feature variables to measure the built environment, I employed the Elastic Net linear model to test the links between the built environment and obesity. The results show that the built environment is highly correlated with body weight. The built environment can explain the 65 percent variance of obesity prevalence across all census tracts in Philadelphia.

## 1.2 Literature Review

Some of the literature on the relationship between different characteristics of the built environment and body weight focus on the physical activity environment. Giles-Corti et al. (2003) used a face-to-face survey and an environmental scan of recreational facilities to get data. Their results showed that healthy, working Australian adults who were overweight were more likely to live near highways, with no sidewalks or sidewalks on one side only, and with no walking or cycle paths within walking distance of the residence. In addition, the results showed that there was a correlation between the lack of access to recreational facilities and obesity. For physical environmental variables, access to footpaths and street type was based on the interviewer's assessment when the interviewer stood in front of the interviewee's home. The distance between the respondent's home and the recreational facilities was obtained by the GIS tool. Saelens et al. (2003) used census data to identify high-walking and low-walking communities based on the number of walking and cycling

trips by neighborhood residents. They found that, compared to low-walking communities, high-walking communities had higher housing density, better street connectivity, and more diverse and easily accessible land use, all of which promoted more physical activity in the form of walking/cycling. Correspondingly, residents in high-walking communities tended to report lower average body mass index (BMI) and were less likely to be overweight than residents of low-walking communities. Rundle et al. (2007) found that the mixed land use density, population density, and public transit density were significantly negatively associated with BMI, while intersection density was not significantly associated with BMI in New York City. In this study, individual-level data were linked with census neighborhood data based on the survey participants' home addresses; mixed land use density was measured by the balance of commercial and residential land uses;[2] public transit density was measured by the number of bus stations and subway stations per $km^2$ in each census tract; and intersection density was measured by the number of street intersections per census tract. Covariates included age, gender, race, education at the individual level, and poverty and race/ethnicity at the census district level. All the above studies measure the built environment in relation to obesity through physical activity, such as land-use mix, connectivity (street pattern, sidewalk coverage, traffic), and access to recreation facilities.

The built environment can also affect body weight through the food environment. Using the 2005 California Health Interview Survey (CHIS) and geographic information system (GIS) tool, Babey et al. (2008) constructed a Retail Food Environment Index (RFEI) to

[2] Land Use Mix Index= 4* (the ratio of building area devoted to residential use * ratio of building area devoted to commercial use) in this study (Rundle et al., 2007).

measure the food environment by dividing the total number of fast-food restaurants and convenience stores by the total number of grocery stores and produce vendors within a given radius around each adult CHIS respondent's home address. The study showed that people having higher RFEI were more likely to be obese or diabetic. Chaparro et al. (2014) conducted a multilevel longitudinal analysis to examine how the spatial density of healthy and unhealthy retail food stores was related to obesity for low-income preschool children. The results showed that a higher density of healthy food stores was associated with weight loss, while the density of unhealthy food stores had nothing to do with children's weight-for-height z-score. Chen et al. (2013) combined geo-referenced data on the location of fast-food restaurants with data on personal health, behavior, and neighborhood characteristics. The local food environment was defined by a 0.5-mile buffer surrounding a person's home address for each person. In order to address potential bias related to the endogeneity of fast food in the determination of BMI and spatial autocorrelation in the error term, this research used instrumental variables (IV) and spatial econometric estimation techniques to investigate the impact of neighboring fast-food restaurants on obesity in the urban food market. All the findings suggest that the built neighborhood environment affects residents' body weight by influencing their physical and diet activities.

All of these built environment studies have used one of the three measurements of the built environment: (1) Perceived measures obtained using interviews or questionnaires; (2) Observational measures obtained through systematic in-person observation; or (3) GIS-based measures(Brownson et al., 2009). All three measurements have limitations. Perceived measures rely on participant or researcher perceptions in surveys, which can be subjective (Blacksher & Lovasi, 2012); observational measures can be costly and time-

consuming; and GIS measurement rely on GIS software, which can be expensive and difficult to use. However, with the development of image recognition technology, GIS tools provide many innovative methods to capture the variables of the built environment.

Salesses et al. (2013) used both geo-tagged images from four cities and image ratings to quantify people's perception of cities and their communities in Boston, New York, Linz, and Salzburg. The image ratings were created by participants' comparing random pairwise images and answering evaluative questions such as "Which place looks safer?" or "Which place looks more upscale?" The significant correlation between violent crime and urban perception validates their measurement of urban perception. Using hundreds of thousands of ratings of Google Street View from an online survey as the training data, Naik et al. (2014) developed a computer vision algorithm called "StreetScore" to predict the perceived safety of a streetscape. "StreetScore" was later used to quantify the physical appearance of streetscapes from Google Street View images so that the relationship between the changes in physical appearance and the changes in demographics and the economy could be investigated (Naik et al., 2017).

Convolutional neural networks (CNN) have been widely used with large data sets in computer vision tasks, such as object recognition, image segmentation, health-related applications, and economic activity estimation. Jean et al. (2016) used survey and Google satellite data from five African countries to train a CNN model to recognize image features that predict consumption expenditure and asset wealth at the "cluster" level.[3] Nguyen et al. (2018) obtained images from Google's Street View Image API and then used the CNNs to

[3] "Cluster" level is roughly equivalent to villages in rural areas or wards in urban areas.

create indicators for street greenness, crosswalks, and building types for each image. Log Poisson regression models were implemented in the data analysis to estimate the association between the built environment features and individual incidences of obesity and diabetes. The control variables included individual-level and zip code-level predisposing characteristics. Neighborhoods were defined by zip code boundaries. Maharana & Nsoesie (2018) used satellite images from Google Static Maps API and the CNN to extract features of the built environment in Los Angeles, Memphis, San Antonio, and Seattle and then investigated the associations between adult obesity prevalence and the built environment at the census tract level.

This paper implements a similar method to what Maharana & Nsoesie (2018) used to study the relationship between the built environment and health outcomes in Philadelphia.

### 1.3 Data

I used Google Static Maps as the primary resource to capture the features of the built environment of Philadelphia. Google Static Maps offers a free plan with a daily download limit of 25,000 requests per day. I divided Philadelphia's geographic span into a square grid and downloaded satellite images accordingly. In this paper, the size of each tile image is 400*400 pixels, covering an area of approximately 150m*150m in the real world (zoom level 18). This study focuses on Philadelphia, which has 384 census tracts. Since the areas of the census tracts vary widely, the number of tile images in each census tract range from 14 to 1294. Approximately 28,000 tile images were downloaded in April 2020. Figure 1.1 shows two sample tile images.

*Figure 1.1 Tile Images Downloaded from Google Satellite Imagery*

It is easy to recognize land-use diversity and street connectivity from the tile image in Figure 1.1. However, what is inside each building is difficult to tell. Therefore, it is challenging to discern the food environment solely from the tile images. In order to provide more information about the food environment in each census tract in Philadelphia, I used Neighborhood Food Retail data from OpenDataPhill.[4] OpenDataPhilly is a catalog of open data in the Philadelphia region. Neighborhood Food Retail data provides block-group-level estimates for the availability of "high-produce supply stores" and "low-produce supply stores." "High-produce supply stores" offer many options for healthier foods. They include supermarkets, produce stores, and farmers' markets. "Low-produce supply stores" contain a limited number of healthy food options and a high number of unhealthy food options. They include fast-food stores, dollar stores, pharmacies, and convenience stores.[5] I transferred these estimates from the block group level to the census tract level and then calculated the percentage of high-produce supply stores among all supply stores. The nominator was the number of high-produce supply stores, and the denominator was the

[4] Data link: https://www.opendataphilly.org/dataset/neighborhood-food-retail, Aug 2019.

[5] For more details about "high-produce supply stores" and "low-produce supply stores", see https://www.phila.gov/media/20190923114738/GHP_FoodAccessRpt_Final_wDate.pdf, Sep 2019.

total number of high-produce and low-produce supply stores. I used the percentage of high-produce supply stores as the primary measurement for food access. A higher rate of high-produce supply stores indicates a better food environment, which means that people living in this census tract tend to have better access to healthy food.

The health outcomes data comes from the PLACES Data.[6] The PLACES project is a collaboration among the CDC, the Robert Wood Johnson Foundation, and the CDC Foundation, which provides city and census tract-level small-area estimates for chronic disease risk factors, health outcomes, and clinical preventive service use across the United States.[7] Obesity prevalence is the main health outcome variable. The annual crude obesity prevalence estimates were calculated based on the respondents' self-reported weight and height. Respondents older than 18 were regarded as obese if their body mass index (BMI) was at least 30 $kg/m^2$. This paper used the most recent data from 2018.

The control variables come from the Census Bureau's Planning Database (PDB), which assembles housing, demographic, socioeconomic, and operational data at the census tract and block levels. I used the 2020 PDB dataset to access demographics and socioeconomic variables, including median household income, percentage of male, percentage of non-white, and percentage of population under the poverty line in 2018. The demographic data in the 2020 PDB dataset is based on the 2010 Census or the American Community Survey (ACS) 5-year files. Since census tracts in Philadelphia did not change from 2010 to 2020,

[6] PLACES data link: https://www.cdc.gov/places/index.html.

[7] The CDC Foundation is an independent nonprofit and the sole entity created by Congress to mobilize philanthropic and private-sector resources to support the Centers for Disease Control and Prevention's critical health protection work.

and my study focused on 2018, I chose the 2014-2018 American Community Survey (ACS) instead of the 2010 Census as the data source of the demographic variables in PDB.

## 1.4 Methodology

### *1.4.1 Process Images with Convolutional Neural Network*

The main innovation of this paper is to use a previously trained CNN to extract data representing the features of the built environment from high-resolution satellite imagery. CNN is a deep learning algorithm that can take an input image, assign weights to pixels in the image, and distinguish the objects in the image.

This paper uses the VGG-16 network as the pre-trained model. VGG-16 is trained over ImageNet, a dataset of over 15 million cleanly labeled, high-resolution images. VGG-16 can classify images into 1000 object categories, including cars, animals, volcanos, lakesides, church buildings, and glasshouses. The picture below shows the architecture of VGG-16.

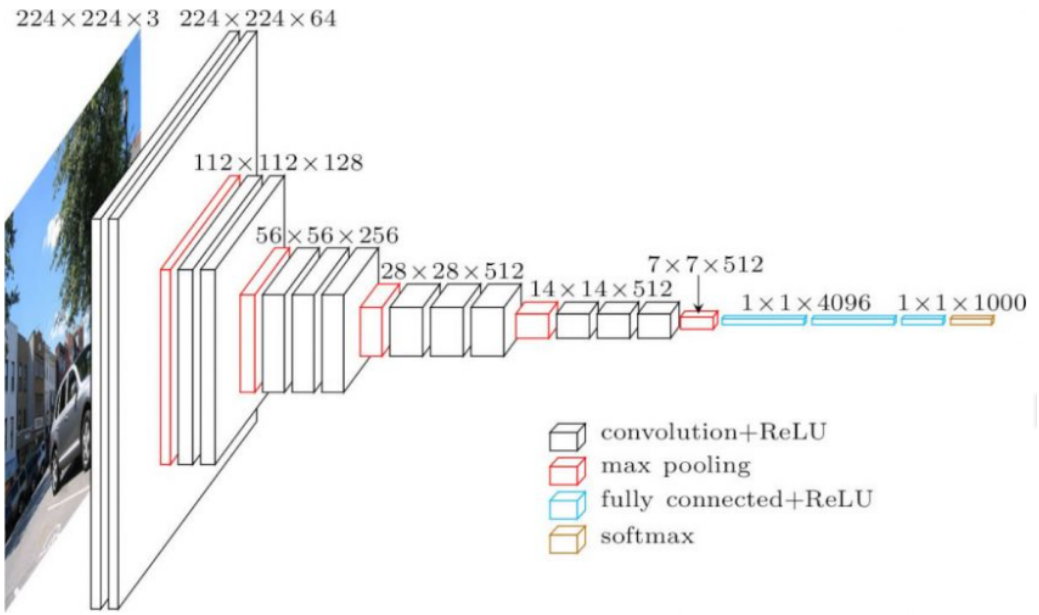


*Figure 1.2 The Architecture of VGG-16*[8]

One main concern of this transferring learning is the input data difference. The input data set ImageNet of VGG includes images of animals, geological formations, natural objects, and many other categories. The images analyzed in this paper are satellite images, including parks, highways, green streets, crosswalks, and diverse housing. As a result, using VGG16 directly may not recognize objects from satellite image.

Since my input data are different from the VGG-16 input data, one way to resolve this difference is to build the classifier based on my input data and adjust the network. This solution requires a large dataset of obesity prevalence for each area represented by a satellite image so that we can label each image based on obesity prevalence and then train

[8] The VGG 16 architecture figure link: https://medium.com/@mygreatlearning/everything-you-need-to-know-about-vgg16-7315defb5918, April 2023. As shown in the architecture figure, VGG16 comprise 16 layers and it is structured into five repeating blocks. Each block has either two or three convolutional layers followed by a max pooling layer. The convolutional layers use 3x3 or 5x5 filters, which are activated using the ReLU function. After the convolutional layers, there are three fully connected layers, each with a different number of neurons. The last layer uses a softmax function to produce output probabilities for the 1,000 classes in the ImageNet dataset.

a new model. However, due to the limited labeled data to indicate high-obesity or low-obesity regions, I used the second fully connected layer of the VGG-16 network to overcome the input data difference problem in this paper. Using the second fully connected layer of the VGG-16 can transform a two-dimensional image into a single vector of 4,096 dimensions, which contains only the most important descriptors of the image. I employed this technique to transform each satellite image into a feature vector of length 4,096. These 4,096 variables do not have a specific meaning, but they serve as an indicator of the built environment, including color, gradient, edge, height, length, etc. In other words, each image can be represented by these 4,096 feature variables. I calculated each feature variable's mean value within each census tract. The feature variables were combined with the health outcome of obesity for data analysis.

### *1.4.2 Model*

The association between the built environment and obesity prevalence can be estimated using the linear regression model (1):

$$y_i = \alpha_0 + \alpha_1 Food_i + \alpha_2' B_i + \varepsilon_i \qquad (1)$$

$y_i$ represents obesity prevalence, which is the percentage of the population that is obese in census tract $i$. $Food_i$ refers to food availability, which is measured by the percentage of high-produce supply stores relative to the total supply stores in each census tract $i$. $B_i$ is the vector of 4,096 variables drawn from the CNN. As noted, these 4,096 variables, including gradient, edge, height, length, and color, can represent the physical neighborhood in each census tract. Each census tract is regarded as one observation. I used this model as the main model in this paper.

I constructed a comprehensive measurement of the built environment by including feature variables extracted from satellite images and a food access variable. One concern for this measurement is the potential correlation between food access and the feature variables. To avoid a multicollinearity problem, I built the linear regression model (2) to test the relationship between the feature variables from satellite images and obesity prevalence without the food access variable:

$$y_i = \gamma_0 + \alpha\gamma_1' B_i + \varepsilon_i \quad (2)$$

Many studies point out that demographic and socioeconomic factors contribute to obesity at the individual and community levels. To capture the effect of demographic and socioeconomic factors on obesity, I used the linear regression model (3) to study the relationship between the built environment and obesity prevalence.

$$y_i = \rho_0 + \rho_1 Food_i + \rho_2' B_i + \rho_3' X_i + \varepsilon_i \quad (3)$$

$X_i$ is a vector of control variables that may affect obesity rates, including population density, median household income, percentage of male, percentage of non-white, and percentage of population under the poverty line. $\varepsilon_i$ is the error term for census tract $i$.

### *1.4.3 Elastic Net*

There are approximately 5,000 regressors in the three models and only 373 observations. When the number of predictors is larger than the number of observations, overfitting occurs, and the model is referred to as high-dimensional. With a high-dimensional linear model, regularization methods can be used. These methods are suitable machine learning tools for prediction and causal inference. Regularized linear regression is an extension of ordinary least squares (OLS). It minimizes the sum of squared deviations between observed and model-predicted values while imposing a regularization penalty to

reduce model complexity. There are several forms of regularized regression methods. The most common forms are LASSO, Ridge, and Elastic Net regression.

I use the Elastic Net algorithm in this paper since Elastic Net combines the benefits of LASSO and Ridge regression. Elastic Net can eliminate insignificant variables and preserve significant and correlated variables. It is especially powerful when applied to a very large data set, where the number of variables might be in the thousands or even millions. It applies a mix of $l_1$ (Lasso-type) and $l_2$ (Ridge-type) penalties. The estimator can be written as:

$$\hat{\beta} = \arg\min_{\beta} \frac{1}{N}\sum_{i=1}^{N}(y_i - x_i'\beta)^2 + \frac{\lambda}{N}\left[\alpha\sum_{j=1}^{p}\psi_j|\beta_j| + (1-\alpha)\sum_{j=1}^{p}\psi_j\beta_j^2\right]$$

, where $\sum_{j=1}^{p}\psi_j|\beta_j|$ represents the $l_1$ penalty and $\sum_{j=1}^{p}\psi_j\beta_j^2$ represents the $l_2$ penalty.

The $l_1$ norm generates a sparse model, and the $l_2$ norm preserves highly correlated variables. The parameter α determines the relative importance of $l_1$ versus $l_2$ penalization. If α=1, the penalty function reduces to the $l_1$ , or Lasso term, and if α=0, we get the $l_2$, or Ridge, term. $y_i$ indicates the outcome variable. X is the vector of all independent variables.

In summary, this analysis has three stages. First, I use CNN to extract the main features of the built environment from satellite images. Second, I use Elastic Net, a regularization method, to examine the relationship between the built environment and obesity prevalence. Third, I use the same Elastic Net model to evaluate the predictive performance of adding the features from satellite images when regressing obesity on healthy food access.

## 1.5 Results

### *1.5.1 Main Results*

Table 1.1 presents summary statistics for related variables. There are 384 census tracts in Philadelphia, 11 of which have a missing value for food access or obesity.[9] After dropping the 11 census tracts with missing values, the total number of observations was 373. Adult obesity prevalence was the dependent variable. The average percentage of obesity in Philadelphia was 32.25 percent. Food access is proxied by the percentage of high-produce supply stores among all supply stores. The average food access was 13.23 percent, indicating 13.23 percent of stores in Philadelphia were high-produce stores that could offer many options for healthier foods. Population density was calculated by dividing populations by land area in the census tract. The average population density in Philadelphia was about 19,869 people per square mile in 2018.

Using VGG as the pre-trained model, 4,096 variables were extracted from the satellite images to represent the built environment in each census tract. Table 1.1 reports selected feature variables. For example, the mean value of Feature_1 is 1.68, and the mean value of Feature_4096 is 0.37. All these numbers do not have a specific meaning, but they serve as an indicator of the built environment.

*Table 1.1. Summary Statistics*

| | **Mean** | **Min** | **Max** |
|---|---|---|---|
| Health Outcome | | | |
| Obesity Prevalence (%) | 32.25 | 17 | 47.9 |
| Food Environment Measurement | | | |
| High-Produce Supply Stores | 13.45 | 0 | 147 |

[9] Tract ID for 8 census tracts without obesity data: 5000, 9803-9809. Tract ID for 10 census tracts without food availability data: 5000, 9800-9809.

*Table 1.1. (continued)*

| | Mean | Min | Max |
|---|---|---|---|
| Low-Produce Supply Stores | 105.36 | 1 | 495 |
| Food Access (%) | 13.23 | 0 | 66.67 |
| Feature Variables Extracted from Images | | | |
| Feature_1 | 1.68 | 0.22 | 3.2 |
| Feature_2 | 1.74 | 0.21 | 4.19 |
| Feature_3 | 1.17 | 0.21 | 2.78 |
| Feature_4 | .75 | 0 | 2.21 |
| … | … | … | … |
| Feature_4094 | 0.57 | 0 | 2.37 |
| Feature_4095 | 0.09 | 0 | 0.98 |
| Feature_4096 | 0.30 | 0 | 1.07 |
| Demographic and Socioeconomic Variables | | | |
| Gender (Male) % | 47.39 | 33.1 | 96.68 |
| Ethnicity (Non-white) % | 64.66 | 2.25 | 100 |
| Poverty % | 25.38 | 0.89 | 82 |
| Population Density (1000) | 19.87 | 0.56 | 81.26 |
| Observations | 373 | | |

Note. Median household income is in 2018 inflation-adjusted dollars value. Poverty refers to the percentage of the ACS eligible population classified as below the poverty level given their total family or household income in the last year. Population density is expressed as population per square mile.

After extracting the 4,096 feature variables from satellite imagery, I used the Elastic Net model to investigate the association between the built environment and being overweight. First, I randomly split the data into two subsets – a training sample and a test sample. The training sample was used to estimate coefficients of related variables to fit the model, and the test sample was used to evaluate the performance or accuracy of the model. Most studies choose a training sample of 75 percent or 50 percent of the original dataset. Since my sample size is very small, I split 75 percent of data into a random training sample and 25 percent into a test sample. There were 280 observations in the training sample and 93 observations in the testing sample.

Second, I tried different selection methods to fit the model, and I chose the one that had the lowest mean squared error (MSE) with reasonable parameters. I chose the five

folds cross-validation (CV) as the selection method based on previous research (Maharana & Nsoesie, 2018). As a result of using five folds CV selection method, the lasso's penalty parameter, $\lambda$, was 0.40, and the mixing parameter, $\alpha$, was 0.5.

After regularization, I retained the 237 covariates, of which one variable was food availability, and the other 236 variables were part of the features extracted from satellite images. Table 1.2 shows the values of the coefficients for the selected remaining variables. Some of the coefficients of feature variables are positive, while some are not. Since feature variables do not have a specific meaning, Table 1.2 only reports seven feature variables with the largest absolute value of the coefficient and a feature variable with the smallest absolute value of the coefficient. These 236 feature variables can be gradients, edges, and patterns that correspond to the physical neighborhood environment, such as the presence of roads, buildings, trees, water, and land. The coefficient of food access is -1.91, which means a one percentage point increase in the ratio of high-produce supply stores among all supply stores is associated with a decrease in obesity prevalence of 1.91 percentage points in Philadelphia. This is consistent with the hypothesis that an improvement in healthy food access lowers obesity prevalence.

*Table 1.2. Penalized Coefficients for Model 1*

| **Variables** | **Value of Coefficients** |
|---|---|
| Food Access | -1.91 |
| Feature_2605 | 0.53 |
| Feature_2081 | 0.50 |
| Feature_4053 | 0.42 |
| Feature_2073 | 0.40 |
| Feature_1750 | -0.35 |
| Feature_543 | -0.35 |
| Feature_367 | -0.34 |

*Table 1.2. (continued)*

| **Variables** | **Value of Coefficients** |
|---|---|
| … | … |
| … | … |
| Feature_994 | 0.00017 |
| _cons | -3.55e-15 |
| Observations | 280 |

Note. The outcome variable is obesity prevalence. There are 237 non-zero coefficients. The results are based on the Elastic Net Linear model, where $\lambda$ equates to 0.40, and $\alpha$ equates to 0.5. The penalized estimator is used to produce coefficients. Variable rows are in descending order by the absolute values of the coefficients.

I used the penalized estimator to predict the obesity value for the test sample. The mean squared error (MSE) was 20.07. The out-of-sample coefficient of determination ($R^2$) was 0.65. It suggests that the built environment variables can explain 65 percent of between–census tract variance in obesity in the test data set.

To further illustrate the predictive performance of this model, I plotted Figure 1.3 to compare the predicted obesity prevalence and the actual obesity prevalence for the test sample. The y-axis represents the estimates of obesity prevalence based on the features of the built environment, including food access; the x-axis represents the actual obesity prevalence. From the plot, a strong positive correlation between predicted obesity prevalence and actual obesity prevalence can be observed.

All these results suggest that the built environment is highly correlated with obesity.

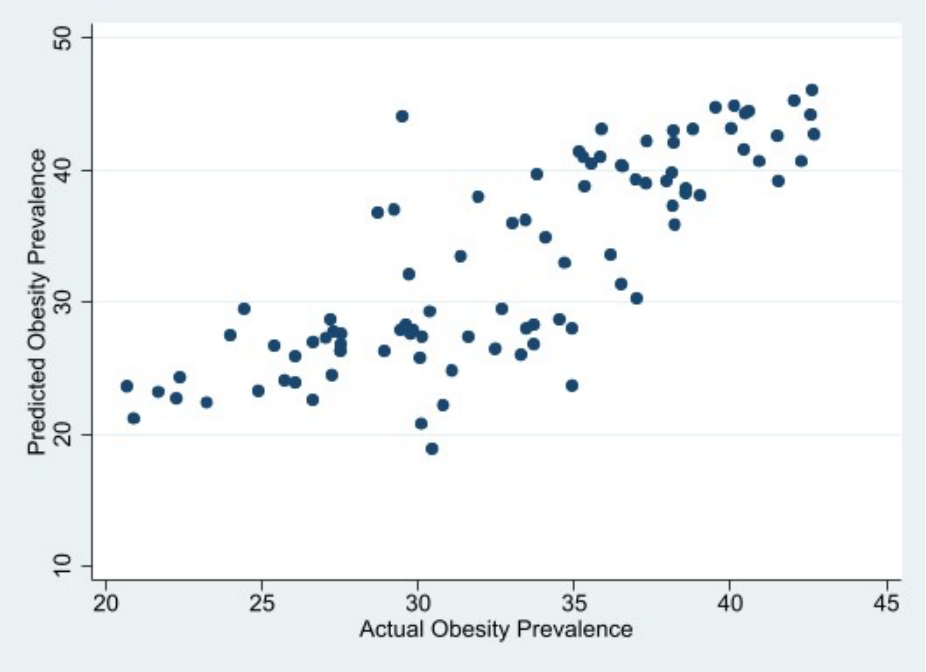


*Figure 1.3 Out of Sample Prediction of Obesity Prevalence and Actual Obesity Prevalence Based on Model 1*

### *1.5.2 Results with Other Models*

Following the same methodology, Table 1.3 and Figure 1.4 reported the results of Model 2, which regresses obesity prevalence on features taken from satellite images without food access. Figure 1.4 has a similar pattern to Figure 1.3. It shows a strong positive correlation between predicted obesity prevalence and actual obesity prevalence. The out of sample $R^2$ is 0.61, which means this model can explain 61 percent variance of the obesity prevalence across all the census tracts. Compared with 65 percent variance in Model 1, out of sample $R^2$ decrease by only 0.04. The slight change in out of sample $R^2$ and the similar pattern of Figure 1.4 in Model 2 shows that not including food access does not severely affect the predictive performance. An explanation is that feature variables from satellite imagery might be representative of healthy food access indicators. This finding can

strongly support the idea that we can use the features extracted from satellite imagery to predict obesity prevalence in an area. What is more, these feature variables can reduce the role of healthy food access in predicting obesity.

*Table 1.3. Penalized Coefficients for Model 2*

| **Variables** | **Value of Coefficients** |
|---|---|
| Feature_2605 | 0.60 |
| Feature_2081 | 0.51 |
| Feature_2073 | 0.43 |
| Feature_543 | -0.39 |
| Feature_4053 | -0.37 |
| Feature_1379 | -0.36 |
| Feature_1457 | -0.35 |
| … | … |
| … | … |
| Feature_994 | 0.00004539 |
| _cons | 0 |
| Observations | 280 |

Note. The outcome variable is obesity prevalence. There are 253 non-zero coefficients. All the results are based on the Elastic Net Linear model where penalized estimator $\lambda$ equates 0.36, and $\alpha$ equates 0.5. Variable rows are in descending order by the absolute values of the coefficients.

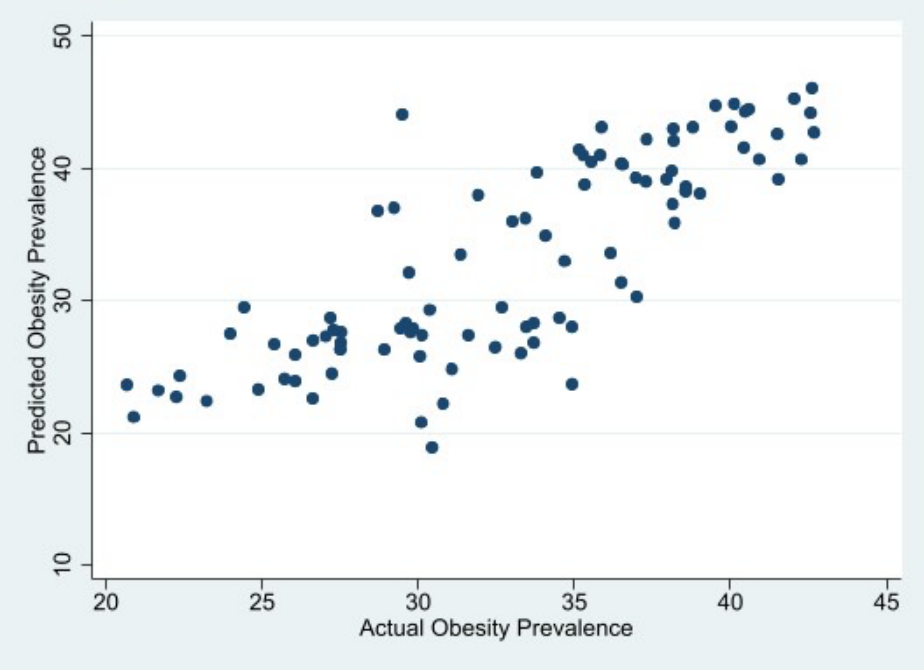


*Figure 1.4 Out of Sample Prediction of Obesity Prevalence and Actual Obesity Prevalence Based on Model 2*

Table 1.4 and Figure 1.5 show the results of Model 3, which regresses obesity prevalence on the built environment controlling for demographic and social economics variables. Out of sample $R^2$ is 0.92, which means this model can explain the 92 percent variance of obesity prevalence across all the census tracts. There are 90 feature variables remaining with non-zero coefficients. Since the feature variables have no specific meaning, I do not include all the coefficients in Table 1.4. Instead, I add the seven feature variables with the largest absolute value of the coefficient and a feature variable with the smallest absolute value of the coefficient.

*Table 1.4. Penalized Coefficients for Model 3*

| **Variables** | **Value of Coefficients** |
|---|---|
| Race (Non-white) | 4.59 |
| Poverty | 1.86 |
| Population Density | -1.58 |
| Median Age | 0.79 |
| Food Access | -0.70 |
| Gender (Male) | -0.40 |
| Feature_2255 | -0.28 |
| Feature_4062 | 0.28 |
| Feature_1456 | -0.22 |
| Feature_335 | 0.21 |
| Feature_838 | 0.20 |
| … | … |
| … | … |
| Feature_225 | 0.0017 |
| _cons | 0.00 |
| Observations | 280 |

Note. The outcome variable is obesity prevalence. There are 90 selected variables. The results are based on the Elastic Net Linear model, where $\lambda$ equates 0.422, and $\alpha$ equates 0.5. Penalized estimator is used to produce coefficients. Variable rows are in descending order by the absolute values of the coefficients.

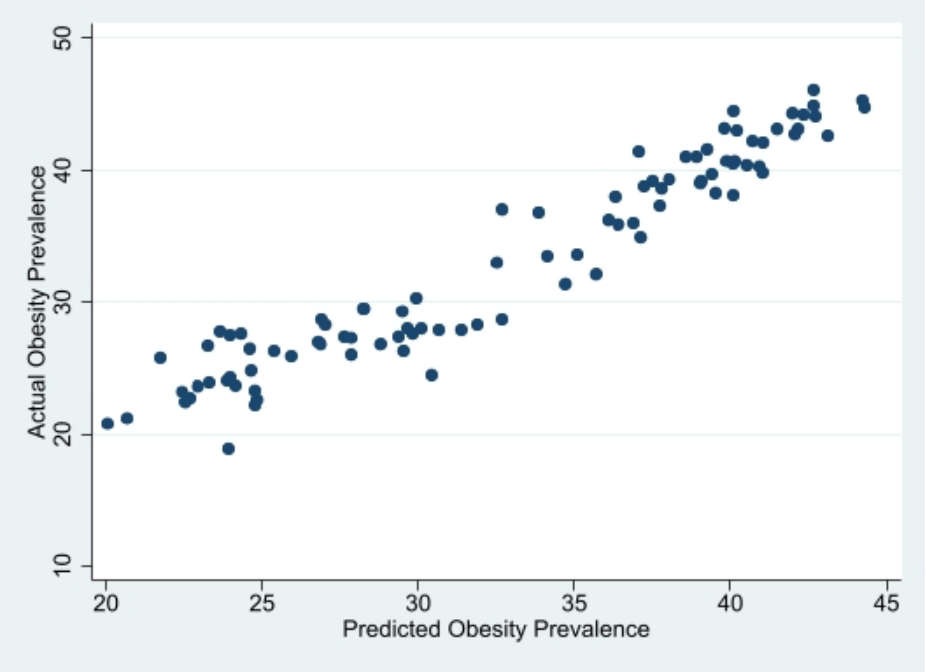


*Figure 1.5 Out of Sample Prediction of Obesity Prevalence and Actual Obesity Prevalence Based on Model 3*

*Table 1.5. Elastic Net Estimate Results in Three Models*

| **Model** | **MSE** | **Out of Sample R-square** | **No. of Selected Variables** |
|---|---|---|---|
| Model 1: Regress obesity on the built environment | 20.7 | 0.65 | 236 |
| Model 2: Regress obesity on features extracted from Google images only (without food access) | 18.1 | 0.62 | 253 |
| Model 3: Regress obesity on the built environment while controlling for demographic and socioeconomic variables | 4.61 | 0.92 | 90 |

Note. Each census is regarded as one observation. All models are estimated with the Elastic Net regression. MSE indicate the lowest mean squared error in each model.

Table 1.5 shows MSE, R-square, and the number of selected variables for the three models. The high value of out-of-sample R-square suggests that my three models fit the data well, thus indicating that the built environment matters in predicting obesity prevalence.

### *1.5.3 Results of Using the Built Environment as Control Variables*

Another purpose of this study is to test the possibility of using this paper's measurement of the built environment in studies related to the environment. Suppose we want to study the relationship between food access and obesity prevalence. In that case, we may choose to regress obesity on food access, as in model (4), or regress obesity on food access with controlling demographic and socioeconomic factors, as in model (5).

$$y_i = \theta_0 + \theta_1 Food_i + \varepsilon_i \quad (4)$$

$$y_i = \omega_0 + \omega_1 Food_i + \omega_2' X_i + \varepsilon_i \quad (5)$$

$y_i$ represents obesity prevalence in census tract $i$. $Food_i$ refers to food availability, which is measured by the percentage of high-produce supply stores relative to the total supply stores in each census tract $i$. $X_i$ is a vector of control variables that may affect obesity rates, including population density, percentage of male, percentage of non-white, and percentage of population under the poverty line. $\varepsilon_i$ is the error term for census tract $i$.

Both analyses may be biased due to omitted variables related to the built environment. The measurement of the built environment in this paper may help avoid such bias. Model 1 has the same structure as Model 4 but controls the built environment by adding 4,096 feature variables extracted from satellite imagery. Similarly, Model 3 has the same structure as Model 5 but controls the built environment by adding 4,096 feature variables extracted from satellite imagery. If the 4,096 feature variables are added in the model, as in Model 1 and Model 3, a regularization method is needed to estimate the model since we do not have enough observations.

To better evaluate the performance of adding the built environment through control variables, I created Table 1.6 to compare the results of Model 1 with Model 4 and Model

3 with Model 5. Columns 2 and 4 in Table 1.6 report OLS results from Models 4 and 5. The coefficients of food access in both column 2 and column 4 are statistically significant, implying that food access is negatively correlated with obesity prevalence. The results show that more access to healthy food lowers obesity prevalence. The coefficient of food access in Model 5 was -0.122, which meant a one percentage point increase in the ratio of high-produce supply stores among all supply stores was associated with a decrease in obesity prevalence by 0.122 percentage points in Philadelphia.

Columns 1 and 3 in Table 1.6 show the Elastic Net regression results of Model 1 and Model 3 that control the built environment. The coefficients of food access in both columns are negative, which also indicates a negative relationship between healthy food access and obesity. To evaluate the predictive performance of the original model and the model that controls the built environment, I compare the results of Model 1 with Model 4 and compare the results of Model 3 with Model 5. The out of sample R-squared value (0.65) in Model 3 is much higher than the R-squared value (0.238) in Model 4. The out of sample R-squared value (0.92) in Model 3 is also higher than out of sample R-squared value (0.83) in Model 4. Higher out of sample R-squared value in both Model 4 and Model 5 indicates that models that control built environment can explain more variance of obesity prevalence across all census tracts in Philadelphia.

*Table 1.6. Regression of Food Access on Obesity*

| **VARIABLES** | **(1)**<br>**Model 1** | **(2)**<br>**Model 4** | **(3)**<br>**Model 3** | **(4)**<br>**Model 5** |
|---|---|---|---|---|
| Food Access | -1.91 | -0.368*** | -0.70 | -0.122*** |
| | | (0.0381) | | (0.0227) |
| Population Density | | | -1.58 | -0.056*** |
| | | | | (0.0158) |
| Median Age | | | 0.79 | 0.164*** |
| | | | | (0.0316) |

*Table 1.6. (continued)*

| VARIABLES | (1) Model 1 | (2) Model 4 | (3) Model 3 | (4) Model 5 |
|---|---|---|---|---|
| Gender (Male %) | | | -0.4 | 0.0560* |
| | | | | (0.0335) |
| Race (Non-white %) | | | 4.59 | 0.162*** |
| | | | | (0.00912) |
| Poverty (%) | | | 1.85 | 0.139*** |
| | | | | (0.0206) |
| Constant | | 37.12*** | | 17.79*** |
| | | (0.6) | | (2.453) |
| Observations | 280 | 280 | 280 | 280 |
| R-squared | 0.65 | 0.238 | 0.92 | 0.828 |

Note. Each census tract is regarded as one observation. Column 1 and Column 3 are estimated with the Elastic Net regression. Column 2 and Column 4 are estimated with OLS regression. Results of OLS regressions in this paper are marked in grey to distinguish them from the results of Elastic Net Regression. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

## 1.6 Discussion

This paper investigates the association between the built environment and obesity. The built environment can affect physical activity through the physical activity environment (such as green area, type of building, road connectivity, and land use). It can also affect people's diet and nutrition intake through the food environment (such as proximity to fast-food restaurants, supermarkets, and convenience stores). Since physical and diet activities play an important role in body weight, the built environment can affect body weight. I used a pre-trained CNN to extract features of the built environment from Google Satellite images, and these features can be regarded as the main measurement of the built environment. To fully capture the food environment, the model also included health food access, which is measured by the percentage of high-produce supply stores among all supply stores. The Elastic Net regression models had a high R-squared, as well

as a high similarity between the predicted obesity percentage and actual obesity prevalence in the test sample. Based on the results, I conclude that the built environment is highly correlated with body weight.

One advantage of this methodology is that I can capture most potential features of the built environment related to body weight, while other studies must focus on a few specific features of the built environment, such as parks, physical activity facilities, and walkability. The results of Model 3 show that my measurement of the built environment reduces the role of food access.

In addition, this study provides a consistent measurement that allows comparisons across studies because the measurement is objective and relies on publicly available data. This consistent measurement of the built environment may also be used as a control variable in environmental studies. Adding the measurement can explain more variance of obesity, especially if data about demographic and socioeconomic factors are not available.

This work has some limitations. First, obesity prevalence is calculated based on self-reported height and weight, which may cause measurement errors for the obesity level. Second, self-selection bias may exist since this is a cross-sectional study, which cannot provide strong support for causality. Third, the satellite images were downloaded in 2020, while the data for other variables came from 2018. The difference in data timing may cause some bias. Fourth, I cannot identify the remaining feature variables in each model.

In the future, I will try to identify the remaining feature variables. It is possible that some combination of these feature variables from satellite imagery indicate some specific features of the built environment, such as a green area building, water, road, etc. Suppose I can figure out the meaning of some combination of the remaining feature variables. In

that case, this research can contribute more to identifying policy prescriptions for healthy living, such as community design and city or neighborhood planning. Also, I will refine the method for a more useful application, from correlation study to causality analysis. I plan to download historical satellite images from Google Earth to conduct a longitudinal study. To improve my research design, I may look at environmental interventions or dramatic changes in geographic land features in the short run in Philadelphia.

# CHAPTER 2

# THE PAID MATERNITY LEAVE AND CHILD HEALTH: EVIDENCE FROM URBAN CHINA

## 2.1 Introduction

Maternity leave policies are designed to help working mothers balance the roles of family and employment, as well as to promote child welfare. Most countries have provided women with at least two or three months of paid leave during the period of giving birth.[10] The current law in Italy offers women one month of employer-paid leave before the birth of a child and four months after birth.[11] Swedish couples share 16 months of job-guaranteed paid leave.[12] In 1993, Bill Clinton, the President of the United States, signed the federal Family Medical Leave Act (FMLA) to mandate a minimum of 12 weeks of unpaid maternity leave. Prior to the passage of this Act, the United States was the only developed nation with no national family leave policy (Hyde et al., 1996). Most studies in developed countries show a positive relationship between maternity leave benefits and child health outcomes (Ruhm, 2000; Winegarden and Bracy, 1995; Stearns, 2015). However, there is limited evidence on whether maternity leave provisions benefit developing countries. To add some evidence to the research area, this paper investigates the relationship between maternity leave and child health in urban China.

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[10] Source: More than 120 Nations Provide Paid Maternity Leave, International Labour Organization, 1998.

[11] Italy - Maternity and paternity leave allowance, accessed Jan 6, 2022, https://ec.europa.eu/social/main.jsp?catId=1116&langId=en&intPageId=4618

[12] Sweden - Parental benefits and benefits related to childbirth, accessed Jan 6, 2022, https://ec.europa.eu/social/main.jsp?catId=1130&intPageId=4808&langId=en

This paper studies whether child health outcomes were affected by an extension of maternity leave implemented in China from 1 87 to 1991. At the national level, paid maternity leave in China was 90 days during the sample period. Beginning with Chongqing City in 1987, each province passed laws that granted extra days of maternity leave if a mother of an infant had a late birth, which means that she had her first child over the age of 24.[13] To qualify for the late birth benefit, the woman must also be employed and married. This reform, which mandated bonus days of maternity leave for employed women who had late childbirths, will be referred to as the Late Childbirth Benefit Policy (LCBP) in this paper. The LCBP expanded the 90-day national maternity leave, which was enacted differently in each province. Based on the variation in implementation time of the LCBP across different provinces, I use a two-way fixed-effects model to estimate whether this extension of paid maternity leave affected children's health in urban China. Since most women in rural areas do household care work or farm work, this research focuses on employed women in urban China. The health outcome is measured by the child's body weight and nutrition intake.

The paper makes several contributions to the economic and child development literature. One contribution is that it studies whether paid maternity leave policy affects children's health in China, proxied by body weight. Some studies have pointed out that self-reported health status would cause high bias due to measurement error (Butler et al., 1987; Natarajan et al., 2010). This paper's survey data on height and weight came from children's physical examinations, which helped avoid self-reporting measurement errors. This paper also examines the effect of LCBP on children's nutrition intake. To the best of

[13] Chongqing is a municipality in China, a provincial-level administrative division under direct control by the Chinese central government.

my knowledge, this is the first study to use body weight and nutrition intake to investigate the causal effect of paid maternity leave entitlement on children's health in China.

Another contribution of this paper is that it studies the effect of maternity leave policy on health outcomes in late childhood. A growing literature explores the impact of maternity leave policy on child health outcomes in early childhood, such as low birth weight, the likelihood of prematurity birth, and infant mortality rate (Rossin,2011; Ruhm,2000; Stearns, 2015; Winegarden and Bracy,1995). A smaller number of studies have examined longer-term maternity leave effects such as (i) educational attainments, such as the average schooling year and grade point average (GPA), and (ii) labor market outcomes, such as wage and employment status (Dustmann and Schönberg,2012; Oreopoulos et al.,2015). Existing studies of long-term maternity leave effects mainly focus on children's educational and lab r outcomes. There is little literature on the impact of maternity leave on later childhood health outcomes. This paper fills the research gap on the effect of maternity leave policy on later childhood health outcomes by investigating children from one to 18 years old.

This paper uses the variation in maternity leave policy from 1987 to 1991 across provinces in urban China to identify the impact of maternity leave on children's body weight. Using a two-way fixed-effects model, I compare health outcomes between the groups affected by the maternity leave reform and the groups not involved. The results show that the extension of maternity leave for working women does not significantly affect children's body weight.

The remainder of the chapter is organized as follows. Section 2 provides a conceptual framework, related research, and the background of the extension policy of maternity leave

in China. Section 3 presents data, empirical specifications, and methods. The main results are reported in Section 4, and robustness checks are listed in Section 5. Finally, section 6 concludes.

## 2.2 Conceptual Framework and Related Work

### *2.2.1 Conceptual Framework*

Almond and Currie (2010) develop a two-period health production function that permits health shocks as follows:

$$h = A\left[\gamma I_1 + (1-\gamma) I_2\right]$$

where h denotes health or human capital as assessed after childhood, and A represents factor productivity. $I_1$ indicates investments received during childhood through age five, while $I_2$ indicates investments received during childhood after age five. $\gamma$ is a shared parameter. For a given level of total investment, $I_1$ is more important than $I_2$ if $\gamma > 0.5$. If $\gamma < 0.5$, $I_1$ is less important than $I_2$. If $\gamma$ equals 0.5, the allocation between $I_1$ and $I_2$ will not affect h. The model opens the door to the possibility that early childhood shocks can have lasting impacts. The expansion of maternity leave can be regarded as a shock in early childhood. Therefore, it is reasonable to expect that the maternity leave policy would affect the early childhood health outcomes and may also affect the later childhood health outcomes.

At least three channels potentially link maternity leave duration to children's health: breastfeeding, intensive mother-infant interaction, and mothers' income. The first channel is that the maternity leave expansion would enhance breastfeeding, thus improving children's health outcomes. Using the data of the National Longitudinal Survey of Children and Youth (NLSCY), Baker and Milligan (2008) investigate the impact of family-leave

expansion on mothers' time away from work, breastfeeding, and short-run health outcomes for infants and mothers. They find that the reform leads to a significant increase in the time women stay home, longer breastfeeding duration, and better infant health outcomes at age 7-12 months. Recent research shows that breastfeeding has significant benefits for infants. Ip et al. (2007) find that breastfeeding reduces the risks of asthma, diabetes, obesity, and sudden infant death syndrome (SIDS). Wehby (2014) uses sibling data from the National Health Interviews Survey and the National Survey of Family Growth in the US to test the effect of breastfeeding on child disability. The results show that prolonged breastfeeding is associated with a reduced risk of child disability, but very short breastfeeding has no impact. These findings suggest that paid leave policies would positively impact children's health by promoting breastfeeding.

Another potential channel is that maternity leave intensifies mother-infant interaction, thus affecting the cognitive ability of the infant and early child development. The quality and quantity of time a mother spends with her child in the first year play an essential role in the child's well-being (Baum, 2003; Berger et al., 2005).

Raising children is a time-intensive activity. Berger et al. (2005) conclude that the interaction between mother and infant is higher among employed women with 12 weeks of maternity leave than those with six weeks of maternity leave. Baum (2003) finds maternal employment during the child's first year of life has a detrimental effect on a child's cognitive development. Daku et al. (2012) find that paid maternity leave increases childhood vaccination rates. These findings highlight the importance of mothers' time investment in childcare. With longer paid maternity leave, mothers can spend more time taking care of their babies and seeking recommended care; thus, infants receive more

preventive care. Overall, the extension of paid maternity leave may increase a mother's time investment in her child, thus affecting her child's health.

Alternatively, there is a potential adverse effect of maternity leave on children's health. In a competitive labor market, mandated benefits, such as parental leave, may reduce economic efficiency by restricting voluntary exchange between employers and employees (Ruhm,1998). Ruhm (1998) provides a detailed discussion of the economic consequences of the rights to paid parental leave in nine European countries between 1969 to 1993. The results show that parental leave increases women's employment but decreases the relative wage at extended durations. Lalive and Zweimüller (2009) examine the effects of two job-protected parental leave reforms in Austria on mothers' fertility and post-birth labor outcomes. They find that the parental leave reform in 1990, which extended maternity leave from one year to two years, significantly reduces the likelihood of mothers' return to work and lowers their earnings in the short run. All these studies point out that maternity leave may hurt the mother's income. The decrease in the mother's income would reduce the family's material resources. Due to the income effect, children may have a worse health status.

The maternity leave entitlement may enhance children's health by increasing breastfeeding duration or intensifying infant-mother interaction. The maternity leave entitlement may also negatively affect children's health by decreasing the mother's income. Given the complex set of pathways from maternity leave to children's health, the net impact of maternity leave is unclear. This paper will estimate the net effect by regressing BMI-related variables on the LCBP policy. This paper aims to provide some evidence on the net

impact of an extension of maternity leave policy on children's body weight and nutrition intake in urban China and investigate the role of each mechanism.

### *2.2.2 Related Research*

There is vast literature documenting the relationship between maternity leave policy and children's health outcomes. Much of the existing work focuses on children's health outcomes in developed countries. Rossin (2011) investigates how the 1993 Family and Medical Leave Act (FMLA) affected children's birth and infant health outcomes in the United States. Using the difference-in-difference (DID) method, the author shows that the unpaid maternity leave FMLA decreased the likelihood of premature birth and increased birth weight, primarily for college-educated and married mothers. Stearns (2015) shows that the paid maternity leaves from temporary disability insurance in the US reduce the percentage of low birth-weight births and the likelihood of early-term birth, primarily for unmarried and black mothers. Winegarden and Bracy (1995) find that an additional week of paid maternity leave is associated with a reduction of infant mortality rate by 0.5 deaths per thousand live births for 17 OECD countries. Ruhm (2000) provides a detailed investigation into the effect of paid parental leave on birth weight and infant or child mortality in nine European countries. These studies show a positive impact of maternity leave on children's health in early childhood in developed countries. Baker and Milligan (2008) investigate the impact of Canadian family-leave expansion from six months to one year in most provinces at the end of 2000. The paper finds no statistically significant effect of parental leave expansion on several child development measurements. It also finds that the reform led to a 48-58 percent increase in months of maternal care children received

during the first year, with a corresponding decrease in full-time maternal employment and unlicensed non-relative care.

Most of the literature on the long-term maternity leave effect has focused on children's educational and labor outcomes. Oreopoulos et al. (2015) use siblings and twin data in Canada to study whether poor early infant health affects subsequent health, education, and labor force attachment. Infant health is measured by birth weight, APGAR scores, and gestation. Their findings show 1) poor infant health is associated with a higher mortality rate of children up to age 17; 2) poor infant health is a strong predictor of high school completion and social assistance take-up; and 3) little evidence of the longer-term effects of infant health on cognitive ability. Another study on the long-term effect of maternity leave examines three major maternity leave policy reforms in Germany and compares the outcomes of children born just before and after each reform. The results from this study suggest that maternity leave had no statistically significant effect on educational or labor market outcomes, although there is a significant delay in mothers' return to work after childbirth (Dustmann & Schönberg, 2012). This paper will study the impact of maternity leave on children in children aged from one to 18 years old and provide evidence on the later childhood impact.

In a recent study, Jia et al. (2018) find a positive relationship between breastfeeding duration and maternity leave duration in urban China. Specifically, extending paid leave by 30 days increases the possibility of breastfeeding for at least six months by 12 percentage points. To address the endogeneity of paid maternity leave duration, they use the late-birth benefit days of paid maternity leave provided by each province plus the common entitlement of 90 days as an instrument for paid maternity leave duration. The

estimates in the reduced form equation show that the provincial paid leave entitlement is positively correlated with paid maternity leave duration employed mothers take in urban China. I analyze the same late childbirth policy but with a different dataset, methodology, and outcomes.

### *2.2.3 Policy Background*

In 1988, the State Council of China issued regulations on the Labor Protection of Women Workers to protect the rights and interests of female workers. According to the law, a woman employed by any enterprise or organization had the right to paid maternity leave for 90 days, including 15 days before childbirth.[14] In addition to the nationally unified maternity leave, many provincial governments extended maternity leave for women having late births as a strategy for birth control and family planning. If a female worker has a late birth, the local government will grant her extra days of paid maternity leave. The requirement for late childbirth varies among different provinces. The general requirement of late childbirth is that women need to be married and older than 23 or 24 years old when they give birth. For example, the birth control regulation in Liaoning Province states that "women who have late childbirth (having the first baby after age 23) will have an additional 45-day maternity leave if they have the One-China Certificate.[15] Thus, the total paid maternity leave for eligible women should be 114 days. The time of implementation of LCBP varies across provinces between 1987 and 1991. Table 2.1 shows the additional days of paid maternity leave for late childbirth, the implementation date, and other related information. This paper examines whether the passage of the LCBP affects children's

[14] The current national paid maternity leave in China is 98 days based on the updated regulation in 2012.

[15] One Child Certificate is a special treatment certificate for having one child only.

health in urban China. My empirical approach relies on the temporal variation of the late birth benefit policy across different provinces to study whether the change of maternity leave duration affects children's body weight.

*Table 2.1. Late Birth Benefit Policy in Different Provinces*

| Province | Bonus days of paid maternity leave for late childbirth | Bonus Months (Intensity) | Time of implementation |
|---|---|---|---|
| Liaoning | 44* | 1.5 | May 1988 |
| Heilongjiang | up to 90* | 3 | February 1990 |
| Jiangsu | 15-30 | 1 | October 1990 |
| Shandong | 60 | 2 | March 1988 |
| Henan | 90 | 3 | July 1990 |
| Hebei | 45 | 1.5 | March 1989 |
| Hunan | 30+30* | 2 | January 1990 |
| Guangxi | 14+20* | 1.13 | January 1989 |
| Beijing | 30 | 1 | June 1991 |
| Shanghai | 15 | 0.5 | August 1990 |
| Chongqing | 20 | 0.67 | July 1987 |

Note. The data comes from "Family Planning Regulation" and "Regulations on Population and Family Planning" issued by each province and mega cities. *Indicate that benefit in this province requires one child certificate, which means parents in the provinces need to have a one-child certificate to prove they only have one child. The mega city Chongqing belonged to Sichuan Province before 1997, so the information about Chongqing was based on the birth control policy in Sichuan Province.

## 2.3 Data

This research uses data from China Health and Nutrition Survey (CHNS). CHNS is an ongoing international collaborative project between the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute for Nutrition and Health at the Chinese Center for Disease Control and Prevention (CCDC). The survey covers over 7,200 households with more than 30,000 persons from communities with

diverse socioeconomic backgrounds in 15 provinces and municipalities in China.[16] It is designed to examine the effects of health, nutrition, and public policies and see how social and economic transformation affects China's health and nutritional status.

There were 23 provinces and four municipalities in China in 2015. CHNS began with eight provinces in 1988 and added Heilongjiang in 1998. Three municipalities joined the study in 2011, and three more provinces joined in 2015. CHNS did not conduct a physical examination in 2015, and Guizhou Province did not implement LCBP from 1987 to 1991. So, this study uses data from respondents living in eight provinces (Liaoning, Heilongjiang, Shandong, Henan, Hubei, Hunan, Guangxi, Jiangsu) and three megacities (Chongqing, Beijing, and Shanghai) collected in ten waves: 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009 and 2011.

The CHNS is a panel dataset providing detailed economic, demographic, and health information in China. The survey's multistage random cluster sampling method is based on different income levels and weighted sampling. The steps are as follows: after randomly selecting four counties and two cities with each province, the CHNS randomly identifies villages and towns in each county and urban and suburban regions in each city. The CHNS team then selects 20 households from each of these communities.

This study's primary measures of health outcomes of children are Z-score height, Z-score weight, and Z-score body mass index (BMI). The CHNS team hired healthcare workers to conduct physical examinations for each survey participant using standard protocols and techniques, including height, weight, head circumference, mid-arm skinfold measurements, and blood pressure for children aged seven or older. Before the survey,

[16] A municipality is a large, densely populated city that acts like a province and is under the direct administration of the central government in China.

Heath workers received specific training in anthropometric measurement techniques. Participants were asked to take off their shoes and coats for each measurement. At least two workers worked together to read and record weight to the nearest tenth of a kilogram with a beam balance scale and height to the nearest tenth of a centimeter with a portable stadiometer (Popkin et al., 1995). With these standard protocols and techniques, the anthropometric data gathered from CHNS largely avoid measurement error. BMI is then calculated based on the value of height and weight collected in the survey[17]. The BMI standard for adults is fixed. For children less than 18 years, the healthy BMI standard varies among different age and gender. Given that the health standards for children differ in various ages groups, the World Health Organization (WHO) recommends Standard Score (Z score) to quantify and describe anthropometric data for children. Child anthropometric data in this paper is transformed to Z scores using the LMS method[18] and the reference data available from the British 1990 Growth Reference.[19]

To further examine the effect of maternity leave extension on children's health issues related to obesity, I use being obese and underweight as dependent variables. Unlike adults, the cutoff for obesity and being underweight varies among the different groups of children. I categorize children as underweight, normal weight, and obese according to the internationally recognized BMI cutoffs for children[20]. The percentile range for being

[17] The BMI is calculated by dividing body weight by the square of the body height and is expressed in units of kg/m^2.

[18] The LMS method summarizes the changing distribution by three curves representing the median, coefficient of variation, and skewness.

[19] I transfer child anthropometric data to Z-scores using the LMS method and the reference data available from the British 1990 Growth Reference.

[20] BMI category variables are generated by Zanthro command in Stata 16.

underweight is less than the 5th percentile. The percentile range for obesity is 95th percentile or greater.

In addition to the BMI-related variables, this paper also uses relative nutrition intake to indicate health status. CHNS provides individual data on dietary intake for three consecutive days. The nutrition intake variables include calories, fat, protein, and carbohydrate. Suggested nutrition intake for children differs among different age groups and gender groups. To compare all children, I divide the observed three-day average nutrition by recommended daily nutrition intake for each group to obtain relative daily nutrition intake.[21] Suggested nutrition intakes come from Chinese dietary reference intakes.[22] If the relative nutrition intake is higher than 1, the daily nutrition intake is higher than the recommended daily nutrition intake for the specific age-gender group.

This paper restricts the CHNS sample to the group targeted by the late birth benefit policy: children whose mothers were married and gave birth at age 24 or older. Some provinces also require a one-child certificate to apply for late birth benefits, which means the benefit is restricted to mothers' first childbirth. Based on these requirements, I exclude children who are not the family's first child and mothers whose first birth occurred at age 23 or younger.

[21] I calculate the relative daily nutrition intake based on the following equations:
Relative fat intake= average three days fat intake / acceptable fat distribution range.
Relative carbohydrate intake = average three days carbohydrate intake/ suggested average requirement for carbohydrate intake.
Relative protein intake= three days protein intake/ recommended protein intake.

[22] The data for these suggested nutrition intakes comes from Chinese dietary reference intakes, last access Jan 4th, 2022, http://www.nhc.gov.cn/wjw/yingyang/201710/fdade20feb8144ba921b412944ffb779/files/0fa10dfb812a48b483d931972df1ccb8.pdf.

The sample in this paper begins in 1980 since China implemented free-market reform and the one-child policy in 1979. Because the State Council of China extended national maternity leave from 90 days to 98 days in 2012, my sample includes the first child in each household who was born between 1980 and 2011. This research also excludes families in rural areas. Most women in rural areas did housework or farm work in the 1980s. Under the household registration system, maternal benefits were mostly available to women in the urban sector, including employees of government agencies, non-profit public organizations, state-owned enterprises (SOEs), and urban collectives (Jia et al., 2018). I do not restrict mothers' marital status since mothers had to be married for childbirth registration in the 1980s. The Chinese household registration system (Hukou) require parents' marriage certificate to register a newborn infant. Without Hukou, children cannot receive social benefits, such as education and public health care. Because of this, most mothers would be married at birth. Because CHNS did not perform the physical examination survey after 2011, the sample in this paper only includes nine survey years from 1989 to 2011.[23]

## 2.4 Methods

I estimate the impact of paid maternity leave extension on children's health with the following two-way fixed-effects linear regression model:

$$Y_{i,p,t,bt} = \alpha_0 + \alpha_1 LCBP_{p,bt} + X'_{i,p,t}\Omega + \alpha_2 G_{p,bt} + \tau_t + \varepsilon_{p,t} \qquad (1)$$

[23] The survey undertaken in 1989 collected individual dietary intake data in China, obtained dietary, clinical, and anthropometric data from children younger than six years and all adults aged 20–45 years. The 1989 survey data do not include children aged seven to 18.

$Y_{i,p,t,bt}$ indicates the health outcome for the child $i$ born in year $bt$ in province $p$ and observed in survey year $t$. $LCBP_{p,bt}$ indicates whether a child's birth year $bt$ is before or after the provision of late birth benefit in province $p$. If a child is born on or after the provision of the late birth benefit, the child's mother is eligible for the late birth benefit imposed in province $p$, then $LCBP_{p,bt} = 1, otherwise\ \ 0$.

$X_{i,p,t}$ is a vector of individual characteristics. I control for the mother's highest education category, age, child gender, mother's birth age, and average household income.[24] A mother's highest education level has five categories: primary school degree, lower middle school degree; higher middle school degree; technical or vocational degree; and university or college degree or higher. $G_{p,bt}$ is the regional GDP per capita in the province p and birth year $bt$. Data for regional GDP per capita comes from the National Bureau of Statistics of China (NBS).[25] Table 2.2 shows the summary statistics for all outcome variables and control variables in this paper.

$\theta_p$ indicates the province fixed effects and $\tau_t$ indicates survey year fixed effects. Province fixed effects represent the time-invariant province-level characteristics that affect children's health. Survey year fixed effects indicate the changes at the national level over the years. Finally, $\varepsilon_{p,t}$ is the error term for province $p$ in year $t$.

I restrict the sample to children whose residing province in the survey year are the same as their birth province so that I can avoid different fixed province effect for the same child. Since urban residents' cross-province migration was highly regulated during the

[24] The household income is inflated to Chinese yuan as of 2011 based on the CHNS data.

[25] National Bureau of Statistics of China (NBS) lack data before 1988. I impute the missing value of regional GDP per capita from 1978 to 1988 based on the national GDP per capita value and the existing regional GDP per capita value.

sample period, I do not discuss the case with migration.[26] As a result, $p$ indicates which province the child $i$ was born in, the same as the province the child $i$ took the survey in year $t$.

In this model, the treatment group is composed of children who were born during or after the year their residing states extended the paid maternity leave due to late childbirth. At the same time, the comparison group consists of children who were born before their residing states imposed the LCBP. $\alpha_1$ is the parameter of interest, which represents the average effect of LCBP on children's body weight.

The impact of LCBP may vary among eligible mothers with different bonus days. For example, Heilongjiang and Jiangsu both implemented LCBP in 1990. However, Heilongjiang offered up to 90 days, while Jiangsu province offered up to 30 days. It is possible that the effect of LCBP on eligible mothers and children in Heilongjiang provinces is more significant than the effect of LCBP on eligible mothers and children in Jiangsu province. It is reasonable to expect that the more bonus days an eligible mother can take, the more her child will be affected by this policy. To capture this effect, I create a variable $Intensity_{p,bt}$ as an alternative treatment variable. $Intensity_{p,bt}$ is the number of bonus months a mother can receive if her child's birth year $bt$ is on or after the implementation of the LCBP in province $p$. If a mother is eligible for the late childbirth benefit imposed in province $p$ when her child is born, then $Intensity_{i,p,bt} = 1 * month$, otherwise it equates 0. Since the average month has 30 days, the bonus month is calculated by dividing bonus

[26] China has a harsh Hukou (household registration system). The 1979-1991 Hukou reform loosed rural-to-urban migration, which enabled rural migrants to work in urban cities. The major migration at that time was within the province. Without a hukou in another city, it's difficult to access the benefit of public education, public health insurance, and some housing subsidies. When people get married and have a baby, they seldom move to another province during that time period.

days by 30. For example, Shanghai granted mothers 15 bonus days, so the value of Intensity is 0.5. Table 2.1 shows the bonus days and the corresponding intensity value by province in China.

## 2.5 Results

### *2.5.1 Sample Characteristics*

Summary statistics are reported in Table 2.2. The variables are separated into three groups: all children, children whose mothers are eligible for LCBP (treatment group), and children whose mothers are ineligible for LCBP (control group). The mean value of BMI is 17.62. Sample means for Z-score BMI, Z-score weight, and Z-score height are 0.05, 0.16, and -0.05. Sample means for BMI related variables among the treatment group are larger than the sample means among the control group. Sample means for relative calories intake, relative fat intake, relative protein, and relative carbohydrate are 0.91, 1.25, 1.23, and 1.47. The sample includes 49 percent boys and 51 percent girls. Children's average age is 9.38. The mean value for the log average household income is 9.61. The average log value of regional GDP per capita in the province and year of birth is 7.4.

*Table 2.2. Summary Statistics*

| **Variables** | **Total** | **Treatment Group** | **Control Group** |
|---|---|---|---|
| BMI Related Variables | | | |
| BMI | 17.62 | 17.77 | 17.52 |
| Z-BMI | 0.05 | 0.53 | -0.25 |
| Z-Height | 0.16 | 0.75 | -0.20 |
| Z-Weight | -0.05 | 0.15 | -0.17 |
| Observations | 2,252 | 867 | 1,385 |
| Nutrition Intake Variables | | | |
| Calorie intake | 0.91 | 0.87 | 0.94 |
| Fat intake | 1.25 | 1.36 | 1.17 |
| Protein intake | 1.23 | 1.27 | 1.20 |

*Table 2.2. (continued)*

| Variables | Total | Treatment Group | Control Group |
|---|---|---|---|
| Carbohydrate intake | 1.47 | 1.19 | 1.67 |
| Observations | 1,946 | 806 | 1,140 |
| Control Variables | | | |
| Gender ((Boys) | 0.49 | 0.45 | 0.51 |
| Child age | 9.38 | 8.44 | 9.97 |
| Mom has a primary school degree or less | 0.21 | 0.11 | 0.27 |
| Mom has a lower middle school degree | 0.31 | 0.29 | 0.32 |
| Mom has a higher middle school degree | 0.23 | 0.20 | 0.26 |
| Mom has a technical or vocational degree | 0.11 | 0.13 | 0.09 |
| Mom has a college degree or more | 0.14 | 0.26 | 0.05 |

Note. Average household income is the log value of average household income, and the household income is inflated to Chinese yuan as of 2011 based on the CHNS data. GDP per capita is the log value of Reginal GDP per capita. Regional GDP is the average GDP per capita in one province in one year.

### *2.5.2 Effects of Paid Maternity Leave on Main Health Outcomes*

Based on Equation 1, I run two-way fixed-effect regression for Z-score weight, Z-score height, and Z-score BMI by controlling for province fixed effects, year fixed effects, and individual characteristics. The estimates of LCBP are represented in Table 2.3, and the estimates of LCBP Intensity are represented in Table 2.4. The coefficients of policy indicator LCBP in the regression of Z-score weight, Z-score height, and Z-score BMI are positive but statistically insignificant. The coefficients of policy indicator Intensity are all insignificant and have the same sign as the coefficients of LCBP. These results indicate that longer paid maternity leave duration does not impact children's body weight in urban China.

*Table 2.3. Effects of LCBP on Body Weight*

| VARIABLES | Z-BMI | Z-Height | Z-Weight |
|---|---|---|---|
| LCBP | 0.0230 | 0.0751 | 0.0394 |
| | (0.108) | (0.105) | (0.0966) |
| Age | 0.0824** | -0.242*** | -0.0829*** |
| | (0.0357) | (0.0382) | (0.0310) |
| Age Squared | -0.00267** | 0.00104 | -0.00146 |
| | (0.00117) | (0.00130) | (0.00112) |
| Gender (Boys) | 0.167*** | 0.155*** | 0.229*** |
| | (0.0506) | (0.0519) | (0.0462) |
| Log (Average household income) | 0.0570 | 0.128*** | 0.123*** |
| | (0.0354) | (0.0387) | (0.0351) |
| Log (GDP per capita in each province) | 0.293 | -0.848*** | -0.249 |
| | (0.184) | (0.189) | (0.167) |
| Mother's birth age | 0.00932 | -0.000664 | 0.00612 |
| | (0.00822) | (0.00863) | (0.00793) |
| Mom has a lower middle school degree | -0.103 | 0.266*** | 0.0987 |
| | (0.0700) | (0.0738) | (0.0669) |
| Mom has a higher middle school degree | 0.135* | 0.464*** | 0.373*** |
| | (0.0763) | (0.0811) | (0.0742) |
| Mom has a technical or vocational degree | 0.155 | 0.592*** | 0.477*** |
| | (0.0988) | (0.0988) | (0.0906) |
| Mom has a college degree or more | 0.146 | 0.572*** | 0.439*** |
| | (0.0960) | (0.103) | (0.0875) |
| Survey year FEs | Y | Y | Y |
| Province FEs | Y | Y | Y |
| Constant | -2.921* | 6.308*** | 1.137 |
| | (1.593) | (1.639) | (1.426) |
| Observations | 2,252 | 2,252 | 2,252 |
| R-squared | 0.091 | 0.300 | 0.273 |

Note. All models use two-way fixed effect linear regression. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

*Table 2.4. Effects of LCBP Intensity on Body Weight*

| VARIABLES | Z-BMI | Z-Height | Z-Weight |
|---|---|---|---|
| Intensity | 0.00109 | 0.0404 | 0.0221 |
| | (0.0467) | (0.0499) | (0.0428) |
| Age | 0.0835** | -0.238*** | -0.0807*** |
| | (0.0355) | (0.0381) | (0.0308) |
| Age Squared | -0.00268** | 0.00105 | -0.00146 |
| | (0.00117) | (0.00130) | (0.00112) |
| Gender (Boys) | 0.167*** | 0.153*** | 0.228*** |
| | (0.0505) | (0.0520) | (0.0462) |
| Log (Average household income) | 0.0569 | 0.128*** | 0.123*** |
| | (0.0354) | (0.0387) | (0.0351) |
| Log (GDP per capita in each province) | 0.306* | -0.815*** | -0.232 |
| | (0.175) | (0.181) | (0.160) |
| Mother's birth age | 0.00925 | -0.000448 | 0.00625 |
| | (0.00824) | (0.00867) | (0.00796) |
| Mom has a lower middle school degree | -0.103 | 0.269*** | 0.101 |
| | (0.0702) | (0.0740) | (0.0672) |
| Mom has a higher middle school degree | 0.135* | 0.464*** | 0.373*** |
| | (0.0763) | (0.0811) | (0.0742) |
| Mom has a technical or vocational degree | 0.154 | 0.590*** | 0.476*** |
| | (0.0987) | (0.0988) | (0.0907) |
| Mom has a college degree or more | 0.145 | 0.569*** | 0.438*** |
| | (0.0959) | (0.103) | (0.0876) |
| Survey year FEs | Y | Y | Y |
| Province FEs | Y | Y | Y |
| Constant | -2.921* | 6.308*** | 1.137 |
| | (1.593) | (1.639) | (1.426) |
| Observations | 2,252 | 2,252 | 2,252 |
| R-squared | 0.091 | 0.300 | 0.273 |

Note. All models use two-way fixed effect linear regression. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Having a higher BMI does not necessarily indicate better health for the child. When BMI becomes too high, children suffer health consequences from being obese. On the other side, people also suffer health risks related to being underweight when their BMI value is too low. I use binary probit regression and binary logistic regression to test whether more

extended paid maternity leave affects the likelihood of being obese and underweight. Column 1 and column 3 in Table 2.5 include the estimates of the binary probit regression of being obese and underweight on the LCBP indicators. Column 2 and column 4 in Table 2.5 include the estimates of the binary logit regression of being obese and underweight on the LCBP indicators. Based on Table 2.5, the estimates of being obese and being underweight are both statistically insignificant. All the results suggest that the change in paid maternity leave reform affected neither the likelihood of being obese nor the likelihood of being obese.

*Table 2.5. Effects of LCBP on Obese and Underweight*

| **VARIABLES** | **Obese** | | **Underweight** | |
|---|---|---|---|---|
| | **(1) Probit** | **(2) Logit** | **(3) Probit** | **(4) Logit** |
| LCBP | 0.170 | 0.416 | 0.073 | 0.145 |
| | (0.195) | (0.406) | (0.142) | (0.262) |
| Age | -0.325*** | -0.668*** | -0.040 | -0.076 |
| | (0.0596) | (0.124) | (0.0449) | (0.0823) |
| Age Squared | 0.0168*** | 0.0356*** | 0.000791 | 0.00156 |
| | (0.00204) | (0.00441) | (0.00146) | (0.00264) |
| Gender (Boys) | 0.0812 | 0.136 | -0.104 | -0.182 |
| | (0.0943) | (0.186) | (0.0666) | (0.123) |
| Log (Average household income) | 0.112 | 0.170 | 0.0266 | 0.0539 |
| | (0.0772) | (0.153) | (0.0461) | (0.0835) |
| Log (GDP per capita in each province) | 0.700** | 1.459** | -0.207 | -0.401 |
| | (0.330) | (0.694) | (0.240) | (0.442) |
| Mother's birth age | 0.0188 | 0.0229 | 0.00297 | 0.00492 |
| | (0.0156) | (0.0311) | (0.0108) | (0.0200) |
| Mom has a lower middle school degree | -0.364** | -0.641** | 0.173* | 0.300* |
| | (0.149) | (0.292) | (0.0932) | (0.169) |
| Mom has a higher middle school degree | -0.100 | -0.110 | -0.0241 | -0.0578 |
| | (0.149) | (0.294) | (0.105) | (0.196) |
| Mom has a technical or vocational degree | 0.0544 | 0.0768 | 0.0592 | 0.105 |

*Table 2.5. (continued)*

| VARIABLES | Obese | | Underweight | |
|---|---|---|---|---|
| | (1) Probit | (2) Logit | (3) Probit | (4) Logit |
| | (0.188) | (0.376) | (0.132) | (0.244) |
| Mom has a college degree or more | -0.0332 | -0.0436 | -0.158 | -0.330 |
| | (0.191) | (0.378) | (0.140) | (0.269) |
| Survey year FEs | Y | Y | Y | Y |
| Province FEs | Y | Y | Y | Y |
| Constant | -6.678** | -12.84** | -0.316 | -0.367 |
| | (2.818) | (5.893) | (2.071) | (3.827) |
| Observations | 2,252 | 2,252 | 2,245 | 2,245 |

Note. Columns (1) and (3) use binary probit regression. Columns (2) and (4) use binary logit regression. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

In addition to BMI-related variables, I conduct regressions on the four relative nutrition intake variables: calories, fat, protein, and carbohydrates. Results are represented in Table 2.6. All the coefficients are statistically insignificant, indicating that the extension of paid maternity leave does not impact children's nutrition intake.

*Table 2.6. Effects of LCBP on Nutrition Intake*

| VARIABLES | Kcal | Fat | Protein | Carbohydrate |
|---|---|---|---|---|
| LCBP | -0.016 | 0.0392 | -0.00656 | -0.0728 |
| | (0.0267) | (0.0385) | (0.0410) | (0.0483) |
| Age | -0.0237** | 0.0715*** | -0.0496*** | 0.0643*** |
| | (0.00950) | (0.0124) | (0.0148) | (0.0163) |
| Age Squared | 0.000329 | -0.00377*** | -1.68e-05 | -0.00187*** |
| | (0.000343) | (0.000424) | (0.000502) | (0.000624) |
| Gender (Boys) | -0.0224* | -0.00142 | 0.0390** | 0.172*** |
| | (0.0125) | (0.0184) | (0.0192) | (0.0230) |
| Log (Average household income) | 0.00584 | 0.0174 | 0.0185 | -0.0241 |
| | (0.00839) | (0.0141) | (0.0128) | (0.0154) |

*Table 2.6. (continued)*

| VARIABLES | Kcal | Fat | Protein | Carbohydrate |
|---|---|---|---|---|
| Log (GDP per capita in each province) | -0.0391 | -0.0813 | -0.160** | -0.0993 |
| | (0.0438) | (0.0636) | (0.0709) | (0.0764) |
| Mother's birth age | 0.000399 | -0.00476 | 0.000911 | 0.00297 |
| | (0.00193) | (0.00291) | (0.00295) | (0.00347) |
| Mom has a lower middle school degree | 0.0211 | 0.130*** | 0.0647** | -0.0677** |
| | (0.0171) | (0.0287) | (0.0266) | (0.0342) |
| Mom has a higher middle school degree | 0.0324* | 0.153*** | 0.138*** | -0.0838** |
| | (0.0196) | (0.0311) | (0.0298) | (0.0382) |
| Mom has a technical or vocational degree | 0.0648*** | 0.242*** | 0.133*** | -0.0867* |
| | (0.0250) | (0.0354) | (0.0355) | (0.0451) |
| Mom has a college degree or more | 0.0503** | 0.216*** | 0.139*** | -0.0795* |
| | (0.0246) | (0.0374) | (0.0369) | (0.0429) |
| Survey year FEs | Y | Y | Y | Y |
| Province FEs | Y | Y | Y | Y |
| Constant | 1.412*** | 1.109* | 2.746*** | 2.214*** |
| | (0.392) | (0.573) | (0.630) | (0.682) |
| Observations | 1,946 | 1,946 | 1,946 | 1,946 |
| R-squared | 0.147 | 0.220 | 0.196 | 0.311 |

Note. All models use two-way fixed effect linear regression. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

### *2.5.3 Heterogeneity by Age*

The effect of paid maternity leave policy may change as the child's age changes. In order to examine the effect among different time periods, I conduct a sub-sample analysis by age. Due to the small sample size, I categorize children's age groups into the following three groups: Ages 1-6, Ages 7-12, and Ages 13-18. Table 2.7 represents the results for all the two-way fixed-effects regressions. The estimates of LCBP and Intensity in the regressions are all insignificant. The result indicates that the extension of paid maternity

leaves does not impact a child's body weight and nutrition intake in early childhood or later childhood.

*Table 2.7. Effects of LCBP on Body Weight by Age*

| | **Z-BMI** | **Z-Height** | **Z-Weight** |
|---|---|---|---|
| | | Age 1-6 | |
| LCBP | 0.112 | 0.189 | 0.196 |
| | (0.217) | (0.261) | (0.206) |
| LCBP Intensity | -0.107 | 0.140 | -0.00797 |
| | (0.116) | (0.128) | (0.104) |
| Observation | 738 | 738 | 738 |
| | | Age 7-12 | |
| LCBP | 0.0605 | 0.135 | 0.113 |
| | (0.215) | (0.188) | (0.169) |
| LCBP Intensity | 0.00632 | -0.0518 | -0.0183 |
| | (0.0813) | (0.0783) | (0.0686) |
| Observations | 839 | 839 | 839 |
| | | Age 13-18 | |
| LCBP | -0.120 | -0.120 | -0.120 |
| | (0.224) | (0.224) | (0.224) |
| LCBP Intensity | 0.00915 | 0.00915 | 0.00915 |
| | (0.0831) | (0.0831) | (0.0831) |
| Observations | 675 | 675 | 675 |

Note. All models use two-way fixed effect linear regression. Personal characteristics factors I control for include the mother's highest education category, child age, child gender, mother's birth age, average household income, and GDP per capita. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

### *2.5.4 Heterogeneity by Gender*

To test whether LCBP affects boys and girls separately, I conduct a sub-sample analysis by gender. Table 2.8 represents estimates for Z-score variables separately by gender in column 1 to column 3. The estimates for girls' Z-score weight, Z-score height, and Z-score BMI are all negative and insignificantly, while estimates for boys' Z-score weight and Z-score BMI are, in general, positive and statistically insignificantly. The only exception is the estimate of LCBP intensity for boys' Z-Hight, which is significant with a 5 percent significant level. The results of binary logit regression of being obese and

underweight by gender are reported in column 5 and column 6 in table 2.8. All the coefficients are insignificant, which indicates that the extension of paid maternity leaves does not impact a child's body weight for both boys and girls.

*Table 2.8. Effects of LCBP on Body Weight by Gender*

| | (1) Z-BMI | (2) Z-Height | (3) Z-Weight | (4) Obese | (5) Underweight |
|---|---|---|---|---|---|
| | Panel 1: Total Sample | | | | |
| LCBP | 0.0230 | 0.0751 | 0.0394 | 0.416 | 0.145 |
| | (0.108) | (0.105) | (0.0966) | (0.406) | (0.262) |
| LCBP Intensity | 0.0011 | 0.0404 | 0.0221 | -0.016 | 0.058 |
| | (0.0467) | (0.0499) | (0.0428) | (0.094) | (0.061) |
| Observations | 2,252 | 2,252 | 2,252 | 2252 | 2245 |
| | Panel 2: Boys | | | | |
| LCBP | 0.148 | 0.113 | 0.131 | 0.426 | 0.0028 |
| | (0.144) | (0.148) | (0.169) | (0.591) | (0.390) |
| LCBP Intensity | 0.0905 | 0.162** | 0.00449 | 0.071 | 0.132 |
| | (0.0635) | (0.0717) | (0.0737) | (0.123) | (0.087) |
| Observations | 1,098 | 1,098 | 1,098 | 1051 | 1049 |
| | Panel 3: Girls | | | | |
| LCBP | -0.119 | -0.0281 | -0.113 | 0.216 | 0.442 |
| | (0.128) | (0.149) | (0.137) | (0.647) | (0.354) |
| LCBP Intensity | -0.0535 | -0.0776 | -0.0535 | -0.027 | -0.042 |
| | (0.0571) | (0.0692) | (0.0571) | (0.131) | (0.089) |
| Observations | 1,154 | 1,154 | 1,154 | 1154 | 1,152 |

Note. Columns (1)-(4) use linear regression. Columns (5)-(6) use the logit regression. Personal characteristics factors I control for include the mother's highest education category, child age, child gender, mother's birth age, and average household income. I add year dummies to control year fixed effect and province dummies to control province fixed effect. Columns (1)-(4) use OLS regression. Columns (5)-(6) use the Logit regression. Robust standard errors in brackets *** p<0.01, ** p<0.05.

Table 2.9 represents estimates for relative nutrition intake outcomes separately by gender. The coefficient of LCBP in the regression of relative carbohydrate intake is negative and statistically significant with a 10 percent significant level. All other coefficients are statistically insignificant. The estimates of nutrition intake support the finding that the LCBP policy did not affect children's nutrition intake for both girls and boys.

*Table 2.9. Effects of LCBP on Nutrition Intake by Gender*

| | **Kcal** | **Fat** | **Proton** | **Carbohydrate** |
|---|---|---|---|---|
| | Panel 1: Total Sample | | | |
| LCBP | -0.0155 | 0.0392 | -0.0066 | -0.0728 |
| | (0.0267) | (0.0385) | (0.0410) | (0.0483) |
| LCBP Intensity | -0.0138 | -0.0155 | -0.00775 | -0.0226 |
| | (0.0118) | (0.0175) | (0.0181) | (0.0214) |
| Observations | 1,946 | 1,946 | 1,946 | 1,946 |
| | Panel 1: Boys | | | |
| LCBP | -0.0242 | 0.0394 | -0.0491 | -0.122* |
| | (0.0397) | (0.0550) | (0.0601) | (0.0730) |
| LCBP Intensity | 0.000360 | -0.0159 | 0.00107 | -0.0219 |
| | (0.0184) | (0.0258) | (0.0290) | (0.0361) |
| Observations | 936 | 936 | 936 | 936 |
| | Panel 2: Girls | | | |
| LCBP | -0.00331 | -0.00331 | -0.00331 | -0.00331 |
| | (0.0371) | (0.0371) | (0.0371) | (0.0371) |
| LCBP Intensity | -0.0252 | -0.00808 | -0.0105 | -0.0326 |
| | (0.0158) | (0.0237) | (0.0228) | (0.0255) |
| Observations | 1010 | 1010 | 1010 | 1010 |

Note. All models use two-way fixed effect linear regression. Personal characteristics factors I control for include the mother's highest education category, child age, child gender, mother's birth age, and average household income. I add year dummies to control year fixed effect and province dummies to control province fixed effect. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

All these results support the previous finding that the extension of paid maternity leaves does not impact a child's body weight and nutrition intake.

### *2.5.5 Regression with Education Interaction Term*

The impact of the extension of maternity leave may vary among eligible mothers with different degrees of education. To further investigate this, I include the education interaction term $LCBP_{p,bt} * HS_{i,p,bt}$ in the two-way fixed effect regression model. If a mother's highest education degree is below the higher middle school, then $HS_{i,p,bt}$ *is* equal to one; otherwise, zero.

Table 2.10 presents the results on the effects of LCBP on children's body weight after adding the interaction term. The coefficients of LCBP are all statistically insignificant. The coefficients of the interaction term in the regression of Z-score BMI and Z-score Weight

are statistically insignificant. The coefficient of the interaction term in the regression of Z-score height is positive and statistically significant.

*Table 2.10. Effects of LCBP with Mother's Education Interactive Term*

| **VARIABLES** | **Z-BMI** | **Z-Height** | **Z-Weight** |
|---|---|---|---|
| LCBP | 0.130 | -0.188 | -0.0182 |
| | (0.144) | (0.135) | (0.126) |
| LCBP**Mom has education less than HS* | -0.138 | 0.339*** | 0.0743 |
| | (0.123) | (0.118) | (0.109) |
| Age | 0.0857** | -0.250*** | -0.0847*** |
| | (0.0357) | (0.0382) | (0.0312) |
| Age Squared | -0.00276** | 0.00125 | -0.00142 |
| | (0.00117) | (0.00130) | (0.00112) |
| Gender (Boys) | 0.169*** | 0.151*** | 0.228*** |
| | (0.0507) | (0.0520) | (0.0463) |
| Log (Average household income) | 0.0549 | 0.133*** | 0.125*** |
| | (0.0354) | (0.0388) | (0.0351) |
| Log (GDP per capita in each province) | 0.306* | -0.881*** | -0.257 |
| | (0.184) | (0.189) | (0.168) |
| Mother's birth age | 0.00988 | -0.00206 | 0.00582 |
| | (0.00826) | (0.00865) | (0.00796) |
| Mom has a lower middle school degree | -0.0976 | 0.253*** | 0.0960 |
| | (0.0701) | (0.0740) | (0.0672) |
| Mom has a higher middle school degree | 0.140* | 0.453*** | 0.370*** |
| | (0.0763) | (0.0811) | (0.0743) |
| Mom has a technical or vocational degree | 0.105 | 0.717*** | 0.504*** |
| | (0.105) | (0.102) | (0.0969) |
| Mom has a college degree or more | 0.0721 | 0.752*** | 0.479*** |
| | (0.109) | (0.115) | (0.0989) |
| Survey year FEs | Y | Y | Y |
| Province FEs | Y | Y | Y |
| Constant | -3.057* | 6.643*** | 1.211 |
| | (1.595) | (1.639) | (1.433) |
| Observations | 2,252 | 2,252 | 2,252 |
| R-squared | 0.091 | 0.302 | 0.273 |

Note. All models use two-way fixed effect linear regression. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 2.11 presents the new results on the effects of LCBP Intensity on children's body weight after adding the interaction term. Similar to the results in Table 2.10, the coefficients of LCBP Intensity are all insignificant. The coefficient of the interaction term

for Z-score BMI is still insignificant. The estimate of the interaction term for Z-score height is statistically positive with a 5 percent significant level, and the estimate of the interaction for Z-score weight is statistically positive with a 10 percent significant level.

*Table 2.11. Effects of LCBP Intensity with Mother's Education Interactive Term*

| **VARIABLES** | **Z-BMI** | **Z-Height** | **Z-Weight** |
|---|---|---|---|
| LCBP Intensity | -0.0181 | -0.0575 | -0.0458 |
| | (0.0629) | (0.0627) | (0.0555) |
| LCBP Intensity* *Mom has education less than HS* | 0.0308 | 0.157** | 0.109* |
| | (0.0668) | (0.0661) | (0.0585) |
| Age | 0.0826** | -0.243*** | -0.0841*** |
| | (0.0354) | (0.0381) | (0.0310) |
| Age Squared | -0.00266** | 0.00113 | -0.00140 |
| | (0.00117) | (0.00130) | (0.00112) |
| Gender (Boys) | 0.166*** | 0.150*** | 0.226*** |
| | (0.0506) | (0.0520) | (0.0462) |
| Log (Average household income) | 0.0571 | 0.128*** | 0.124*** |
| | (0.0354) | (0.0388) | (0.0351) |
| Log (GDP per capita in each province) | 0.300* | -0.844*** | -0.253 |
| | (0.175) | (0.181) | (0.161) |
| Mother's birth age | 0.00907 | -0.00138 | 0.00560 |
| | (0.00825) | (0.00871) | (0.00799) |
| Mom has a lower middle school degree | -0.104 | 0.264*** | 0.0973 |
| | (0.0703) | (0.0742) | (0.0673) |
| Mom has a higher middle school degree | 0.134* | 0.459*** | 0.370*** |
| | (0.0763) | (0.0812) | (0.0743) |
| Mom has a technical or vocational degree | 0.171* | 0.677*** | 0.536*** |
| | (0.103) | (0.100) | (0.0950) |
| Mom has a college degree or more | 0.169 | 0.691*** | 0.523*** |
| | (0.106) | (0.112) | (0.0947) |
| Survey year FEs | Y | Y | Y |
| Province FEs | Y | Y | Y |
| Constant | -2.973* | 6.309*** | 1.183 |
| | (1.534) | (1.592) | (1.386) |
| Observations | 2,252 | 2,252 | 2,252 |
| R-squared | 0.091 | 0.302 | 0.274 |

Note. All models use two-way fixed effect linear regression. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

The insignificant coefficient of LCBP and LCBP Intensity support the main finding that the extension of maternity leave does not impact children's health. The significant positive coefficient of the education interaction term for Z-score Height suggests that mothers with low education may be more able to take advantage of this extended paid maternity leave, so their children may benefit more from this policy. However, my sample is too small. The association in this sub-sample may be found by chance. So, we cannot draw a firm conclusion about the effect of LCBP on mothers with different education levels.

Overall, I do not observe evidence of an effect of LCBP on children's health.

## 2.6 Robustness Checks

### *2.6.1 Event Study Test*

The main concern with this research design is that the outcome variable in each province may not have the same trend before and after changes in policy. To address this problem, I use the event study design to test the assumption of parallel trends. I extend Equation (1) by decomposing $LCBP_{p,bt}$ into a set of policy lead and lag variables as the following Equation:

$$Y_{i,p,t,bt} = \beta_0 + \sum_{-9}^{-2} \delta_j \, 1\big(LCBP_{p,bt} = 1\big) + \gamma LCBP_{p,0} + \sum_{1}^{9} \rho_i \, 1\big(LCBP_{p,bt} = 1\big) + \beta_1' X_{p,t} + \beta_2 G_{p,bt} + \theta_p + \tau_t + \varepsilon_{p,t} \quad (2)$$

In the event study design, the reference group is the year prior to paid maternity leave expansion. $\gamma$ measures the contemporaneous effects of the Late benefit policy. $\rho_i,\ j \subset (1, 9)$ , includes eight parameters (lags) that represent estimates of the effect of late birth benefit after the policy adoption. The indicator for -9 years equates to 1 if province *p*

imposes the benefit policy in $bt$ +9. I use nine lag periods and nine post periods to do the event study test. Table 2.12 shows the estimate of the event study test based on Equation 2. The estimates are all insignificant. This is consistent with our finding that there is no impact of LCBP on children's health.

*Table 2.12. Event Study*

| VARIABLES | Coefficient | Variables | Coefficients |
|---|---|---|---|
| Expansion year | -0.577 | Year +1 | 0.00341 |
| | (0.875) | | (1.020) |
| Year -9 | -0.906 | Year +2 | -0.336 |
| | (1.741) | | (1.302) |
| Year -8 | -1.005 | Year +3 | -0.767 |
| | (1.542) | | (1.609) |
| Year -7 | -1.111 | Year +4 | -0.359 |
| | (1.519) | | (1.910) |
| Year -6 | -1.343 | Year +5 | 1.177 |
| | (1.408) | | (2.133) |
| Year -5 | -1.083 | Year +6 | 0.922 |
| | (1.366) | | (2.431) |
| Year -4 | -0.947 | Year +7 | 1.980 |
| | (1.191) | | (2.804) |
| Year -3 | -1.131 | Year +8 | 5.029 |
| | (1.075) | | (4.068) |
| Year -2 | -0.900 | Year +9 | 1.425 |
| | (1.109) | | (2.911) |
| Constant | 21.28*** | | |
| | (3.608) | | |
| Observations | 1,455 | | |
| R-squared | 0.135 | | |

Note. The model is estimated based on Equation 2. It is controlled for personal characteristics, province fixed effects, and year fixed effects. Samples include Liaoning, Heilongjiang, Shandong, Henan, Hubei, Hunan, Guangxi, Guizhou, Jiangsu, Chongqing, Beijing, and Shanghai. In the event-study design, the reference group is the year prior to paid maternity leave expansion. The indicator for Year -9 equates to 1 if a province imposes the benefit policy in $bt$ +9. The indicator for Year +9 equates to 1 if the province imposes the benefit policy in $bt$ -9. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.

### *2.6.2 Leave One Out Analysis*

It is possible that a policy may have a greater effect on one province when other provinces are not affected by the policy at all. Putting all the provinces adopting the policy as a group, we only can get an average effect on all the provinces. In order to ensure that the results are not driven by one province, this paper sequentially excludes each LCBP adopting province from the sample and runs regression based on Equation 1. Table 2.13 reports the results. All the estimates are insignificant, which is consistent with the main results.

*Table 2.13. Leave One Out Test*

| VARIABLES | Liaoning | Heilongjiang | Jiangsu | Shandong | Henan | Hebei | Jiangsu | Guangxi | Beijing | Shanghai | Chongqing |
|---|---|---|---|---|---|---|---|---|---|---|---|
| LCBP | -0.042 | 0.024 | 0.064 | 0.043 | -0.059 | 0.004 | 0.026 | 0.096 | 0.032 | 0.024 | 0.017 |
| | (0.110) | (0.122) | (0.114) | (0.115) | (0.115) | (0.111) | (0.112) | (0.117) | (0.110) | (0.109) | (0.108) |
| Intensity | -0.039 | -0.037 | -0.009 | 0.007 | 0.063 | -0.007 | 0.008 | -0.007 | 0.005 | 0.006 | -0.002 |
| | (0.049) | (0.065) | (0.048) | (0.049) | (0.049) | (0.047) | (0.048) | (0.048) | (0.047) | (0.047) | (0.047) |
| Observations | 2,059 | 2,088 | 1,999 | 2,076 | 1,983 | 2,062 | 2,053 | 1,964 | 2,154 | 2,184 | 2,224 |

Note. Each column shows the effect of LCBP on BMI after excluding each province. The name of each column is the province that is excluded. For example, column 2 shows the regression result after excluding the observations in Liaoning provinces. All models use two-way fixed effect linear regression. Personal characteristics factors I control for include the mother's highest education category, child age, child gender, mother's birth age, average household income, and GDP per capita. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

## 2.7 Conclusions

Using data from a national survey in China, this paper estimates the effect of paid maternity leave on children's health aged from one to 18 in urban China. This analysis shows no significant impact of the paid maternity leave duration on child body weight and child nutrition intake. This result is consistent with the finding from Baker and Milligan (2009). They investigate the impact of Canadian family-leave expansion from six months to one year in most provinces at the end of 2000 and find no statistically significant effect on most indicators of health outcome for children aged 13-24 months.

The three potential channels that link the expansion of paid maternity leave policy and children's health status may help better explain the insignificant result of the extension of maternity leave in this paper. The first channel is breastfeeding. The second channel highlights how the extension of paid maternity leave may affect a child's body weight by changing the mother-infant interaction. The third channel is through the mother's income effect. The CHNS provides limited information about breastfeeding and the actual time a mother spends with her child. However, Jia et al. (2018) examine the same LCBP as I use and find that the bonus days of LCBP duration are positively related to actual days new mothers take leaves, so a mother can spend more time taking care of her child. They also find that the implementation of LCBP increases breastfeeding duration in urban China. Their study provides evidence that the paid maternity leave policy will positively affect children's health in China by promoting mothers' breastfeeding behaviors and intensifying mothers-infant interaction. Given the suggestive evidence of the positive impact through the first and second channels, one possible explanation of the insignificant result is that the

extension of paid maternity leave on mothers' income negatively affects mothers' income in urban China. In Chapter 3, I use the same data and methodology to study the impact of LCBP on mothers' labor outcomes in urban China. My results in Chapter 3 support this explanation. More details will be discussed in Chapter 3.

One concern of this paper is data limitation. I only have 2252 observations in the sample. Given the current data limitations of a small sample, I cannot draw firm conclusions on this relationship. Another concern is the lack of data about the take-up rate of paid leave benefits. It is quite possible that the paid leave entitlements and the actual day mothers take for paid maternity leave are quite different, which can bias the results. Therefore, it is interesting to further explore whether this is a firm finding and in which condition an extension of paid maternity.

# CHAPTER 3

# THE ASSOCIATION OF PAID MATERNITY LEAVE AND MOTHERS' HEALTH AND LABOR OUTCOMES IN URBAN CHINA

## 3.1 Introduction

Maternity leave policies can help working mothers balance the roles of family and employment as well as promote child health. Based on the International Labour Organization report, most countries have implemented maternity leave policies. More and more countries have extended the length of maternity leave to enhance the welfare of mothers and their children. However, some studies have shown that long-term maternity leave may hurt the women's labor market attachment and career development. The ideal recommended length for maternity leave is unknown. To add some evidence to the research area, I examine the extension of paid maternity leave policy from 1987 to 1991 in China. Since the implementation time of this extension policy varies across provinces, this paper employs a two-way fixed-effects model to investigate whether the extension of paid maternity leave policy can affect mothers' health, employment, and wage rate in China.

The results show this extension of maternity leave increases the possibility of mothers remaining employed but may have a negative effect on mothers' wage rate. This paper also finds no significant impact on mothers' health outcome.

## 3.2 Related Work

### *3.2.1 Literature Review*

A lot of literature documents the relationship between maternity leave and maternal employment. Baker & Milligan (2008) investigate the impact of Canadian family-leave expansion from six months to one year in most provinces at the end of the year 2000. The results show that the reform led to a 48-58 percent increase in the number of months of maternal care that children received during the first year, with a corresponding decrease in full-time maternal employment and unlicensed non-relative care.

Some studies investigate how maternity leave affects a mother's decision to return to work after childbirth. Dustmann & Schönberg (2012) examine three major maternity leave policy reforms in Germany and compare outcomes for children born just before and after each reform. The results from this study suggest that maternity leave would bring a significant delay in the mothers' return to work after childbirth. Berger & Waldfogel (2004) study the relationship between maternity leave coverage in the U.S. and the maternity leave that these mothers take, as well as their employment decisions from 1988 to 1996. Their findings indicate a strong correlation between pre-birth employment and post-birth work, with women who are employed prior to giving birth returning to work quicker than those who are not. Additionally, when it comes to mothers who are employed before giving birth, those who have access to maternity leave coverage are more inclined to take leave for up to 12 weeks but less likely to take leave beyond 12 weeks. The results suggest that maternity leave coverage is associated with both the decision to take leave and the length of time that new mothers stay home after giving birth. All these studies suggest a positive relationship between the duration of maternity leave coverage and the actual time off work mothers take surrounding childbirth.

In addition to employment status, some studies investigate the effect of maternity leave on both the mothers' employment status and their earnings. Lalive & Zweimüller (2009) examine the impact of two job-protected parental leave reforms in Austria on mothers' fertility and their post-birth labor outcomes. They find that the first parental leave reform in 1990, which extended the maximum duration of parental leave from 1 year to 2 years, significantly reduced the mothers' return to work, and it lowered their earnings in the short run. The second parental leave reform in 1996, which reduced parental leave from two years to eighteen months, improved their employment and earnings. A study by Tanaka (2005) find that maternity leave is associated with a decrease in the mothers' earnings, with a one-month increase in leave length associated with a 2.4 percent decrease in earnings in the first year after childbirth.

These studies mainly focus on mothers' employment status within one year after childbirth. In the short term, taking maternity leave may result in a temporary reduction in earnings, as mothers take time off work to care for their newborns. However, over the long term, the impact of maternity leave on mothers' labor outcomes is undetermined.

Waldfogel (1999) find that the Family and Medical Leave Act (FMLA) in the United States has little effect on wage while modestly increasing employment; however, this last result is sensitive to the model estimated. Ruhm (1998) studies the rights to paid parental leave in nine European countries between 1969 and 1993, chooses men as a comparison group, and then estimates the impact of paid parental leave on the gap between female and male labor market outcomes. The results show that parental leave would increase the employment of women but may decrease the relative wage at an extended duration. Rossin-Slater et al. (2013) employ a difference-in-difference approach to study how California's

program affects mothers' leave-taking after childbirth and their subsequent labor outcomes. The results show that the overall use of maternity leave increased by three weeks. However, they do not find a significant impact on the mothers' subsequent employment and their wage. Byker (2016) uses monthly panel data from the Survey of Income and Program Participation (SIPP) and differences-in-differences (DD) model to investigate the labor market impacts of paid leave laws in California and New Jersey in the months directly preceding and following birth. The results show that US-style short-duration paid leave increases the labor force attachment of women who otherwise would have exited the labor force temporarily in the months surrounding childbirth. The impact is more for less-educated women who have little access to paid leave in the absence of a mandate.

On the one hand, the maternity leave policy improves women's job security and retention rates. On the other hand, taking a long leave from work may result in a loss of skills and experience, making it more difficult for women to return to work at the same level as before or to advance in their careers. Overall, the impact of maternity leave on mothers' labor outcomes in the long term is unclear.

### *3.2.2 Policy Background*

The length of paid maternity leave in China was extended nationwide from 56 days to 90 days in 1988. After that, many provincial governments granted mothers extra days of paid maternity leave if they had late childbirth. Mothers were eligible for the bonus of late childbirth if they gave birth to their first child at the age of 24 or older. The bonus day and implementation time vary across provinces (see Table 2.1 for details). Based on the variation in implementation time of the Late Childbirth Benefit Policy (LCBP) across

different provinces, I use a two-way fixed-effects model to estimate whether this extension of maternity leave will affect children's health in China.

## 3.3 Data, Sample, and Variables

### *3.3.1 Data*

The source of the data is the China Health and Nutrition Survey (CHNS), an ongoing international collaborative project between the National Institute of Nutrition and Food Safety at the Chinese Center for Disease Control and Prevention (CCDC) and the Carolina Population Center at the University of North Carolina at Chapel Hill.

There are 23 provinces and four municipalities in China. However, not all of them were included in the latest survey conducted by the China Health and Nutrition Survey (CHNS) in 2015. CHNS initially began with eight provinces in 1988 and later added Heilongjiang as the ninth province in 1998. In 2011, three municipalities joined the study, followed by three more provinces in 2015. However, physical examinations were not conducted during the 2015 survey, and the implementation of LCBP in Guizhou Province was not done between 1987 and 1991. Therefore, this study utilizes data collected from respondents residing in eight provinces (Liaoning, Heilongjiang, Shandong, Henan, Hubei, Hunan, Guangxi, Jiangsu) and three major cities (Chongqing, Beijing, and Shanghai) during ten survey waves conducted in 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, and 2011.

This paper restricts the CHNS sample to the group targeted by the late birth benefit policy: mothers who were married and gave birth at the age of 24 or older. In certain provinces, eligibility for the late birth benefit was limited to the first childbirth and required a one-child certificate. Consequently, I have excluded children who are not the family's

first child and mothers who give birth for the first time at the age of 23 or younger based on these eligibility criteria. The sample in this paper begins in 1980 since China implemented free-market reform and the one-child policy in 1979.

In addition to the previous selection criteria, this research excludes families residing in rural areas. This is because most women in rural areas were engaged in household or agricultural work, and maternal benefits were primarily available to women in the urban sector under the household registration system in the sample period. This system predominantly benefited employees of government agencies, non-profit public organizations, state-owned enterprises (SOEs), and urban collectives, as highlighted by Jia et al. (2018). However, I do not restrict the mothers' marital status since marriage was a requirement for childbirth registration in the 1980s, and the Chinese household registration system (Hukou) necessitated parents' marriage certificates for newborn infant registration. Without Hukou, children would be ineligible to receive social benefits such as education and public healthcare. Due to the lack of physical examination surveys conducted by CHNS after 2011, this research's sample only includes data collected during the nine survey years between 1989 and 2011. My sample includes mothers who gave birth to their first child between 1980 and 2011 in urban China.

### *3.3.2 Health Outcome Variables*

This paper uses the mothers' body mass index (BMI), nutrition intake, and self-reported health status to measure their health status. There are four values for self-reported health status in CHNS: "excellent" (1), "good" (2), "fair" (3), or "poor" (4).

The CHNS project team collects height and weight measurements for each survey participant using standard protocol and techniques. BMI is calculated as a person's weight

in kilograms divided by height in meters squared. An adult who has a BMI less than 18.5 is classified as underweight, while an adult who has a BMI greater than 30 is classified as obese.

Individual nutrition intake data is provided by CHNS, which includes three consecutive days of nutrition intake for calories, fat, protein, and carbohydrates.

### *3.3.3 Labor Outcome Variables*

The labor outcomes of the mothers can be measured by the log value of wage, employment status, and average working days per week. The wage in this paper is calculated by the average monthly wage in the last year. Working time is measured by the average working days per week last year.

Government-owned companies in China typically offer more generous maternity leave policies than private companies. Mothers who work in a government-owned company may have a higher take-up rate of paid leave benefits. To capture the different effects of LCBP for mothers with different job types, I categorize mothers' job types into two types based on the ownership of the company. The CHNS survey collects eight job types: 1. Government; 2. State service/institute; 3. State-owned enterprises; 4. Small collective enterprise; 5. Large collective enterprise; 6. Family contract farming; 7. Private, individual enterprise; 8. Three-capital enterprise. I define a mother as working in a private company if she works in family contract farming or a private, individual enterprise. I define a mother working in a government-owned company if a mother's job type belongs to the

government, state service/institute, state-owned enterprises, small collective enterprise, or large collective enterprise.[27]

### *3.3.4 Control Variables*

Many factors determine the health outcomes of the mothers. The personal characteristics factors that I control for include the mother's highest education category, her age, the age that she gave birth, and her average household income.[28] A mother's highest education level has five categories: primary school degree, lower middle school degree; technical or vocational degree; university or college degree, and master's degree or higher.

## 3.4 Empirical Specification

I use a two-way fixed-effects linear regression model to examine the effects of the extended paid maternity leave as the following:

$$Y_{i,p,t,bt} = \alpha_0 + \alpha_1 LCBP_{p,bt} + X'_{i,p,t}\Omega + \theta_p + \tau_t + \varepsilon_{p,t} \qquad (1)$$

$Y_{i,p,t,bt}$ indicates the labor outcome for the mother $i$ who gives birth in year $bt$ in province $p$ and observed in survey year $t$. $LCBP_{p,bt}$ indicates whether the mother gave birth to her first child before or after the provision of late birth benefit in province $p$ in year $bt$. If the mother is eligible for the late birth benefits imposed in province $p$, then $LCBP_{p,bt} = 1, otherwise\ \ 0$. $X_{i,p,t}$ is a vector of individual characteristics. I controlled for

[27] Collective enterprises in China have a unique structure, where ownership is formally vested in the residents of the area where the enterprise is located, but in practice, they are managed and controlled by the local government.

[28] The household income is inflated to Chinese yuan as of 2011 based on the CHNS data.

the mothers' highest education category, age in the survey year, age at first birth, and average household income.[29]

$\theta_p$ indicates the province fixed effects and $\tau_t$ indicates birth year fixed effects. Province fixed effects represent the time-invariant province-level characteristics that affect children's health. Birth-year fixed effects indicate the changes at the national level over the years. Finally, $\varepsilon_{p,t}$ is the error term for province $p$ in year $t$.

## 3.5 Results

### *3.5.1 Sample Characteristics*

Table 3.1 shows the summary statistics for all outcome variables and control variables in this paper. The mothers' labor outcomes are measured by their working status, log value of wage, and average working days in one week. Table 3.1 shows that 85 percent of mothers are currently working. Among those working mothers, 86 percent of them work in public-sector companies. The mean value of mothers' log wage is 6.15. The average working days in the past week was 5.6 days. The mothers' health outcomes are measured by their BMI in a survey year, log value of BMI, and average 3-day nutrition intake. The mean value of the mothers' BMI is 22.7. The sample's means for 3-day average calorie intake, fat intake, protein, and carbohydrate are 2019.72, 72.42, 67.64, and 2274.04.

[29] The household income is inflated to Chinese yuan as of 2011 based on the CHNS data.

*Table 3.1. Summary Statistics*

| Variables | Mean | Min | Max | Observations |
|---|---|---|---|---|
| Mothers' Labor Outcomes variables | | | | |
| Working status | 0.85 | 0 | 1 | 3429 |
| Working in a big company | 0.86 | 0 | 1 | 3347 |
| log (Wage) | 6.15 | 2.63 | 11.29 | 2145 |
| Working days | 5.6 | 0 | 7 | 2446 |
| Mothers' Health Outcomes variables | | | | |
| Self-reported health status | 2.26 | 1 | 4 | 1382 |
| BMI | 22.7 | 13.05 | 37.92 | 2927 |
| Log (BMI) | 3.11 | 2.57 | 3.64 | 2927 |
| Calorie intake | 2019.72 | 248.39 | 13100.49 | 2765 |
| Fat intake | 72.42 | 3.37 | 272.57 | 2765 |
| Protein intake | 67.04 | 5.79 | 1375.29 | 2765 |
| Carbohydrate intake | 274.04 | 42.7 | 1373.45 | 2765 |
| Control Variables | | | | |
| Mother's age in survey year | 38 | 24 | 55 | 3429 |
| Mother's birth age | 27 | 24 | 47 | 3429 |
| Number of children | 1.2 | 1 | 4 | 3429 |
| Average Household income | 12180 | 0 | 295546 | 3,429 |
| Mother's education with a primary school degree or less | 0.2 | 0 | 1 | 3,429 |
| Mother's education with a lower middle school degree | 0.29 | 0 | 1 | 3,429 |
| Mother's education with an upper middle school degree | 0.25 | 0 | 1 | 3,429 |
| Mother's education with a technical or vocational degree | 0.11 | 0 | 1 | 3,429 |
| Mother's education with a university/college degree or above | 0.15 | 0 | 1 | 3,429 |

Note. This table presents the summary statistics of both dependent and independent variables used in the two-way fixed effect model. Both wage and average household income are inflated to Chinese yuan as of 2015 based on the CHNS data

The average age of mothers in a survey year is 38, and their average age to give birth to their first child is 27. The average household income is 12180 yuan. The average number of children for each mother is 1.2. For the mother's education level, the results show that 20 percent of them have a primary degree or below, 29 percent have a lower middle school

degree, 25 percent have a higher middle school degree, 11 percent have a technical or vocational degree, and 15 percent have university/college or above degree.

### *3.5.2 Effects of Paid Maternity Leave on Labor Outcomes*

Estimates in Table 3.2 and Table 3.3 provide evidence regarding the impact of LCBP on mothers' labor outcomes. Table 3.2 reports the regression results of policy indicator LCBP on mothers' labor outcomes. The estimate of LCBP in the regression of mothers' log wage is -0.0748, which is small but statistically significant at a 5 percent significant level. The estimate of LCBP in the regression of average weekly working days is statistically insignificant.

*Table 3.2. Effect of LCBP on Mothers' Labor Outcomes*

| VARIABLES | (1) Working Status | (2) Log (Wage) | (3) Working Days |
|---|---|---|---|
| LCBP | 0.909*** | -0.075** | 0.054 |
| | (0.205) | (0.034) | (0.0616) |
| Mothers' age in the survey year | -0.0709*** | -0.001 | -0.000 |
| | (0.013) | (0.002) | (0.004) |
| Mothers' birth age | -0.106 | 0.145*** | 0.199*** |
| | (0.134) | (0.0400) | (0.062) |
| Number of children | 0.0314 | 0.005 | -0.073** |
| | (0.120) | (0.020) | (0.033) |
| Mother's education with a lower middle school degree | -0.075 | 0.0207 | -0.141* |
| | (0.157) | (0.042) | (0.074) |
| Mother's education with an upper middle school degree | 0.109 | 0.0931** | -0.185*** |
| | (0.170) | (0.041) | (0.071) |
| Mother's education with a technical or vocational degree | 1.638*** | 0.160*** | -0.307*** |
| | (0.266) | (0.0456 | (0.077) |
| Mother's education with a university/college degree or above | 2.638*** | 0.385*** | -0.437*** |
| | (0.432) | (0.049) | (0.077) |
| Log (Average household income) | 0.304*** | 0.440*** | -0.0419 |
| | (0.071) | (0.029) | (0.040) |

*Table 3.2. (continued)*

| VARIABLES | (1) Working Status | (2) Log (Wage) | (3) Working Days |
|---|---|---|---|
| Survey year FEs | Y | Y | Y |
| Province FEs | Y | Y | Y |
| Constant | 4.396*** | 5.280*** | 5.778*** |
| | (0.977) | (0.115) | (0.185) |
| Observations | 3,096 | 2,145 | 2,446 |
| R-squared | 0.316 | 0.887 | 0.194 |

Note. This table presents the results of regressions based on Equation 1. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Columns (1) use the Logit model. Columns (2)-(3) use OLS regression. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The coefficient estimates of the policy indicator on working status are statistically positive. The significant estimate indicates a positive impact of LCBP on mothers' working status. To estimate the "effects" in the scale of interest, I calculate the marginal effects (dy/dx) of LCBP on the working status and working in a big company. Table 3.3 shows the average marginal effects. The average marginal effect of LCBP on working status is 0.087, which suggests that the implementation of LCBP increases the probability of remaining employed by 8.7 percentage points.

*Table 3.3. Average Marginal Effects of LCBP on Mothers' Working Status*

| | **All** | **Government-owned company** | **Private company** |
|---|---|---|---|
| LCBP | 0.087*** | 0.064*** | 0.287*** |
| | (0.0193) | (0.0198) | (0.018) |
| Individual controls | Y | Y | Y |
| Year FEs | Y | Y | Y |
| Location FEs | Y | Y | Y |
| Observations | 3,096 | 2,561 | 397 |

Note. This table presents the average marginal effects of LCBP on mothers' working status. Variance is approximated with the Delta Method. I control mothers' highest education category, child age, child gender, mother's birth age, and average household income, mother's job type. I add year dummies to control year

fixed effect and province dummies to control province fixed effect. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Overall, the extension of maternity leave increases the mothers' possibility of remaining employed but has a negative impact on their wage rate. In some cases, extended absences may result in a loss of working skills and experience, as well as a decrease in productivity and confidence. This can make it more difficult for women to return to work at the same level as before or to advance in their careers, so mothers' wage rate can be negatively affected. The negative impact on the wage rate helps explain the finding in Chapter 2.

### *3.5.3 Effects of Paid Maternity Leave by Job Type*

While the basic entitlement to maternity leave is the same in both government and private sectors, the actual duration of maternity leave can differ between government and private sector employees in China. The effect of paid maternity leave policy may vary among mothers working in different sectors. To examine the impact of LCBP for mothers working in two types of companies, I conducted a sub-sample analysis by job type. The estimates of LCBP are represented in Table 3.4. The coefficients of LCBP in both models are statistically significant and positive. However, the coefficient of LCBP for government companies is smaller than the coefficient of LCBP in private companies.

*Table 3.4. Effect of LCBP on Labor Outcomes by Job Type*

| | (1) Working Status | (2) Log (Wage) | (3) Working Days |
|---|---|---|---|
| | Working in a government-owned company | | |
| LCBP | 0.696*** | 0.0683 | 0.0683 |
| | (0.218) | (0.0608) | (0.0608) |
| Observation | 738 | 738 | 738 |

*Table 3.4. (continued)*

| | (1) Working Status | (2) Log (Wage) | (3) Working Days |
|---|---|---|---|
| | Working in a private company | | |
| LCBP | 2.417*** | -0.131 | 0.0961 |
| | (0.761) | (0.150) | (0.327) |
| Observations | 839 | 839 | 839 |

Note. All models use two-way fixed effect regression. Columns (1) use the Logit model. Columns (2)-(3) use OLS regression. Personal characteristics factors I control for include mothers' highest education category, child age, child gender, mother's birth age, and average household income. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Columns 2 and 3 in Table 3.4 present the average marginal effect of LCBP for mothers working by job type. The average marginal effect of LCBP (0.287) for mothers working in a private-owned company is higher than the average marginal effect of LCBP (0.064) for mothers in a government-owned company. These results indicate that the positive impact of LCBP is larger for mothers working in a small company. The larger impact may be caused by a larger marginal effect of LCBP in the private sector. It is possible that government companies already provide generous maternity leave policies before the extension of maternity leave, while private companies lack similar policies in place. Therefore, an extension of maternity leave benefit could be more beneficial for mothers who work in private companies.

### *3.5.4 Effects of Paid Maternity Leave by Child Age*

The effect of the paid maternity leave policy may change as a child's age changes. A child's age can measure how many years have passed since mothers were affected by the policy. In order to examine the effect on the mothers' labor outcome among different time periods, I conducted a sub-sample analysis by child age. Table 3.5 categorizes mothers based on children's age into the following four groups: "within 5 years after childbirth",

"6-10 years after childbirth"," 11-15 years after childbirth", and "more than 15 years after childbirth".

*Table 3.5. Effect of LCBP on Body Weight by Years after Childbirth*

| | Working Status | Log (Wage) | Working Days |
|---|---|---|---|
| | 0-5 years after childbirth | | |
| LCBP | 0.0451** | -0.153** | -0.017 |
| | (0.020) | (0.077) | (0.101) |
| Observation | 741 | 552 | 607 |
| | 6-10 years after childbirth | | |
| LCBP | 0.002 | -0.267** | -0.037 |
| | (0.046) | (0.110) | (0.181) |
| Observations | 892 | 609 | 678 |
| | 11-15 years after childbirth | | |
| LCBP | 0.008 | -0.17 | -0.131 |
| | (0.087) | (0.127) | (0.278) |
| Observations | 798 | 521 | 597 |
| | More than 15 years after childbirth | | |
| LCBP | 0.081 | -0.064 | 0.125 |
| | (0.057) | (0.090) | (0.179) |
| Observations | 998 | 463 | 564 |

Note. All models use two-way fixed effect regression. Columns (1) use the Logit model. Columns (2)-(3) use OLS regression. Personal characteristics factors I control for include the mother's highest education category, child age, child gender, mother's birth age, and average household income. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 3.5 represents the results for all the two-way fixed-effects regressions with different child age groups. The estimates of LCBP in working days in the regressions are all insignificant among all child age groups. For mothers' working status, I find a positive effect of LCBP for the group "within 5 years" and no effect of LCBP for the other three groups, which indicates that maternity leave mainly affects mothers' working status in the short run.

For mothers' wage rate, I find a negative effect of LCBP for the group "within 5 years" and the group "6-10 years". There is also an interesting finding that the negative

effect for "6-10 years" group is larger than the negative effect for "within 5 years" group. This indicates that the negative effect of LCBP on mothers' wages may increase over time. Compared to the impact of LCBP on mothers' working status, the impact on mothers' wage can last longer. It is possible that the extended maternity leave may make employers more hesitant to hire or promote female workers. Mothers may lose the chance to be promoted, thus affecting the wage in the longer term.

### *3.5.5 Effects of Paid Maternity Leave on Health Outcomes*

Table 3.6 reports the estimates of the two-way fixed-effect regression for BMI, the logarithm value of BMI, and four nutrition intake variables by controlling for province-fixed effects, year-fixed effects, and individual characteristics. The estimates of BMI and logarithm value of BMI are positive and statistically insignificant. The estimates of calories, fat, protein, and carbohydrate intakes are all statistically insignificant. These results indicate that longer paid maternity leave duration does not affect the mothers' body weight in urban China.

*Table 3.6. Effect of LCBP on Mothers' BMI-Related Health Outcomes*

| VARIABLES | (1) BMI | (2) Log (BMI) | (3) Kcal | (4) Fat | (5) Protein | (6) Carbo |
|---|---|---|---|---|---|---|
| LCBP | 0.218 | 0.0116 | 35.30 | 1.618 | -1.087 | 0.218 |
| | (0.198) | (0.0086) | (44.46) | (2.608) | (2.856) | (0.198) |
| Mother's age in the survey year | 0.102*** | 0.0046*** | 3.418 | 0.332* | -0.0415 | 0.102*** |
| | (0.0144) | (0.0006) | (2.888) | (0.173) | (0.164) | (0.0144) |
| Mother's birth age | -0.0252 | -0.00107 | -7.166 | -0.644** | -0.294* | -0.0252 |
| | (0.0231) | (0.0010) | (4.437) | (0.290) | (0.178) | (0.0231) |
| Number of children | -0.211* | -0.00767 | -9.601 | -9.012*** | -4.411*** | -0.211* |
| | (0.124) | (0.0053) | (26.76) | (1.414) | (1.386) | (0.124) |
| Mom has a lower middle school degree | -0.485*** | -0.0184** | -9.765 | 6.617*** | 1.969 | -0.485*** |
| | (0.175) | (0.0074) | (34.15) | (1.996) | (2.019) | (0.175) |

*Table 3.6. (continued)*

| VARIABLES | (1) BMI | (2) Log (BMI) | (3) Kcal | (4) Fat | (5) Protein | (6) Carbo |
|---|---|---|---|---|---|---|
| Mom has an upper middle school degree | -0.931*** | -0.0377*** | -75.81** | 5.721*** | 1.454 | -0.931*** |
| | (0.184) | (0.0078) | (34.30) | (2.091) | (1.749) | (0.184) |
| Mom has a technical or vocational degree | -1.449*** | -0.0589*** | -74.77* | 8.287*** | 2.537 | -1.449*** |
| | (0.209) | (0.0089) | (42.70) | (2.564) | (2.076) | (0.209) |
| Mom has a university/college degree or above | -1.507*** | -0.0623*** | -112.6** | 6.874** | 2.001 | -1.507*** |
| | (0.232) | (0.0100) | (43.99) | (2.668) | (2.226) | (0.232) |
| Log (Average household income) | 0.102*** | 0.0046*** | 3.418 | 0.332* | -0.0415 | 0.102*** |
| | (0.0144) | (0.0006) | (2.888) | (0.173) | (0.164) | (0.0144) |
| Survey year FEs | Y | Y | Y | Y | Y | Y |
| Province FEs | Y | Y | Y | Y | Y | Y |
| Constant | 21.90*** | 3.070*** | 2,373*** | 78.68*** | 85.36*** | 21.90*** |
| | (0.704) | (0.0299) | (144.6) | (9.127) | (7.776) | (0.704) |
| Observations | 2,927 | 2,927 | 2,765 | 2,765 | 2,765 | 2,927 |
| R-squared | 0.130 | 0.131 | 0.156 | 0.078 | 0.044 | 0.130 |

Note. This table presents the results of linear regressions based on Equation 1. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Columns (3)-(6) show the impact of LCBP on mothers' nutrition intakes. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

This paper also examines the effect of LCBP on log (BMI) to address skewness. Having a higher BMI does not necessarily indicate better health. When BMI becomes too high, mothers will suffer health consequences from being obese. Conversely, people also suffer health risks related to being underweight when their BMI is too low. I use binary logistic regression to test whether more extended paid maternity leave affects the likelihood of being obese and underweight. Table 3.7 includes the estimates of the binary regression of being obese and underweight on the LCBP indicators. Based on Table 3.7, the estimates

of being obese and underweight are insignificant. All the results suggest that the extension of paid maternity leave reform does not affect the likelihood of being obese or underweight.

*Table 3.7. Effect of LCBP on Mothers' Obese and Underweight*

| VARIABLES | (1) Obese | (2) Underweight |
|---|---|---|
| LCBP | 0.0824 | -0.435 |
| | (0.251) | (0.356) |
| Mother's personal characteristics | Y | Y |
| Survey year FEs | Y | Y |
| Province FEs | Y | Y |
| Constant | -1.759* | -0.198 |
| | (0.925) | (1.301) |
| Observations | 3,148 | 3,148 |
| R-squared | 0.0492 | 0.0401 |

Note. this table presents the results of Logit regressions based on Equation 1. Mothers' personal characteristics factors include the mother's highest education category, mother's age in the survey year, number of children, mother's birth age, and average household income. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.8 shows the coefficient estimates of LCBP on mothers' self-reported health status. The estimates of LCBP on health status are statistically insignificant, which suggests the passage of LCBP does not affect self-reported health status.

*Table 3.8. Effect of LCBP on Mothers' Self-reported Health Status*

| VARIABLES | (1) "Excellent" | (2) "Good" | (3) "Fair" | (4) "Poor" |
|---|---|---|---|---|
| LCBP | 0.249 | 0.166 | | 1.244 |
| | (0.370) | (0.249) | | (0.689) |
| Mother's age in the survey year | -0.0180 | -0.0142 | | 0.176*** |
| | (0.0279) | (0.0187) | | (0.0541) |
| Mother's birth age | 0.0219 | -0.0104 | | -0.142** |
| | (0.0433) | (0.0297) | | (0.0711) |
| Number of children | -0.238 | 0.0555 | | -0.0818 |
| | (0.270) | (0.142) | | (0.313) |
| Mother's education with a lower middle school degree | 0.439 | 0.195 | | -0.527 |
| | (0.325) | (0.180) | | (0.400) |

*Table 3.8. (continued)*

| VARIABLES | (1) "Excellent" | (2) "Good" | (3) "Fair" | (4) "Poor" |
|---|---|---|---|---|
| Mother's education with a lower middle school degree | 0.439 | 0.195 | | -0.527 |
| | (0.325) | (0.180) | | (0.400) |
| Mother's education with upper middle school degree | 0.616* | 0.309 | | -0.411 |
| | (0.331) | (0.190) | | (0.419) |
| Mother's education with a technical or vocational degree | 0.893** | 0.252 | | -1.674** |
| | (0.370) | (0.239) | | (0.782) |
| Mother's education with a university or college degree | 0.791** | 0.610** | | -14.10 |
| | (0.400) | (0.263) | | (488.0) |
| Mother's education with a master's degree or above | 0.0132 | 16.02 | | 1.377 |
| | (5,717) | (3,007) | | (8,992) |
| Log (Average household income) | -1.05e-05 | -8.53e-06 | | -3.89e-05 |
| | (1.11e-05) | (7.17e-06) | | (2.52e-05) |
| Survey year FEs | Y | Y | | Y |
| Province FEs | Y | Y | | Y |
| Constant | -0.00939 | 1.574** | | -4.558** |
| | (1.219) | (0.791) | | (2.046) |
| Observations | 1,382 | 1,382 | | 1,382 |

Note. This table presents the results of multinomial logistic regression based on Equation 1. Personal characteristics factors I control for include the mother's highest education category, mother's age in the survey year, number of children, mother's birth age, and average household income. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Overall, the extension of maternity leave does not affect mothers' body weight, nutrition intake, the possibility of being underweight, the possibility of being obese, and the feeling of health status. All these results suggest that the extension of maternity leave would not impact mothers' health status.

## 3.6 Robustness Checks

### *3.6.1 Event Study Test*

One challenge I may encounter in this work is the potential invalidity of the parallel trend assumption. The treatment group is composed of mothers who gave birth to their first child after the provision of late birth benefit in province $p$ in year $bt$, while the comparison group is composed of mothers who gave birth to her first child before the provision of late birth benefit in province $p$ in year $bt$. The key assumption of the model is that the underlying trends of the two groups are similar (the parallel trend assumption). We must assume that in the absence of the late childbirth benefit policy, the trends in labor outcomes between the treatment and control groups would be similar. No other factors might affect these outcomes during the same time as the late birth benefit policy. To address this concern, I will use the event study design to test the parallel trend assumption in the section of the robust check. I extend the Equation (1) by decomposing $LCBP_{p,bt}$ into a set of policy lead and lag variables as the following Equation:

$$Y_{i,p,t,bt} = \beta_0 + \sum_{-9}^{-2} \delta_j \, 1\big(LCBP_{p,bt} = 1\big) + \gamma LCBP_{p,0} + \sum_{1}^{9} \rho_i \, 1\big(LCBP_{p,bt} = 1\big) + \beta_1' X_{p,t} + \beta_2 G_{p,bt} + \theta_p + \tau_t + \varepsilon_{p,t} \qquad (2)$$

In the event study design, the reference group is the year prior to paid maternity leave expansion. $\gamma$ measures the contemporaneous effects of LCBP. $\rho_i$ includes eight parameters (lags) that represent estimates of the effect of late birth benefit after the policy adoption. The indicator for -9 years equates to 1 if province p imposes the benefit policy in $bt$ +9. I use nine lag periods and nine post periods to do the event study test. Table 3.9 shows the estimate of the event study test based on Equation 2. Almost all the estimates are insignificant.

*Table 3.9. Event Study*

| VARIABLES | (1) Working Status | (2) Log (Wage) | (3) Working Days |
|---|---|---|---|
| Expansion year | -0.0250 | -2.554 | -0.143 |
| | (0.278) | (1.756) | (0.503) |
| Year -9 | -0.0754 | -2.684 | -0.565 |
| | (0.525) | (3.212) | (0.977) |
| Year -8 | -0.0697 | -2.766 | -0.638 |
| | (0.496) | (3.056) | (0.914) |
| Year -7 | -0.0260 | -2.637 | -0.509 |
| | (0.470) | (2.872) | (0.869) |
| Year -6 | 0.0707 | -3.023 | -0.304 |
| | (0.443) | (2.708) | (0.808) |
| Year -5 | -0.0226 | -3.001 | -0.343 |
| | (0.409) | (2.535) | (0.763) |
| Year -4 | -0.0970 | -1.888 | -0.246 |
| | (0.382) | (2.373) | (0.704) |
| Year -3 | 0.0132 | -2.162 | -0.278 |
| | (0.350) | (2.228) | (0.651) |
| Year -2 | -0.00998 | -3.222 | -0.496 |
| | (0.327) | (2.034) | (0.609) |
| Year -1 | 0.101 | -2.075 | -0.313 |
| | (0.298) | (1.839) | (0.568) |
| Year +1 | -0.101 | -1.078 | -0.258 |
| | (0.236) | (1.594) | (0.446) |
| Year +2 | 0.126 | -1.555 | -0.120 |
| | (0.219) | (1.534) | (0.400) |
| Year +3 | -0.136 | -0.401 | 0.0520 |
| | (0.193) | (1.358) | (0.348) |
| Year +4 | 0.151 | 1.134 | -0.135 |
| | (0.166) | (1.560) | (0.300) |
| Year +5 | 0.220 | -1.597 | 0.168 |
| | (0.135) | (1.047) | (0.255) |
| Year +6 | 0.0965 | -0.521 | -0.126 |
| | (0.119) | (1.015) | (0.214) |
| Year +7 | 0.172* | -0.444 | -0.100 |
| | (0.0978) | (0.940) | (0.164) |
| Year +8 | 0.191* | -0.0962 | -0.0506 |
| | (0.0990) | (0.929) | (0.151) |
| Constant | 4.292*** | 4.862* | 5.666*** |
| | (0.385) | (2.710) | (0.689) |

*Table 3.9. (continued)*

| VARIABLES | (1) Working Status | (2) Log (Wage) | (3) Working Days |
|---|---|---|---|
| Observations | 1,391 | 1,914 | 1,544 |
| R-squared | 0.899 | | 0.249 |

Note. The model is estimated based on Equation 2. It is controlled for personal characteristics, province fixed effects, and year fixed effects. Samples include Liaoning, Heilongjiang, Shandong, Henan, Hubei, Hunan, Guangxi, Guizhou, Jiangsu, Chongqing, Beijing, and Shanghai. In the event-study design, the reference group is the year prior to paid maternity leave expansion. The indicator for Year -9 equates to 1 if the province s imposes the benefit policy in $bt$ +9. The indicator for Year +9 equates to 1 if the province s imposes the benefit policy in $bt$ -9. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

### *3.6.2 Leave One Out Analysis*

Another concern is that a policy may have a more significant effect on one province when other provinces may not be affected by the policy at all. Putting all the provinces adopting the policy as a group, we only can get an average effect on all the provinces. To ensure that the results are not driven by one province, this paper sequentially excludes each LCBP adopting province from the sample and runs regression.

Table 3.10 reports the estimates. The coefficients of LCBP on mother's wage level are all negative but only statistically significant with 5 percent level in two subsamples: Shandong and Hunan. This suggests that the result on wage may be sensitive to models. It's better to further study the impact of LCBP on the mothers' wage.

*Table 3.10. Leave One Out Test*

| VARIABLES | Liaoning | Heilongjiang | Jiangsu | Shandong | Henan | Hebei | Hunan | Guangxi | Beijing | Shanghai | Chongqing |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Log(wage) | | | | | | |
| LCBP | -0.041 | -0.038 | -0.039 | -0.079** | -0.040 | -0.053 | -0.072** | -0.041 | -0.056 | -0.038 | -0.044 |
| | (0.039) | (0.036) | (0.038) | (0.037) | (0.037) | (0.036) | (0.035) | (0.036) | (0.035) | (0.035) | (0.035) |
| Obs | 1,483 | 1,540 | 1,389 | 1,486 | 1,467 | 1,496 | 1,490 | 1,483 | 1,540 | 1,389 | 1,486 |
| | | | | | Working Status | | | | | | |
| LCBP | 0.974*** | 0.805*** | 1.051*** | 0.888*** | 0.997*** | 0.884*** | 0.508* | 0.947*** | 0.801*** | 0.912*** | 0.869*** |
| | (0.297) | (0.289) | (0.307) | (0.287) | (0.297) | (0.297) | (0.287) | (0.292) | (0.279) | (0.288) | (0.278) |
| Obs | 1,842 | 1,869 | 1,699 | 1,827 | 1,796 | 1,832 | 1,800 | 1,875 | 1,854 | 1,920 | 2,014 |

Note. Each column shows the effect of LCBP on BMI after excluding each province. The name of each column is the province that is excluded. For example, column 2 shows the regression result after excluding the observations in Liaoning provinces. All models use two-way fixed effect linear regression. Personal characteristics factors I control for include the mother's highest education category, child age, child gender, mother's birth age, average household income, and GDP per capita. I add survey year dummies to control survey year fixed effects and province dummies to control province fixed effects. Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

## 3.7 Conclusion

Beginning in 1987, provincial governments in China granted mothers extra days of paid maternity leave if they had late childbirth. This paper evaluates the impacts of this extension of maternity leave on mothers' health and labor outcomes in Urban China. Using China Health and Nutrition Survey data and two-way fixed-effects methodology, I find that the extension of maternity leave does not impact mothers' health status. For mothers' labor outcomes, I find that longer maternity leave is positively correlated with a higher chance of mothers remaining employed, but it is negatively associated with their income levels.

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