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The contribution of Western fast food to fast-growing body mass in China

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Abstract

The westernization of Asian countries has led to the rapid expansion of Western-style fast food restaurants, which are believed to be fueling an unprecedented rise in body mass in these countries. This study tests this belief using longitudinal data from China. Exploiting the opening of a Western-style fast food restaurant in a particular community, we conduct a transition analysis to make a more convincing causal interpretation than the standard cross-sectional or fixed-effects approach. Considering several measures of fatness, we find no robust evidence of Western fast food having a substantial effect overall, but there is some indication of effect heterogeneity.

Keywords: body mass index, arm fat ratio, waist-to-hip ratio, obesity, transition analysis, China, fast food

JEL code: I12, I15, L83

1. Introduction

The westernization of Asian countries has led to the rapid expansion of Western-style fast food restaurants. The world's largest fast food company, Yum! Brands Inc., which owns Kentucky Fried Chicken (KFC), Pizza Hut, and Taco Bell, operates over 11,800 fast food outlets in 15 Asian countries, with 5,827 in China alone.[1] The second largest fast food company, McDonald's, operates more than 7,500 outlets in these countries.[2] In China, Western fast food restaurants have only been in the market since the late 1980s and early 1990s. Their expansions have been rapid in the last two decades, with over 4,500 KFC, 1,260 Pizza Hut, and 2,000 McDonald's outlets operating today. Figure 1A depicts the emergence of KFC and McDonalds's from the late 1980s onwards. Both chains took off in the late 1990s, with accelerating growth beginning in 2000. KFC has been expanding more aggressively than McDonald's, with outlets in almost all of China by 2007 (Shen and Xiao, 2013).

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[1] Data from the Yum Inc.'s website: http://www.yum.com/company/map.asp.

[2] http://en.wikipedia.org/wiki/List_of_countries_with_McDonald's_restaurants

[Insert Figure 1]

In parallel with this rise in Western-style fast food outlets, overweight and obesity rates have reached epidemic proportions in many Asian countries. In China, the body mass index (BMI) increased from 21.5 in 1989 to 24 in 2011, as shown in Figure 1B. This growth is equivalent to approximately 6 kilograms of weight gain for an average Chinese person. Xi et al. (2012) find that from 1993 to 2009, obesity in China[3] increased from 3 to 11% for men and from 5 to 10% for women, while abdominal obesity[4] increased from 8 to 28% for men and from 28 to 46% for women. Ramachandran and Snehalatha (2010) report similarly rapid trends for India, Taiwan, and South Korea. The rapid rise in overweight and

[3] Defined as a BMI of 27.5 or higher.

[4] Defined as a waist circumference of 90 centimeters or higher for men and 80 centimeters or higher for women.

obesity rates are concerning since they have serious health consequences.[5] It has been a general belief that this obesity epidemic is caused by excessive consumption of Western-style fast foods (Bell et al., 2001, 2002; Astrup et al., 2008; Ji and Cheng, 2009), and policymakers have targeted fast food chains in the past decades by restricting advertisement during children's television programs and banning outlets from opening (Popkin, 2006; Nestle, 2006). Public health campaigns have also been launched to encourage people to make healthier food choices and to require that fast food outlets to publish nutritional information on their food (Burton et al., 2006; Termini et al., 2011).

The aim of this study is to test whether the concomitant spread of Western-style fast foods and body mass is truly causal. The positive correlation between the expansion of Western-style fast food and growing body weight may simply reflect various changes

[5] The World Health Organization (WHO) identifies being overweight and obese as major causes of disability and premature death, as it significantly increases the risk of many chronic diseases such as cardiovascular diseases, diabetes mellitus, hypertension, and certain cancers (WHO, 2003, 2005)

entailed in rapid economic growth and westernization. The rising income, for example, has shifted diets at home from carbohydrate-rich staples like rice and beans towards diets rich in meat, fat, oil, and dairy products (Pingali, 2007), which may have increased overweight and obesity rates. At the same time, it is rational for profit-maximizing fast food chains to expand in areas where the demand for their products is high. If this is why we observe a positive relationship, the above-mentioned interventions that target fast food chains will not be effective. Therefore, determining whether the relationship is causal is imperative for policymakers.

The existing literature provides little hard evidence for Asian policymakers. While past causal studies tend to find that fast food restaurants have little impact, most of them are from the United States, and most Asian studies do not provide causal interpretations (Singh et al. 2006; Chiang et al. 2011; Odegaard et al. 2012). Wang and Shi (2012) and Xu et al. (2013) are two exceptions. Using panel data from China, Wang and Shi (2012) focus on school-aged children and find that fast food restaurants have no impact on the nutritional intake of these children. Using the same data and a variant of the fixed-effects approach, Xu et al. (2013) study adults, and, in contrast to Wang and Shi (2012), they find that fast food restaurants have a significant positive effect on waist-to-height and waist-to-hip ratios among urban women and the rural population. The size of the estimated impact, however, is questionably large: for example, the average waist-to-hip ratio of urban women is estimated nearly to double its current level for every additional fast food restaurant.

We offer new causal evidence for Asian countries by conducting a transition analysis with an event study structure combined with propensity score matching. The treatment variable is the *opening* of the first Western-style fast food outlet in a particular community. For obtaining reliable causal estimates, this approach has several advantages over the standard cross-sectional and panel data fixed-effects models. First, transition analysis with an event study structure is a simple and intuitive approach for modeling the gradual response of people's eating behavior to new fast food outlets and the slow process of body weight adjustment (Hall et al., 2011), whereas a standard fixed-effects approach requires that the effect is instantaneous: that is, the whole effect of an increase in fast food outlets on weight takes place by the next period. The fixed-effects approach can address this issue to some extent by including lagged effects but additional parametric assumptions that are involved in this generalization complicate its interpretation. In contrast, our approach simply compares changes in body measurements with the baseline level in both the short run and the long run without relying on parametric assumptions. Second, the use of a fixed-effects approach is justified only when the omitted factors are time-invariant and there is no other relevant time-varying omitted factor. Because many of our variables such as body measurements and access to fast food exhibit time trends, which may well be different across communities, standard fixed-effects models are difficult to justify. We instead employ a propensity matching technique to ensure that our causal evaluation is based on "comparable" units, and thus the treatment assignment in our analysis is as good as random. Third, fixed-effect models have symmetry assumption by design. In our context, this implies that the effects of the opening and closing of a fast food outlet have the same magnitude with opposite signs. This is unrealistic, as weight tends to display downward rigidity (Franz, 2001; Hill et al., 2012).

We use data derived from a large panel survey from China, the China Health and Nutrition Survey (CHNS). The CHNS contains detailed individual anthropometry measures and information on Western fast food outlets. No other longitudinal data set in Asia has these features. For more reliable results, we use multiple fatness measures. In particular, we consider not only the conventional body mass index (BMI) but also the arm fat index (AFI), which measures the percentage of the volume of the arm that is fat, and the waist-to-hip ratio (WHR), which indicates abdominal obesity.

Our findings show that there is no strong evidence for a causal link between the opening of Western fast food outlets and any of the three aforementioned measures of obesity. The belief that Western-style fast food has caused the Chinese upsizing in body weight is a myth. This may rationalize why targeting fast food restaurants has failed to reduce obesity so far.

2. Literature Review

To the best of our knowledge, most serious causal studies of the fast food effect on body mass and obesity are from the United States. These studies use proximity to fast food outlets as the treatment variable.[6] Currie et al. (2010) conduct a school-level analysis using Californian public primary schools, and they find that only schools that have a fast food restaurant nearby experience a rising obesity problem. Proximity is measured by the distance between the closest fast food restaurant and the school, within 0.1, 0.25, and 0.5 miles. They find significantly higher obesity rates (by 6.3 percentage points) in schools within 0.1 miles of a fast food restaurant relative to schools that are within 0.25 and 0.5 miles from a fast food restaurant. However, only a few schools have a fast food

[6] Numerous cross-sectional studies also use this strategy: for example, Davis and Carpenter (2009).

restaurant within 0.1 miles (7%), and thus having fast food restaurants near schools cannot explain the rapid increase in teenage obesity in the United States in the last decades. Alviola IV et al. (2014) estimate the impact of the number of fast food restaurant near schools and find that an additional fast food restaurant within a 1-mile radius of a school increases the obesity rate among students by 1.23 percentage points.

At the individual level, Anderson and Matsa (2011) use the instrumental variable (IV) technique to address the endogeneity of fast food consumption. A positive correlation between obesity and fast food restaurants may simply reflect individual heterogeneity in desired caloric intake, as those who tend to consume more calories (e.g., eat large meals) also prefer to eat at fast food restaurants. They focus on a sample of rural residents, because in urban areas, almost everyone has easy access to one or more fast food restaurants. The supply of fast food restaurants is instrumented by proximity to an interstate highway; residents of communities near highways experience a boost in the supply of fast food restaurants. They find that fast food restaurants have little effect on adult obesity. Dunn (2008) also finds no effect in rural areas, but there are strong effects on females and race minorities (Blacks and Hispanics) in medium-density counties. However, his estimates have wide intervals; assuming a height of 167 cm, the 95% confidence interval of a standard deviation increase in the number of fast food restaurants (about 11) ranges from 1 to 25 pounds of weight gain in a year.

For Asian countries, there has not been any serious attempt comparable to those U.S. studies except for Wang and Shi (2012) and Xu et al. (2013). Wang and Shi (2012) conduct a difference-in-differences analysis and find that the presence of fast food restaurants has no impact on the calorie, carbohydrate, fat, or protein intake of Chinese children aged 6-18, especially those from low-income households. Xu et al. (2013) also estimate a version of the difference-in-differences equation. Their study is probably the closest to ours, using older waves of CHNS. They use the number of Western fast food restaurants in the community or within a 1-kilometer radius around the community as the measure of accessibility to fast food, and they estimate Bayesian Hierarchical regressions. Focusing on differential impacts of fast food restaurants in rural versus urban areas and among men versus women, they find that the effect of fast food takes some time (over 2 years) to be reflected in waist-to-hip and waist-to-height ratios. Significant impacts are found among urban women and the rural population. The number of fast food restaurants may, however, be a noisy measure to use. For instance, since we share the same data source, we can observe inconsistency in how questions regarding fast food were asked in older surveys (before 2004) relative to the more recent ones. As a consequence, when these data are merged together, the changes in responses across waves may simply reflect technical differences rather than true trends.

Other Asian studies are either cross-sectional or observational studies. Chiang et al. (2011) find that a high density of fast food outlets near schools (within 500 meters) increases the risk of obesity in boys. Singh et al. (2006) also find a positive correlation between the frequent consumption of fast food (more than 3 times a week) and BMI among teenagers in India. Focusing on fast food's impact on chronic diseases, Odegaard et al. (2012) follow participants for five years to see how the intake of various fast foods affect blood sugar levels. They find that participants who reported eating these foods more than twice a week have a 27% greater risk of developing type 2 diabetes and a 56% greater risk of dying from coronary heart diseases compared to those who reported little or no intake. They find that those who reported more frequent intake of Western-style fast foods are actually more educated, in contrast to what is typically found in U.S. data, where fast food consumption tends to be associated with low education and low socioeconomic status.

In this study, we follow the U.S. literature in using spatial variations in Western-style fast food outlets to identify the causal effect of fast food restaurants. We use data from China. China is the most populous nation, and thus its overweight and obesity problems will have a marked impact on the global burden of diseases. In the past decade, about 1.2% of Chinese adult men have become overweight or obese each year, a rate that is exceeding those found in Australia, the U.K., and the U.S. (Popkin, 2008). During 1992–

2012, the prevalence of China's adult overweight and obesity rates has more than doubled from 20 to 42% based on the Chinese standard of BMI≥24, and with no change in the trend, this rate is projected to reach 61.5% by 2030 (Zhu et al., 2016). Consequently, the cost of health services due to obesity-related health problems is projected to grow from 4% of GDP in 2000 to nearly 9% in 2025 (Popkin, 2008), even before accounting for pharmaceutical expenditures. The International Diabetes Federation has forecasted that China will represent 72% of people with diabetes (143.5 million) in the Asian region in 2035 (International Diabetes Federation, 2014).[7]

3. Methodology

Our transition framework involves information from three points in time: $t-1$, t, and $t+1$. The information at $t-1$ defines our population: we focus our analysis on communities that had no Western fast food outlet at $t-1$. This population selection makes the

[7] http://www.idf.org/atlasmap/atlasmap

interpretation of our results clear and transparent. For this population, we identify the opening of a fast food outlet over the period between $t-1$ and t. Let the indicator variable $FFOpen_{j,t} \in \{0,1\}$ denote the opening of at least one Western fast food outlet between time $t-1$ and t in community j.This variable classifies the communities in our sample into treatment and control groups, and this causal evaluation framework resembles the standard structure of event studies. However, because dietary habits and body measures take a considerable amount of time to react to access to Western fast food, we incorporate this event study structure into a standard transition analysis approach. The dependent variable, $\Delta Y_{ij,t+1} \equiv Y_{ij,t+1} - Y_{ij,t}$, is the change in the fatness measure of individual i in community j over the period between t and $t+1$. Specifically, we employ the following linear specification:

(1) $$\Delta Y_{ij,t+1} = \delta_{FFOpen} \cdot FFOpen_{j,t} + C_{j,t}\pi + X_{ij,t}\beta + \varepsilon_{ij,t} ,$$

where δ_{FFOpen} is our parameter of interest, $C_{j,t}$ is a vector of the community-specific variables, $X_{ij,t}$ contains demographic and socioeconomic characteristics of individual *i*, $\varepsilon_{ij,t}$ is the error term, and π and β are unknown parameters to be estimated. We also consider the change in outcome variables over the period between t and $t+2$ as a "mid-term."

Our transition framework can be compared with the standard cross-sectional and fixed-effects approaches, which can be expressed using the following model:

(2) $$Y_{ij,t} = \delta_{FF} \cdot FF_{j,t} + C_{j,t}\pi + X_{ij,t}\beta + a_j + \varepsilon_{ij,t} \ ,$$

where $FF_{j,t}$ indicates at least one Western fast food outlet in community *j* at time *t*, δ_{FF} is the parameter of interest, and a_j is community-specific unobserved factors. When we cannot assume that the treatment is randomly assigned, the fixed-effects approach is often used because it allows us to obtain consistent estimates—even when a_j is correlated with $FF_{j,t}$ or other independent variables—by effectively comparing *change* in $Y_{ij,t}$ with *change* in $FF_{j,t}$, or formally by

(3) $$\Delta Y_{ij,t+1} = \delta_{FF}\Delta FF_{j,t+1} + \Delta C_{j,t+1}\pi + \Delta X_{ij,t+1}\beta + \Delta\varepsilon_{ij,t+1}.$$

The estimated δ_{FF} will be biased, however, unless several strong assumptions are satisfied. First, the fast food effect is concurrent: that is, the effect of the opening or closing of fast food outlets on $Y_{ij,t}$ takes place only between t and $t+1$. This is quite a strong assumption because weight adjustment is highly gradual (Hall et al., 2011; Ng et al., 2012; Xu et al., 2013). Moreover, the impact of fast food restaurants may take some time to materialize because consumers may take time to find out about the restaurants, acquire a taste for them, form a habit of going to them, and spread the word. We do not claim that any weight gained immediately after the fast food outlet opening is irrelevant. Indeed, our focus is on a short-term weight gain over 2-4 years. Within the fixed-effects families, perhaps a dynamic fixed-effects model is more plausible, but it too requires specific parametric assumptions. The standard dynamic panel data models impose a certain symmetrical structure (e.g., Card and Hyslop, 2009). In our case, this symmetrical structure implies that the effects of the opening and closing of a fast food outlet have the same magnitude with opposite signs. However, clinical studies have documented that body weight display downward rigidity, and many individuals struggle to lose weight

(Franz, 2001; Hill et al., 2012). By applying the transition framework only for communities with no Western fast food outlet at $t-1$, we do not impose such a restriction in our analysis.

Second, fixed-effects approaches allow for a time-constant omitted factor, a_j, but not a time-varying omitted factor. Any time-varying unobservable factor correlated with the presence of fast food outlets may lead to biased estimates. For example, the estimate is biased if the entry and timing decision of fast food companies is based on their profit maximization, which takes into account time-varying $C_{j,t+1}$ and $X_{ij,t+1}$. This potential source of bias also exists in our transition framework. We attempt to minimize this bias by exploiting the broad set of covariates in the CHNS and by using a careful propensity matching procedure. Another disadvantage of fixed-effects approaches is that time-constant variables need to be discarded by design, whereas out transition framework allows us to use the variation in time-constant, community-specific variables.

If the opening of fast food outlets is not random, and if communities with and without outlets are substantially different, then the estimation of a causal parameter is achieved by parametric assumptions such as the linearity structure in Equation (1). To address this concern, we employ a matching approach that ensures comparability by using only communities with similar characteristics in the treatment evaluation. More specifically, we match with respect to characteristics that fast food companies may use in their expansion strategy such as the size of the community's area, population density, the presence of an Asian supermarket, the presence of a Western supermarket, the availability of a train station, accessibility to the internet, and community obesity rate. Given the similarity between these factors, $FFOpen_{j,t}$ in successfully matched communities is as good as random in relation to the obesity and dietary trends in those communities.

As there are many characteristics to match, the standard approach is to use propensity score matching to overcome the dimensionality problem. Matches are found according to a one-dimensional propensity score of treatment. We use a logit model to predict this propensity score—that is, $\Pr(FFOpen_{j,t} = 1)$. Because the variation in $FFOpen_{j,t}$ comes from both community and time, the unit of observation in the matching equation is community-time. Using the calculated propensity scores, we find the "nearest neighbor" to each treated community based on a metric called caliper, which is the absolute difference between the propensity scores of the treated and untreated communities. We label the resultant sample as the "matched sample."[8]

We conduct and present our analysis as follows. First, we examine trends in fatness measures over time. Second, we report the "fast food effect" obtained from the standard pooled ordinary least squares (OLS) and fixed-effects models based on Equation (2) in order to highlight the bias in these widely used models. Third, we report the results of our main models, the transition regression (Equation (1)). Fourth, we repeat this analysis for the mid-term effect. Here, the sample size is halved because it requires the entire

[8] We compare our approach with the kernel method, an alternative matching strategy, and find that the nearest neighbour approach yields better comparability than the kernel method.

span of our available data (5-year change). The matched sample is reestimated. Fifth, we conduct subsample analysis by sex, age, income, and current height to explore heterogeneity in the fast food effect. The split by income is motivated by the fact that Western-style fast food is rather expensive in China.[9] Meanwhile, the split by baseline BMI is motivated by prior studies that find that the impact of fast food is concentrated among those who are already heavy (e.g. Ebbeling et al., 2004; Spiegel, 2000). Finally, we estimate quantile regressions to investigate heterogeneity in the fast food effect across the distribution of the obesity measures. Throughout this paper, it is important to note that our estimates can only be interpreted as local effects. As a consequence of the focus on first openings and the use of the matching strategy, our estimates are obtained from a rather small number of communities, and thus our estimates cannot be used to infer the causal effect at the national level.

4. Data

[9] The cost of a McDonald's meal is RMB 23 (www.mcdonalds.com.cn/); with this amount, one can buy almost 3 kilograms of rice.

The data are derived from the China Health and Nutrition Survey (CHNS). The CHNS was first collected in 1989 and has been implemented every 2-4 years since. The CHNS uses a stratified multistage sample design with random clusters, and in 1989 it surveyed households within 218 communities across 9 different Chinese provinces (Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, and Guizhou), where 56% of the total population resided. The first wave was representative of each province. In the first wave, an average community is 16 square kilometers in size (standard deviation of 78 square kilometers) and has 5,195 people in 1,250 households. In each community, households were randomly selected. In the first wave, there are on average 21 households per community with a standard deviation of 2. To maintain the representativeness of the survey, the subsequent waves added newly formed households to the original households, along with replacement households and communities to replace those that were no longer participating in the survey. Further details of the survey can be found in Popkin et al. (2010).

The CHNS contains a broad set of anthropometric variables. They are measured by a health worker, and hence measurement errors and reporting bias are expected to be minimal. We study three measures of fatness, because no measure is perfect and using multiple measures ensures the robustness of our results. The first measure is the body mass index (BMI), which is the most common measure of body mass, and is defined as weight in kilograms divided by the square of the height in meters (kg/m^2). Although most extensively used in the literature, BMI is not necessarily the best measure of fatness. It does not distinguish between body fat and lean body mass, and its relationship with body fat percentage is affected by factors such as age, gender, and physical activity (see Buckhauser and Cawley, 2008, for further discussion). BMI also does not correlate well with the visceral fat mass (VFM), which is a signal of various chronic conditions.

The second measure is the arm fat index (AFI), which measures the fat percentage of the arm. AFI is calculated from two variables: the mid-upper arm circumference (MUAC) and the triceps skin fold (TSF), which measures the thickness of the fat area surrounding the muscle. AFI is defined by the following formula: $AFI = 100 \times (MUAA - MUAMA)/MUAA$, where MUAA stands for mid-upper arm area (given by $MUAC^2/4\pi$), and MUAMA stands for mid-upper arm muscle area (the circumference of the bone and muscle portions of the mid-upper arm, given by $\frac{1}{4\pi} \times \left(MUAC - \left(\pi \times \frac{TSF}{10}\right)\right)^2$).

The third measure is the waist-to-hip ratio (WHR), which is a standard measure of abdominal obesity and is defined by the ratio between the circumferences of the waist and the hip. In contrast to BMI, AFI and WHR correlate strongly with VFM and the centralization of body fat, and they have also been recommended in clinical practice as better reflectors of health risks, especially for those with high mortality risk (e.g., older individuals) and for females who tend to experience significant hormonal changes that are not captured by BMI (Bhurosy and Jeewon, 2013). However, AFI is not as reproducible as BMI and WHR, as it depends on the health practitioner who performs the pinch test.

The availability of Western fast food restaurants is obtained at the community level. The survey asked a community representative whether there is an outlet of KFC, McDonald's, Pizza Hut, or "other" brands in the community. We do not use the count of these outlets because this information relies on the community representative's knowledge, and hence relatively large measurement error is expected. We instead create an indicator variable for the presence of at least one outlet of either KFC, McDonald's, or Pizza Hut in the community, and this indicator defines "access to Western fast food" in this study. These three brands are the largest Western fast food brands in China, so it is unlikely that the community representative is unaware of their presence. The data set does not have the exact geographical information of these fast food outlets; however, we note that, in China, these big Western fast food chains offer a relatively cheap (or free) delivery service within the neighborhood. Thus, even if you do not live next to a fast food outlet, accessibility to fast food is still very high. Chinese people also travel to eat regularly. During 2006, 2009, and 2011, according to the CHNS, 49%, 56%, and 60% of households ate out for lunch or dinner, respectively. In addition, our transition framework, which utilizes the panel structure of the data, may overcome this lack of exact location data. As with the "other" type of fast food stalls, we have limited information about them (e.g., the type of food they sell), and so we treat them as a covariate.

We use the opening of the first Western fast food outlet in the community as our treatment variable. This variable is constructed by combining two consecutive waves of the CHNS. For our econometric approach to be valid, it is important that the first Western fast food restaurant seldom exits the market within a few years of its entry because, otherwise, we cannot accurately observe the entry and exit of the first fast food outlet in the CHNS. We expect that this condition is reasonable in our context. As evident from their rapid expansion, these fast food companies did not exit their new market very often. They must have done substantial research before opening a store in a particular community. Moreover, their parent company's economic reserves can assist in avoiding closure. For example, despite a growing number of KFC franchisees, about 90% of KFC outlets are still company-owned.[10]

The control variables are individual and community characteristics at the base year. Individual characteristics include age, sex, education, household size, working status, and household real income from all sources before tax. The community variables include an urban dummy, the size and population of the community, the inflation-adjusted price of rice (we use the free market price of the rice type that is commonly consumed in a given community), the presence of Asian supermarkets, the presence of Western supermarkets, accessibility to the internet, the presence of a train station, and province dummies. In the matching equation, we include all of the community characteristics, the community average of all individual characteristics, and the community average of base-period body measures (height, BMI, AFI, and WHR).

[10] https://hbr.org/2011/11/kfcs-radical-approach-to-china

We use the latest four waves of the CHNS (2004, 2006, 2009, and 2011) in which information about the presence of fast food restaurants is available consistently.[11] The transition analysis of Equation (1) involves three points in time: $t-1$, t, and $t+1$. The first two points identify the opening of a first Western fast food restaurant in the community, and t and $t+1$ define the outcome variables. To focus on the causal effect of opening, we exclude communities that already had a Western fast food outlet at $t-1$, and we find that our main results are robust to their exclusion. For the short-term effect, we create a stacked sample consisting of 2 time sets. This structure is similar to standard event studies. Time set 1 consists of the opening of a Western fast food restaurant during

[11] Henan and Hubei provinces are excluded because information on fast food is missing in some years. In addition, to ensure that community representatives provide reliable information, we check the consistency of their answers to some variables over time and their answers to basic questions such as the presence of markets, electricity, paved roads, etc. We excluded communities with unreliable answers as follows. First, we excluded 4 communities that report a very small number of households in one wave but over 500-fold more in the next wave. Second, we excluded communities with large variation in recorded population density over time (over 4 in standard deviation). Lastly, we excluded communities with a very large area size; these communities have no Western fast food restaurants.

2004–2006 and the transition in outcomes during 2006–2009, with the base period being 2006. There are 10 communities with an opening in this time set. Time set 2 consists of an opening during 2006–2009 and the transition in outcomes during 2009–2011, with the base period being 2009. There are 4 communities with an opening in this time set. For the mid-term analysis, we use the opening of Western fast food restaurants during 2004–2006 and the change in outcomes during 2006–2011, with the base period being 2006.

Our population of interest is adults 20 years of age and older in the base year, who we observe at times t and $t+1$ (presence as an individual in $t-1$ is not necessary). After data cleaning,[12] the sample for the transition analysis consists of 2,402 and 2,276 in time sets 1 and 2, respectively, comprising a total of 4,678 adults. For the mid-term analysis, the sample size is 2,020.

[12] We further exclude individual outliers: those whose change in BMI is more than 18 units in absolute value and those whose change in AFI is more than 40 units.

5. Results

Table 1 shows the prevalence of fatness in China from 2006 to 2011 according to BMI, AFI, and WHR. To ensure the reliability of the anthropometric data, we also report the change in height, which should be relatively stable over such a short time span. The figures in the height column of Table 1 verify this. We show the overall trend as well as the community-specific trend both with and without a Western fast food restaurant. In 2006, an average Chinese person had a BMI of 23.046, and then BMI steadily increases to 23.687 over the next 5 years. Because Asians have a shorter stature than Westerners, they generally have a lower BMI level than Westerners. The WHO recommends a modification of the standard BMI thresholds for overweight and obesity: a BMI greater than 24 is used to indicate overweight status instead of 25, and a BMI of 29 or greater is used to indicate obese status instead of 30 (WHO Expert Consultation, 2004). Using this threshold, we can see that the trend in the average Chinese BMI is reaching the lower bound of overweight. Consistently, the average overweight and obese rate combined together in the sample increases from 36.5% in 2006 to 42.2% in 2011. These figures compare well with those reported in past studies.

We see the same upward trend for the overall mean WHR. In contrast, the trend in AFI is declining. Because these measures capture different aspects of fatness, they may not always agree with each other. Disaggregating by the presence of a local Western fast food restaurant, the mean BMI, AFI, and pooled overweight and obese (Overweight/Obese) rate are higher in communities where there is a Western fast food restaurant, but the mean WHR is smaller than that in communities where there is no Western fast food restaurant. From 2006 to 2011, BMI and WHR appear to grow regardless of the access to Western fast food. This growth is statistically significant. In contrast, AFI is stable in communities that do not have a Western fast food restaurant and significantly declined in communities with Western fast food opening.

[Insert Table 1]

Table 2 shows the results from standard models: pooled OLS, community fixed-effects (FE) regression, and individual FE regression. We start with a simple specification with only the fast food variables as the covariate, and we sequentially add individual- and community-specific covariates to assess the size of potential bias due to confounding factors. The standard errors of the estimates are corrected for clustering at the community level. The simplest pooled OLS indicates that the presence of Western fast food outlets significantly increase BMI and AFI by 0.77 and 6.09 (about 3% and 18% from the mean BMI and AFI), respectively. The combined results for overweight and obese in the overweight/obese column are consistent with those of BMI, which can be expected since it is derived from BMI.[13] Adding observables and various fixed effects substantially reduces the positive effects of Western fast food on BMI and AFI, suggesting the size of

[13] The result for obesity is consistent and available from the authors. We report the results for the combined overweight and obese rates as it is closer to the center, which suits the linear probability model better from the statistical viewpoint than a value near zero or one.

the potential bias due to confounders. The effects of fast food on BMI and AFI estimated from the individual FE model (in the last row) are less than half of those from the pooled OLS with no control, although they still have a 5% statistical significance. The effect of fast food on the risk of at least overweight is also reduced and has no statistical significance. None of the three models finds an effect on WHR.

The last set of results shown in Table 2 reveals the effect of fast food on height. We do this analysis as a placebo test because the presence of fast food outlets should not substantially increase the average height of Chinese individuals. We find that all three models show highly significant effects of Western fast food outlets. This clearly indicates that results from the standard approaches are highly undependable.

[Insert Table 2]

Moving on to the transition analysis, Table 3 first reports some baseline characteristics split by $FFOpen$ and shows how propensity score matching can minimize some of these differences. The logit results for the matching equation are provided in Appendix A. Before matching, we see a very unequal distribution of estimated propensity scores. Among the communities with no opening, the mean probability of an opening is only 0.045, while among the communities with an opening, the estimated odds are much higher, 0.417. Communities with an opening tend to be more populated, richer and better developed than those without an opening. They also have considerably taller residents with higher BMI, much higher AFI, and lower WHR. The large disparity in the mean WHR is concerning. Thus, in choosing the matched sample, we place great emphasis on the comparability of the three fatness measures across the two types of communities.[14] To define similar communities, we consider several narrow calipers. A

[14] With propensity score matching, we cannot get every covariate aligned. For instance, before matching, the two communities are similar in average area size, but after matching, untreated communities are larger on average. In contrast, matching makes the

caliper of 0.01 results in 8 matched pairs, while a smaller caliper of 0.005 results in 4 matched pairs and a larger caliper of 0.02 results in 9 matched pairs. Across these three specifications, we find that the caliper of 0.01 gives the best comparability in the baseline mean BMI, AFI, and WHR. In order potentially to increase the sample size, we also consider allowing for multiple matches by keeping the caliper fixed. However, doing so brings back the gap in the baseline mean WHR. In the end, we prefer the one-to-one nearest neighbor matching with the 0.01 caliper.

[Insert Table 3]

Table 4 reports our main results from the transition analysis. The upper panel of the table uses all communities in the sample, while the bottom panel reports the results for the matched sample. In the short term, which is 3-5 years after a Western fast food opened,

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two communities more alike in terms of population density, price, access to internet, and the presence of a Western supermarket and other fast food outlets.

generally, BMI and WHR increase while AFI shrinks. However, there is a lot of variability with respect to the change in AFI, which may be explained by data collection across survey waves. In the most basic specification without controls, we find a significant impact only for WHR: the emergence of a Western fast food restaurant accelerates WHR growth by 0.014, or 67% relative to the mean WHR growth in treated communities. Adding controls does not seem to alter this magnitude.[15] Meanwhile, we find no evidence that an opening has an impact on BMI or AFI and, rightly so, it has no impact on height.

Imposing comparability across communities, we find that the significant impact on WHR is not robust. While the opening has a sizeable positive impact on BMI, it is imprecisely estimated and not significant at any conventional significance level. This occurs across all fatness measures. Although our data set does not cover all Chinese provinces and

[15] The results for control variables are not reported but available from the authors upon request. In general, the results are as expected. For instance, the growth in the fatness measures tends to slow down with age and is slower among highly educated individuals.

excludes big cities like Beijing and Shanghai, we note that it covers provinces where the majority of the population lives. Furthermore, the CHNS's sampling design has ensured that communities in each province are chosen in such a way that they represent different levels of socioeconomic status and remoteness. Hence, we can be confident that our results have broad relevance. In fact, big cities may not add to the transition analysis, as fast food restaurants had already opened in these cities by 2004 (i.e., there is no new opening). Moreover, if people in these cities always have access to fast food, it violates one of the conditions of a valid impact evaluation analysis, which is that all units must have a positive probability of getting treatment and no unit gets treated with certainty. Several U.S. studies exclude urban areas in their analyses for this reason.

The limited impact of fast food is not inconsistent with previous studies.[16] Ng et al. (2012) find that a one-time dietary change has limited impact on body weight. In their sample of adult men, a one-time diet change explains only 3-4% of the weight gain over a 15-year period. Katan and Ludwig (2010) suggest that a single change in diet, even if permanent, may trigger compensatory mechanisms that limit long-term effects on body weight. Similarly, Anderson and Matsa (2011) find that those who overeat tend to reduce their calorie consumption at other times.

[Insert Table 4]

Table 5 shows the mid-term effect of Western fast foods, about 5-7 years after the opening of the first Western fast food outlet in the community. As in the case of the short-term results in Table 4, we find a significant impact on WHR, but it is not robust to

[16] Reestimations of Table 4 including communities with a Western-style fast food outlet at baseline yield fast food opening coefficients (s.e.) of 0.034 (0.199) for BMI, -0.631 (2.287) for AFI, and 0.014 (0.007) for WHR.

communities' baseline characteristics. All in all, both short-term and long-term results show no strong evidence of a positive effect of Western fast food outlets.

[Insert Table 5]

Table 6 explores impact heterogeneity. We use the full sample for this to make sure we have large enough observations for subsample analyses. First, we disaggregate by sex. For males, we find consistently positive coefficients across the fatness measures, while for females, we find a positive coefficient only for WHR. Although we know that any significant impact here is not robust, if there is any heterogeneity, males seems to be at higher risk of a quickly expanding waist. Second, we split the sample by age group and find no strong evidence of substantial heterogeneity. If anything, those in their 50s are more susceptible to a fast-growing waistline. Next, we split the sample by income and stature in the base period. Here, we find no strong support for either hypothesis; the impact of fast food is concentrated at the high end of income distribution and among those who are already heavy. If anything, the higher risk group includes those in middle-income households who are relatively lean. Finally, we estimate quantile regressions. The confidence intervals of the estimates are quite large and they overlap across the different quantiles. Hence, we conclude no evidence of a heterogeneous impact by weight that people have gained.

[Insert Table 6]

6. Conclusion

This paper investigates whether Western-style fast food chains contribute to the rapidly growing body mass in Asian countries in the recent decades. Our strategy is to use the opening of the first Western fast food restaurant in a community and estimate its impact on future weight growth. Using Chinese adults as a case study, we find no strong support that these foods are the driving force behind the obesity epidemic. Different fatness measures show different trends, but they consistently show no robust causal link from Western fast food. There are some indications of effect heterogeneity, with mature males in mid-income households who are relatively lean having the highest risk of a faster-growing waistline. Our findings suggest that targeting Western-style fast food restaurants to tackle obesity problem is not effective.

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