ECONSTOR
Make Your Publications Visible.

A Service of

ZBW Leibniz-Informationszentrum Wirtschaft
Leibniz Information Centre for Economics

Nie, Peng; Ding, Lanlin; Sousa-Poza, Alfonso

Working Paper

Obesity inequality and the changing shape of the bodyweight distribution in China

Hohenheim Discussion Papers in Business, Economics and Social Sciences, No. 24-2018

Provided in Cooperation with:
Faculty of Business, Economics and Social Sciences, University of Hohenheim

Suggested Citation: Nie, Peng; Ding, Lanlin; Sousa-Poza, Alfonso (2018) : Obesity inequality and the changing shape of the bodyweight distribution in China, Hohenheim Discussion Papers in Business, Economics and Social Sciences, No. 24-2018, Universität Hohenheim, Fakultät Wirtschafts- und Sozialwissenschaften, Stuttgart, https://nbn-resolving.de/urn:nbn:de:bsz:100-opus-15403

This Version is available at:
https://hdl.handle.net/10419/183240

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

WWW.ECONSTOR.EU

Mitglied der Leibniz-Gemeinschaft

UNIVERSITY OF HOHENHEIM

200 YEARS 1818 2018

Hohenheim Discussion Papers in Business, Economics and Social Sciences

OBESITY INEQUALITY AND THE CHANGING SHAPE OF THE BODYWEIGHT DISTRIBUTION IN CHINA

Peng Nie
Xi'an Jiaotong University

Lanlin Ding
Xi'an Jiaotong University

Alfonso Sousa-Poza
University of Hohenheim

Research Area INEPA

24-2018

wiso.uni-hohenheim.de

Discussion Paper 24-2018

Obesity inequality and the changing shape of the bodyweight distribution in China

Peng Nie, Lanlin Ding and Alfonso Sousa-Poza

Research Area "INEPA – Inequality and Economic Policy Analysis"

Download this Discussion Paper from our homepage:

https://wiso.uni-hohenheim.de/papers

ISSN 2364-2084

Die Hohenheim Discussion Papers in Business, Economics and Social Sciences dienen der schnellen Verbreitung von Forschungsarbeiten der Fakultät Wirtschafts- und Sozialwissenschaften. Die Beiträge liegen in alleiniger Verantwortung der Autoren und stellen nicht notwendigerweise die Meinung der Fakultät Wirtschafts- und Sozialwissenschaften dar.

Hohenheim Discussion Papers in Business, Economics and Social Sciences are intended to make results of the Faculty of Business, Economics and Social Sciences research available to the public in order to encourage scientific discussion and suggestions for revisions. The authors are solely responsible for the contents which do not necessarily represent the opinion of the Faculty of Business, Economics and Social Sciences.

Obesity inequality and the changing shape of the bodyweight distribution in China

Peng Nie[a,b,*], Lanlin Ding[a] and Alfonso Sousa-Poza[a,b,c]

[a] *School of Economics and Finance, Xi'an Jiaotong University, 710061 Xi'an, China*

[b] *Institute for Health Care & Public Management, University of Hohenheim, 70599 Stuttgart, Germany*

[c] *IZA, Bonn, Germany*

Abstract

Using data from the China Health and Nutrition Survey (CHNS), this study analyses changes in bodyweight (BMI and waist circumference) distributions between 1991 and 2011 among adults aged 20+ in China. To do so, we quantify the source and extent of temporal changes in bodyweight and then decompose the increase in obesity prevalence into two components: a rightward shift of the bodyweight distribution (mean growth) and a (re)distributional skewing. Our analysis reveals a clear rightward distributional shift combined with a leftward skewing. Although the relatively large size of this skewing in the first decade analysed reflects an increase in obesity inequality, this inequality growth subsides in the second decade. Nevertheless, over the entire 20-year period, obesity inequality increases significantly, especially among females, younger age groups, rural residents and individuals with low socioeconomic status.

JEL Classification: D30; D63; I10; I14;

Keywords: BMI; Waist circumference; Obesity inequality; Decomposition; China

[*] Correspondence: Peng Nie, School of Economics and Finance, Xi'an Jiaotong University, 710061 Xi'an, China, Email: Peng_Nie@uni-hohenheim.de.

Obesity inequality and the changing shape of the bodyweight distribution in China

1. Introduction

The ever-rising levels of overweight and obesity worldwide make obesity one of the most prominent issues in global public health (Ng et al., 2014), with over 1.9 billion adults aged 18 and older being overweight in 2014 and a further 600 million being actually obese (WHO, 2016). Nonetheless, recent trends in adult obesity rates vary substantially across countries, increasing rapidly in most developing countries like China but slowing or stabilizing in some developed countries such as the U.S. and UK (Lu et al., 2016). In all regions, however, being overweight or obese is linked with an increased prevalence of chronic disease, including cardiovascular disease, stroke, type 2 diabetes and a subset of cancers (Hill and Peters, 1998), as well as particular social and mental health risks (OECD, 2012).

China presents a uniquely interesting case of weight change because of its rapid transition from historical undernutrition to a sharp increase in overweight and obesity (Xi et al., 2012; Zhai et al., 2009). China has also witnessed a major shift in diet – most notably, an increased intake of edible oils, fried foods, animal-sourced foods and snacks – accompanied by a sharp decline in occupational and domestic physical activity (PA), which combination tripled the prevalence of adulthood overweight from 11.7% in 1991 to 29.2% in 2009 (Gordon-Larsen et al., 2014). China's rates of obesity-related non-communicable diseases (NCDs) have also increased dramatically and have become the major risk factors for morbidity, disability and mortality (Popkin, 2008). The country's prevalence of diabetes, for instance, nearly quadrupled between 1994 and 2008 from 2.5% (Pan et al., 1997) to 9.7% (Yang et al., 2010). As a result, China spends 24 billion yuan annually, 2.46% of its annual national health care expenditure, on overweight, obesity and their complications (Qin and Pan, 2016). This expenditure clearly indicates the magnitude of the challenge posed by this rapidly increasing obesity to China's health care system (Zhao et al., 2008).

Statistically, the rise in obesity prevalence (or mean bodyweight) in China can be attributed to two factors: a rightward shift of the bodyweight distribution, indicating that the entire population is growing heavier, or an increase in distributional left-skewness, reflecting more rapid weight gain in one population subset (notably the more obese) and thus rising obesity inequality – or a combination of both. Understanding which is the case is important because

the former would call for population-wide policies, whereas the latter would signal a need for policies targeted at groups particularly affected by obesity. Obesity inequality may also play an important role when assessing obesity's persistence: On the one hand, general increases in a population's bodyweight (i.e., a rightward distributional shift) may alter norms and perceptions of ideal bodyweight in the entire population, which can cement higher obesity rates. On the other hand, an increase in distributional skewness, by mainly affecting only a specific portion of the population, may not have such lasting effects. In fact, there is empirical evidence that perceptions of ideal bodyweight are changing. In the U.S., for example, the percentage of overweight (but not obese) individuals who describe their weight as "about right" (rather than "overweight") has increased significantly, from 14% to 21% among women and from 41% to 46% among men (Burke and Heiland, 2018). Blanchflower et al. (2009) also show that, for a given level of overweight, the wider an individual's deviation from the average weight within a region, the stronger his or her feelings of being overweight. Given the large body of evidence on obesity's negative psychological effects (e.g. Katsaiti, 2012), which increase with the deviation from the overall population (Wadsworth and Pendergast, 2014), a rise in obesity inequality could accentuate obesity-related stigma and discrimination.

Yet despite the importance of knowing how a country's bodyweight distribution has changed over time, little research on this topic exists. In fact, we are aware of only four such studies, the first being Contoyannis and Wildman's (2007) analysis of Canadian National Population Health Survey (NPHS) and Health Survey of England (HSE) data, which demonstrates a polarization over time in both nations towards the right-end of the BMI distribution, with the English polarizing towards the upper tails at a faster rate than the Canadians. Subsequent work by Sahn (2009), which draws on Demographic Health Survey data from 30 developing and transitional countries, not only reveals a sharp rise in overweight among women in Latin America and the Middle East but shows that in most countries, female BMI distributions are becoming markedly more unequal. On the other hand, Madden (2011), using 2002–2007 data from the Survey of Lifestyle, Attitudes and Nutrition in Ireland, identifies a marginal decrease in obesity over this period, which he also attributes primarily to a change in the shape of the BMI distribution (as opposed to a change in average level). Lastly, Pak et al. (2016) employ four waves of National Health and Nutritional Examination Survey (NHANES) data to investigate the inter-temporal changes in BMI distribution among U.S. adults between 1971 and 2014. In addition to showing that the early phase of the obesity epidemic is mostly attributable to increasing skewness while recent increases reflect a population-wide increase,

these authors demonstrate that within-group inequality accounts for the majority of the increase in obesity inequality, which is worsening over time.

Our study thus aims to provide the first analysis of long-term distributional changes in bodyweight among Chinese adults aged 20+ by examining changes in both the BMI and waist-circumference (WC) distributions over the 1991–2011 period. This approach is important because in China central obesity is much more prominent than general obesity whose negative health effects are less severe (Xi et al., 2012). In addition to applying Kakwani's (1997) technique to decompose total change in obesity prevalence into a mean-growth and a redistribution component, we also employ conventional inequality measures (Gini and generalized entropy) to provide a univariate assessment of obesity inequality. Lastly, we decompose obesity inequality into within-group and between-group to throw light on whether disproportionate obesity increase is a population-wide phenomenon or the result of changing demographic composition.

2. Data and Methods

2.1. Data and study population

The data are taken from 8 waves of the China Health and Nutrition Survey (CHNS) – 1991, 1993, 1997, 2000, 2004, 2006, 2009, and 2011 – covering nine provinces (Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi and Guizhou) with different social, economic and health characteristics (Zhang et al., 2014). The survey's multi-stage random cluster sampling method (based on different income levels and weighted sampling) entails the following steps: After randomly selecting four counties and two cities within each province, the CHNS randomly identifies villages and towns in each county and urban and suburban regions in each city. It then selects 20 households from each of these communities. The data thus capture a broad spectrum of the spatio-temporal dynamics of the Chinese populations' social, economic and health situations (Zhang et al., 2014).

Our final analytic sample is restricted to adults aged 20 and older for whom detailed demographic, socioeconomic and anthropometric information is available. We exclude from the sample pregnant females; the 1989 wave, which is limited to adults aged 20–45; and the most recent 2015 wave, which provides no anthropometric information. These exclusions leave 8 rounds of CHNS data from 1991 to 2011 and a final sample size of 72,732 BMI observations. When reporting our results, we focus primarily on two periods: 1991-2000 (the early period)

and 2000-2011 (the late period). In addition, because waist circumference data are only available from 1993 onwards, for this variable, our early period runs from 1993 to 2000 and our sample size is only 63,493.

2.2 Obesity variables

In the CHNS, weight is measured to the nearest 0.1 kg on a calibrated beam scale with the subject wearing only lightweight clothing, while height is measured to the nearest 0.1 cm using a portable stadiometer with the subject barefoot (Xi et al., 2012). We adopt BMI (in kg/m^2) as one proxy of body weight and define general obesity according to the Working Group on Obesity in China (WGOC) criterion; that is, BMI $\geq$ 28 kg/m^2 (Zhou and the Cooperative Meta-Analysis Group of the WGOC, 2002). Waist circumference (WC) is measured (in cm) at the midpoint between the bottom of the ribs and the top of the pelvis. Abdominal obesity among males is defined as WC $\geq$ 85cm and among females as WC $\geq$ 80cm (Zhou and the Cooperative Meta-Analysis Group of the WGOC, 2002). Our use of CHNS's clinical measures of respondent weight, height and WC is advantageous because it eliminates the reporting bias inherent in self-reported weight and height (Shields et al., 2011), which tends to result in underestimation of BMI (Burkhauser and Cawley, 2008).

2.3 Demographic and socioeconomic variables

To capture subpopulation heterogeneity in obesity inequality, we introduce several demographic and socioeconomic characteristics, including gender (1 = male, 0 = female), age group (20–39 years, 40–59 years and 60+ years), educational level (0 = low: illiterate/primary school, 1 = medium: middle school/high school and 2 = high: technical or vocational degree /university/master's degree or higher), household income level (recoded into terciles: 0 = low, 1 = medium and 2 = high) and region (1 = urban, 0 = rural).

2.4 Methods

Stochastic dominance test. In addition to being common in economic studies of inequality and poverty (Davidson and Duclos, 2003, 2013), the stochastic dominance (SD) test, a non-parametric distributional comparison among continuous variables (Cowell and Flachaire, 2015), is widely used in obesity studies (Madden, 2011; Pak et al., 2016; Sahn, 2009). Applying this intuitively appealing technique to our BMI and WC measures is particularly appropriate given that SD focuses primarily on comparisons over the entire bodyweight distribution and is

thus independent of the selection of an obesity threshold (Pak et al., 2016). More specifically, after defining first-order dominance as

$$D_t^1(x) = \int_0^x dF_t(y) \qquad (1)$$

we are able to express second-order and higher-order dominance as

$$D_t^s(x) = \int_0^x D_t^{s-1}(y)dy, \;\; s \geq 2 \quad (2)$$

We then define $F_{t_n}(x)$ and $F_{t_{n-1}}(x)$ as two cumulative distribution functions (CDF) of our bodyweight measures (BMI and WC), with t_n and t_{n-1} denoting two time points of *n* and *n-1*, respectively. The distribution at time t_n stochastically dominates the distribution at time t_{n-1} at order *s* if the following pair of conditions hold:

$$D_{t_n}^s(x) \leq D_{t_{n-1}}^s(x) \qquad (3)$$

$$D_{t_n}^s(x) < D_{t_{n-1}}^s(x) \qquad (4)$$

where equation 3 indicates that the distribution at time t_n stochastically dominates the distribution at time t_{n-1} at order *s*, and equation 4 indicates the case of strict dominance. In addition to using simple *t*-statistics to test the null hypothesis (H_0: $D_{t_{n-1}}^s(x) - D_{t_n}^s(x) = 0$) for a series of test points along the distribution, we test the significance over the whole bodyweight domain to identify which part of the bodyweight distribution varies most (cf. Pak et al. 2016). Order *s* dominates when the null hypothesis is rejected for at least one test point at the 1% significance level without any reversal in the signs of difference (Madden, 2011). Although the choice of number of test points is quite arbitrary, the more test points used, the more likely the null hypothesis will be rejected, so most studies choose 10 to 30 points (Sahn, 2009; Pak et al. 2016). We alternatively employ 10, 30, 40 and even 80 test points, but our results do not change. Non-dominance exists when the differences are not significant or when the two cumulative distributions cross. Given that the interpretation of higher-order SD is less intuitive (Sahn, 2009) and our focus is on explaining variations in bodyweight distribution, we follow the convention of only analysing the first-order SD test.

Growth-inequality decomposition. Because SD tests can only make comparisons between bodyweight distributions, they say nothing about the underlying mechanisms of upwards or downwards shifts in the bodyweight distribution. We therefore additionally employ Kakwani (1997) decomposition to disentangle the total change in obesity prevalence into a mean-growth

and a redistribution component. By doing so, we hope to assess how much of the obesity increase is driven by a horizontal shift in bodyweight distribution (i.e., an increase in mean BMI or WC) and how much by a change in distribution pattern (e.g., an increased skewness towards the upper tail of the BMI or WC distribution) (Pak et al., 2016). Although prior studies employ a variety of methods to decompose poverty into growth and redistribution components (Datt and Ravallion, 1992; Jain and Tendulkar, 1990), these methods all produce an often difficult-to-interpret residual effect, which prevents sole attribution of changes in the measure of interest (in our case, bodyweight) to the growth and inequality effects. Kakwani (1997) describes this latter as the violation of an intuitively natural axiom. A further drawback of these approaches is that the growth and redistribution components differ dependent on choice of reference point, which itself is quite arbitrary (Datt and Ravallion, 1992). Kakwani (1997) thus suggests avoiding such arbitrary choice by using all periods as reference points, a procedure successfully employed in income and health inequality analyses (Christiaensen, 2002; Dhongde, 2007; Sahn and Younger, 2005) that also eliminates the residual term (Sahn, 2009). In our case, the obesity rate at time *t* can be expressed as follows:

$$OB_t = OB(T|m_t; c_t) \qquad (5)$$

where OB_t represents obesity prevalence at time t, and T is the obesity threshold (28 for BMI-based obesity, 85cm for male WC-based obesity and 80cm for female WC-based obesity). m is the average BMI, and c is the Lorenz curve denoting the CDF of the BMI probability distribution.

Changes in obesity rates between t_n and t_{n-1} can be decomposed as

$$OB_{t_n} - OB_{t_{n-1}} = G(t_{n-1}, t_n) + R(t_{n-1}, t_n) + \varepsilon(t_{n-1}, t_n) \quad (6)$$

where $G(\cdot)$, $R(\cdot)$, and $\varepsilon(\cdot)$ represents the growth, redistribution and residual parts, respectively. More specifically, we define the growth and redistribution components as follows:

$$G = OB\left(T\middle|m_{t_n}; c_{t_{n-1}}\right) - OB\left(T\middle|m_{t_{n-1}}; c_{t_{n-1}}\right) \qquad (7)$$

$$R = OB\left(T\middle|m_{t_{n-1}}; c_{t_n}\right) - OB\left(T\middle|m_{t_{n-1}}; c_{t_{n-1}}\right) \qquad (8)$$

where G denotes the change in obesity prevalence attributable to a horizontal shift in the bodyweight distribution while the relative position (measured by Lorenz curve) is kept constant. R indicates the observed change in the relative position while the average bodyweight remains constant. Then, following Kakwani (1997), total change in obesity prevalence can be exactly decomposed into the average growth and redistribution effects as follows:

$$OB_{t_n} - OB_{t_{n-1}} = \hat{G}(t_{n-1}, t_n) + \hat{R}(t_{n-1}, t_n) \quad (9)$$

where $\hat{G}$ and $\hat{R}$ respectively denote the growth and redistribution components of changes in obesity prevalence as specified by

$$\hat{G} = \frac{1}{2}[OB\left(T\middle|m_{t_n}; c_{t_{n-1}}\right) - OB\left(T\middle|m_{t_{n-1}}; c_{t_{n-1}}\right)] + \frac{1}{2}[OB\left(T\middle|m_{t_n}; c_{t_n}\right) - OB\left(T\middle|m_{t_{n-1}}; c_{t_n}\right)] \quad (10)$$

$$\hat{R} = \frac{1}{2}[OB\left(T\middle|m_{t_{n-1}}; c_{t_n}\right) - OB\left(T\middle|m_{t_{n-1}}; c_{t_{n-1}}\right)] + \frac{1}{2}[OB\left(T\middle|m_{t_n}; c_{t_n}\right) - OB\left(T\middle|m_{t_n}; c_{t_{n-1}}\right)] \quad (11)$$

In equations 10 and 11, the Kakwani decomposition for two-period comparisons takes an equally weighted average of two decompositions, one in the reference year and the other in a later year. In the case of three periods, we adopt multilateral comparisons to decompose the obesity prevalence into the growth ($\tilde{G}_{ij}$) and redistribution ($\tilde{R}_{ij}$) effects (Kakwani, 1997):

$$\tilde{G}_{ij} = \frac{1}{n}\sum_{k=1}^{n}\left(\hat{G}_{ik} + \hat{G}_{kj}\right) \quad (12)$$

$$\tilde{R}_{ij} = \frac{1}{n}\sum_{k=1}^{n}(\hat{R}_{ik} + \hat{R}_{kj}) \quad (13)$$

where i and j range from 1 to n (in our case, n=3), and $\hat{G}_{ij}$ and $\hat{R}_{ij}$ follow the same specifications as in equations (10) and (11).

Obesity inequality measures (Gini and generalized entropy). Although SD tests provide partial rankings of bodyweight distributions, they do not identify cardinal distributional differences. At the same time, the Kakwani technique used to decompose the total change in obesity rates is heavily dependent on the selection of an obesity threshold (Pak et al., 2016). Therefore, as a complementary approach, we also introduce Gini and generalized entropy (GE) measures to track the cardinal changes in obesity inequality. The Gini coefficient, a measure of statistical dispersion in a particular distribution, is a popular and widely used index measuring inequality (Yitzhaki, 1983). In essence, the Gini index, which ranges from 0 (complete equality) to 1 (complete inequality), is twice the area between the Lorenz curve and the 45-degree line (Cowell and Flachaire, 2015). Following Pak et al. (2016), we express this measure as

$$Gini_t = \frac{2}{m_t N_t^2}\sum_{i=1}^{N_t} BMI_{it} r_{it} - \frac{N_t + 1}{N_t} \quad (14)$$

where *N* is the sample size, *m* is the average BMI, BMI_{it} is the individual BMI value at time *t*, and r_{it} denotes the ranking of i^{th} BMI at time *t* in ascending order (with an equivalent expression for WC).

Because the Gini index is sensitive to changes around the distributional mode, we also adopt GE measures that are flexible enough to allow greater sensitivity away from the distributional middle (Shorrocks, 1984; Yang, 1999). We express the GE index as

$$GE_t(\omega)\frac{1}{w(w-1)}[\frac{1}{N_t}\sum_{i=1}^{N_t}(\frac{BMI_{it}}{m_t})^w - 1] \quad (15)$$

where ω is a scaling parameter representing the weight given to distances between individual BMI at different parts of the BMI distribution (with the same equation used for WC). The mean logarithmic deviation (MLD) is the limiting case when $\omega = 0$ (GE(0)), while the Theil index is the limiting case when $\omega = 1$ (GE(1)) (Cowell and Flachaire, 2015), which assures equal treatment of the differences between individual BMI levels at different parts of the BMI distribution. GE(2) is half the square of the coefficient of variation (Jenkins and Kerm, 1999). Because these GE(ω) indices vary in their sensitivities to differences in different distributional areas, the more positive (negative) the ω, the more sensitive GE(ω) to BMI differences at the top (bottom) of the distribution (Jenkins and Kerm, 1999). As robustness checks, we also set ω to 0 and 2, thereby enabling comparisons with Pak et al.'s (2016) outcomes for the U.S. population.

The use of SD tests and the Kakwani decomposition alone, however, does not allow us to identify which changes in obesity inequality are driven by changing subpopulation characteristics and which by a population-wide shift in bodyweight distribution. Rather, for this task, we introduce a GE-based decomposition by subgroup that splits the GE index into within-group and between-group inequality (Shorrocks, 1984):

$$GE_t(\omega) = GE_t(\omega)_{within-group} + GE_t(\omega)_{between-group} \quad (16)$$

$$GE_t(\omega)_{within-group} = \sum_j \frac{BMI_{t,j}}{BMI_t} GE_{t,j} \quad (17)$$

$$GE_t(\omega)_{between-group} = \sum_j \frac{BMI_{t,j}}{BMI_t} \ln(\frac{BMI_{t,j}/BMI_t}{N_{t,j}/N_t}) \quad (18)$$

where $GE_{t,j}$ and $BMI_{t,j}$ represent the GE index and BMI at subgroup *j* and time *t*, respectively (with a similar approach applied for WC). In equation 16, the first term denotes the weighted

sum of inequality within groups, while the second term designates the component driven by the heterogeneity in inequality between groups. We calculate this latter by assuming that everyone within a group has that group's mean bodyweight. From this expression, we can thus obtain the proportion of total bodyweight inequality attributable to inequality within groups and the proportion attributable to inequality between groups. If the relative contribution of total bodyweight inequality attributable to between-group inequality is negligible and the change of within-group inequality across time is comparable over groups, then the increasing bodyweight inequality is probably not driven by changes in the population's demographic composition but by changes in the population at large (Pak et al., 2016). To detect possible heterogeneities in population subgroups, we also perform a decomposition of the Theil index by age, gender, education, household income and region, as well as combinations of these categories.

3. Results

As shown by the Fig.1 illustration of the BMI kernel density and CDF curve between 1991 and 2011, not only did the BMI distribution generally shift to the right but the prevalence of obesity prevalence (BMI $\geq$ 28 kg/m^2) increased significantly from 3.2% in 1991 to 11.6% in 2011. The same pattern is evident for WC (Fig. 2), with the prevalence of central obesity increasing from 24.4% in 1993 to 56.4% in 2011. Taken together, these observations confirm that our analysis covers the start of the obesity epidemic. Nonetheless, it is also worth noting that the obesity prevalence in China is still much lower than that in the U.S. four decades ago and that as yet, extreme obesity (i.e., BMI $\geq$ 40 kg/m^2) is still not a major problem in China.

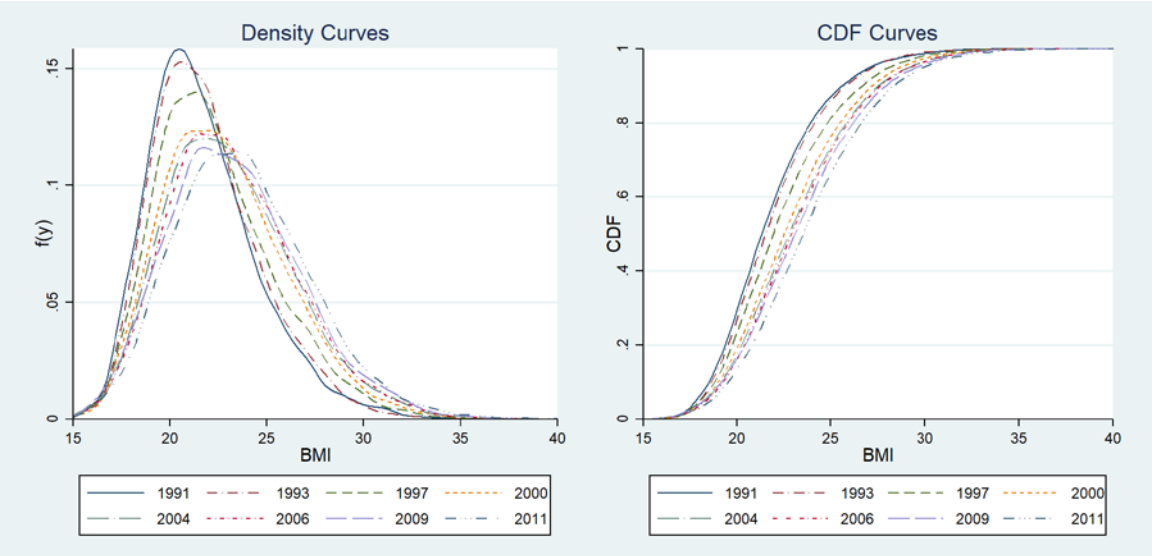

Fig.1 BMI distribution over time, 1991–2011

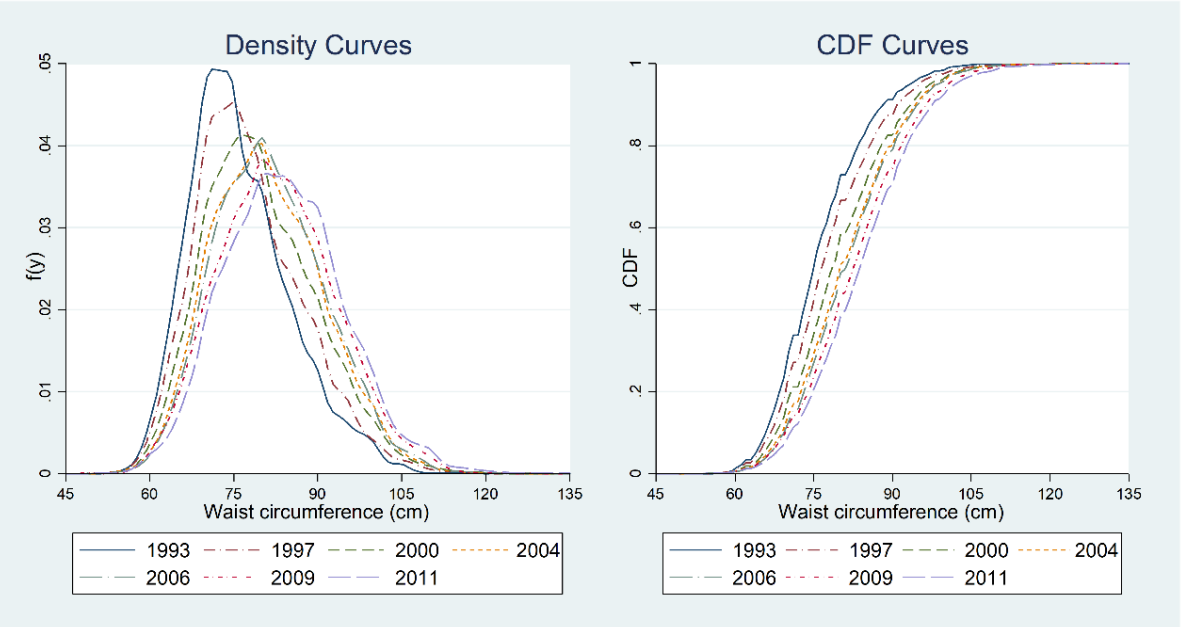

Fig.2 WC distribution over time, 1993–2011

Because exact assessment of CDF differences is difficult, in Figs. 3 and 4, we graph the differences for different periods, revealing a clear rightward shift in the BMI distribution. The mostly negative CDF differences responsible for this shift reflect an increase in bodyweight, with the largest negative values encountered at a BMI of around 23 and a WC of approximately 79. The shift thus indicates a significant reduction in the proportion of individuals with normal bodyweight, one that is most evident in the differences between 1991 and 2011. Over these two decades, the probability of having a BMI (WC) under 23 (80) dropped by close to (more than) 30 percentage points.

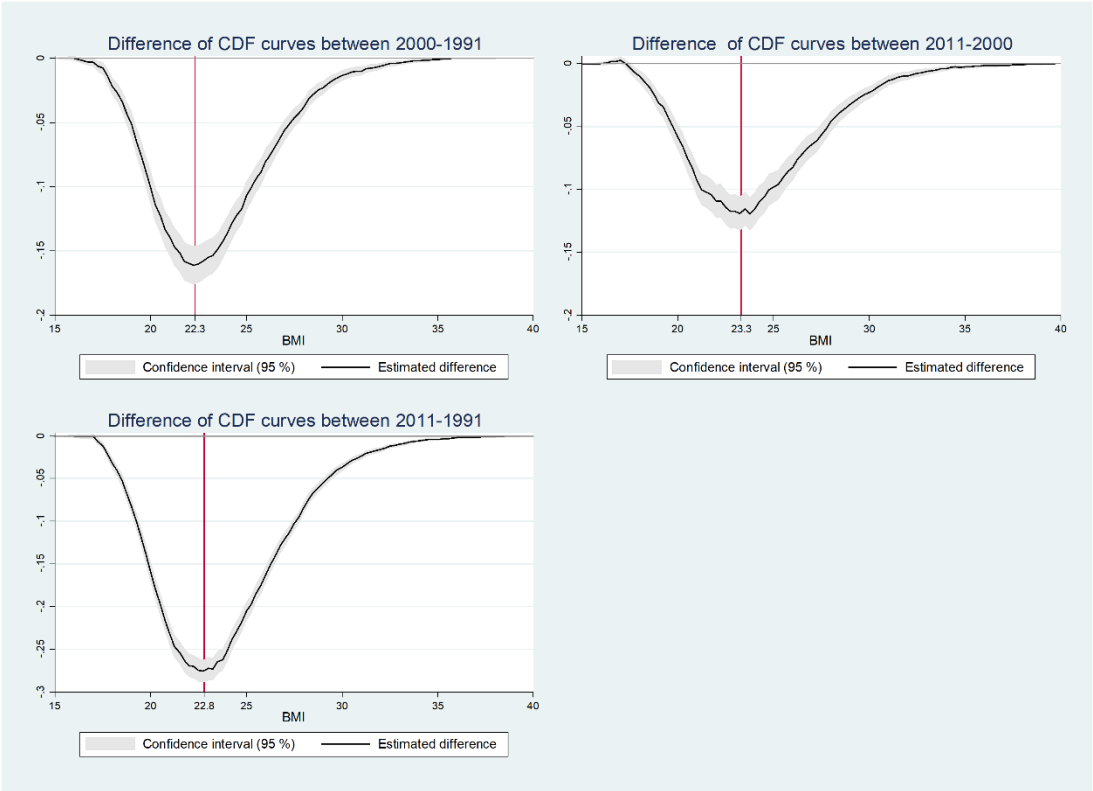

Fig. 3 Differences in the BMI CDF curve: 2000–1991, 2011–2000 and 2011–1991

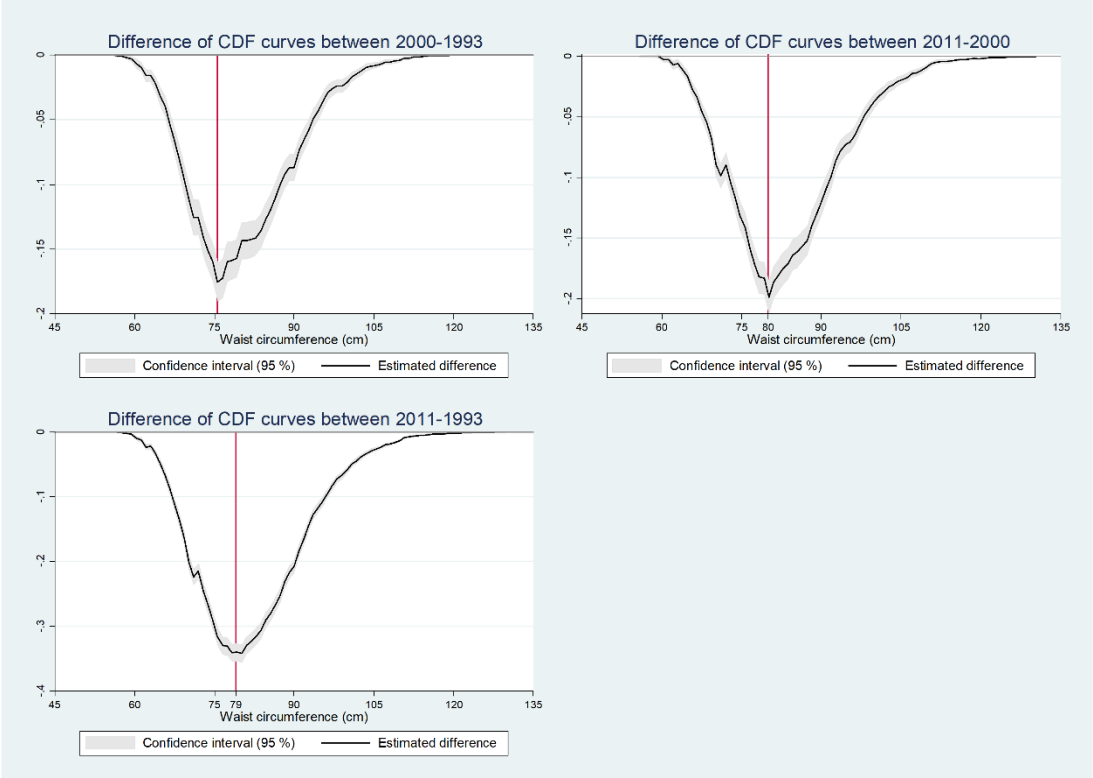

Fig. 4 Differences in the WC CDF curve: 2000–1993, 2011–2000 and 2011–1993

The results in Table 1 also reveal a first-order stochastic dominance for all wave-to-wave comparisons, as well as for the periods 1991(1993)–2000, 2000–2011 and 1991(1993)–2011. Because the first-order SD tests are in essence based on comparisons of the CDF curves in two distributions, this first-order stochastic dominance is reflected in the predominantly negative values in Figs. 3 and 4.

Table 1 First-order stochastic dominance test for BMI and WC

Survey Year	Dominance Test BMI	Dominance Test WC
1991-1993	1	
1993-1997	1	1
1997-2000	1	1
2000-2004	1	1
2004-2006	1	1
2006-2009	1	1
2009-2011	1	1
1991 (1993)-2000†	1	1
2000-2011	1	1
1991 (1993)-2011†	1	1

Note: 1 designates first-order stochastic dominance.
†WC data only available for 1993–2011.

In addition to the stochastic dominance test, deriving the growth incidence curve can provide insights into the magnitude of the bodyweight increase and describe which part of the bodyweight distribution contributes more to the overall growth between two periods. The growth incidence curves in Fig. 5 therefore show the percentage change at each percentile, with the horizontal line representing the mean growth rate. Whereas the early period is marked by significant distributional skewing with BMI growth not only higher at the upper end but above average in most of the upper half; in the later period, the growth incidence curve becomes flatter with very few significant growth rate differences across the distribution. Only below the 20th percentile do we observe significantly lower growth rates than the average. Fig. 5 thus reveals a growing inequality (i.e., an increase in distributional left-skewness) at the end of the last century followed by a more equal rise in BMI at the beginning of this century. In fact, there is clear evidence of ongoing skewing over the entire 20 years caused by above average BMI

growth in the upper parts of the distribution. The pattern for the WC growth incidence curves is similar to those for BMI (Fig. 6). Also evident over the entire period are below-average growth rates below the 20th percentile. This pattern of rising inequality in the early stages of the obesity epidemic followed by more equal growth rates in the entire population to some extent mirrors developments in the U.S., in which significant distributional left-skewing between 1976–1994 (i.e., in the early stages of the obesity epidemic) is followed in the next decade by relatively equal growth rates across the entire distribution (Pak et al., 2016).

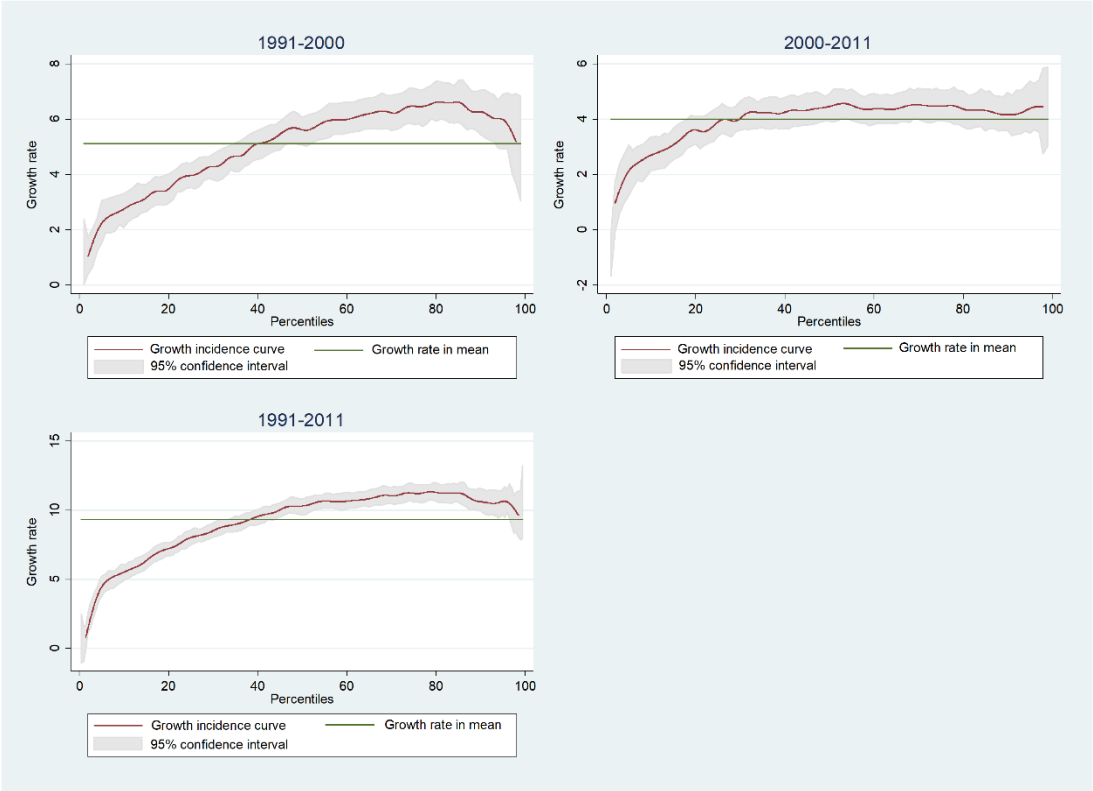

Fig. 5 BMI growth incidence curves

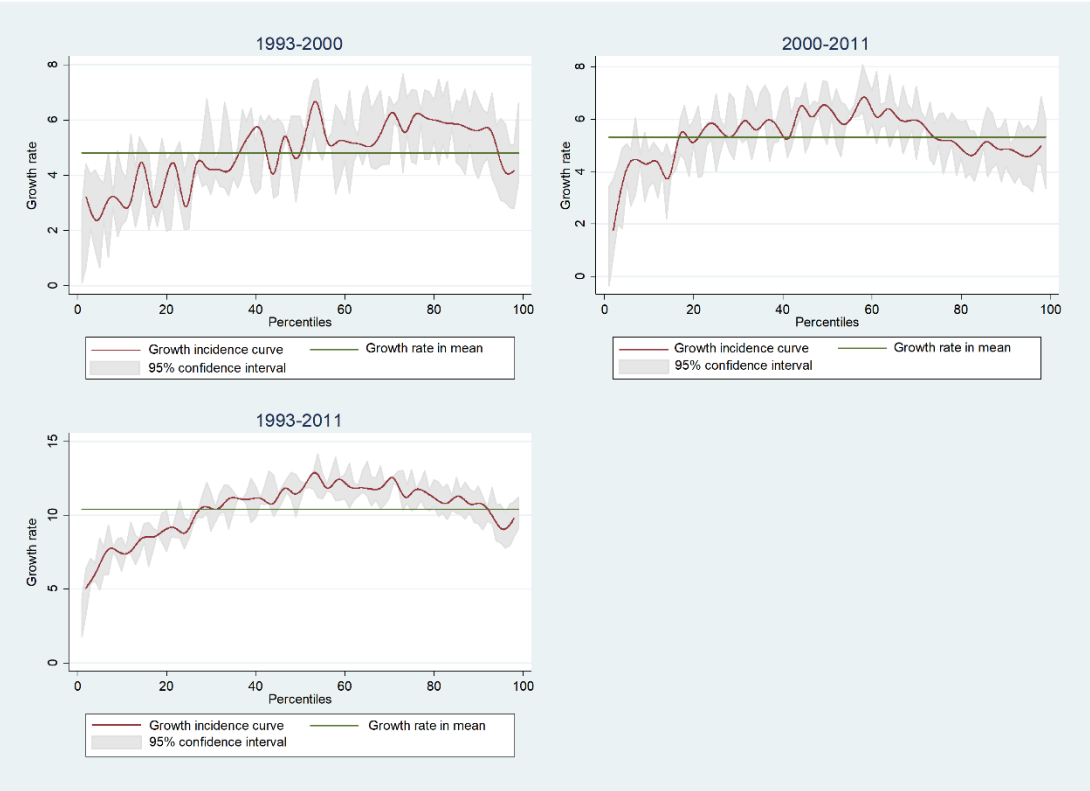

Fig. 6 WC growth incidence curves

Using Kakwani (1997) decomposition to partition the total changes in obesity prevalence into a growth and redistribution component also allows us to quantify how much of the obesity increase is due to rightward distributional shift and how much to distributional skewing. As Table 2 shows, in the early period, general (BMI-based) obesity rose by 3.78 percentage points, 84% of it attributable to the growth component and about 16% to distributional skewing. Hence, although the rising inequality in the early period (as shown in Fig. 5) significantly affected the rise in obesity rates, the general mean growth in BMI was more important. The flattening of the growth incidence curves in Fig. 5 is also mirrored by the redistribution component's drop in importance in the later period to a mere 8%. Over the entire two decades, about 11% of the 8.37% point increase in obesity is attributable to distributional skewing; that is, to the rise in obesity inequality.

Table 2 Decomposition of increase in general obesity prevalence into mean-growth and redistribution components

Survey year	Difference	Growth component (G)	Redistribution component (R)	G/(G+R) (%)	R/(G+R) (%)
1991-2000	0.0378	0.0317	0.0061	83.86	16.14
		(0.0011)	(0.0017)		
2000-2011	0.0459	0.0423	0.0036	92.16	7.84
		(0.0014)	(0.0021)		
1991-2011	0.0837	0.0741	0.0096	88.53	11.47
		(0.0025)	(0.0037)		

Note: Standard errors are in parentheses.

Because assessments of central obesity apply different obesity thresholds for men and women, Table 3 reports the Kakwani (1997) decomposition for both genders. In the early period, the prevalence of central obesity among men rose by 16% points, 17% of it due to redistribution. In the later period, the prevalence increased by another 20% points, while the redistributive components declined to 6%. Over the entire study period (1993–2011), central obesity increased by 37% points among men, about 11% of it attributable to redistribution, whereas the rise among women, at 28% points, was lower, with about 10% of it due to redistribution.

Table 3 Decomposition of increase in central obesity prevalence into mean-growth and redistribution components

Gender	Survey year	Difference	Growth component (G)	Redistribution component (R)	G/(G+R) (%)	R/(G+R) (%)
Male	1993-2000	0.1644	0.1367	0.0277	83.15	16.85
			(0.0038)	(0.0043)		
	2000-2011	0.2021	0.1890	0.0131	93.52	6.48
			(0.0043)	(0.0048)		
	1993-2011	0.3665	0.3257	0.0408	88.87	11.13
			(0.0081)	(0.0090)		
Female	1993-2000	0.1226	0.1147	0.0079	93.56	6.44
			(0.0036)	(0.0053)		
	2000-2011	0.1554	0.1370	0.0184	88.16	11.84
			(0.0040)	(0.0043)		
	1993-2011	0.2781	0.2517	0.0264	90.51	9.49
			(0.0077)	(0.0097)		

Note: Standard errors are in parentheses.

Because Kakwani decomposition has the disadvantage of being highly dependent on the obesity cut-off value, however, it offers little in the way of a differentiated look at the entire BMI distribution. We overcome this weakness by using a univariate concentration index that tracks the cardinal growth of obesity inequality. According to Table 4, both the Gini and GE indices have risen in the two decades under analysis, indicating that general obesity inequality has increased. More specifically, the Gini value rose from 0.0724 in 1991 to 0.0791 in 2000 to 0.0823 in 2011, about a 14% increase across the entire two decades. Over the same time period, the GE index increased only moderately, while the magnitudes of the two GE indices – GE(0) and GE(2) – remained quite comparable. These observations imply that our finding of increasing obesity inequality is very robust irrespective of the relative importance attributed to the lower or upper tails of the distribution. The results for inequality in central obesity are quite similar, with the Gini index increasing from 0.0654 to 0.0708 between 1993 and 2011.

Table 4 Inter-temporal trends in obesity inequality

Survey year	Gini index	95% CI	Difference between *t* and *t*-1	% change between *t* and *t*-1	Sensitivity analysis	
					GE(0)	GE(2)
BMI						
1991	0.0724	0.0712-0.0736			0.0083	0.0087
2000	0.0791	0.0779-0.0802	0.0067***	9.2541	0.0098	0.0101
2011	0.0823	0.0812-0.0833	0.0032***	4.0455	0.0106	0.0108
1991-2011			0.0099***	13.6740		
WC						
1993	0.0654	0.0643-0.0665			0.0067	0.0069
2000	0.0695	0.0686-0.0705	0.0041***	6.2691	0.0075	0.0077
2011	0.0708	0.0699-0.0717	0.0013***	1.8705	0.0079	0.0079
1993-2011			0.0054***	8.2569		

Note: CI denotes 95% confidence intervals; GE refers to generalized entropy. *** indicates 1% significance in the *t*-test for differences between the inequality indexes for two different sampling periods.

The rise in inequality is also evident in Figs. 7 and 8, which plot the Gini coefficient for all waves based on different socioeconomic and demographic characteristics. Both males and females have experienced a sharp growth in obesity inequality, although that among females is

uniformly higher than that among males. On the other hand, despite a significant rise in obesity inequality among younger adults (aged 20–39), the change among older adults (aged 40–59 and 60+) has remained stable. One striking development is the significant rise in obesity inequality in rural areas, which has now surpassed that in urban areas. With regards to education, we observe that unequal growth is particularly associated with lower educational levels (illiterate and primary school), although this growth is more pronounced for BMI than WC. It should also be noted that if bodyweight levels differ significantly between genders, the Gini coefficient is dependent on the gender balance within an educational or income category. As this unequal balance is particularly true for WC, we also report gender-specific figures for education and income. In terms of income, obesity inequality has risen in all income categories but is highest among lower income individuals.

Overall, therefore, obesity inequality appears to be on the rise in most socioeconomic and demographic groups but is particularly high among women, individuals with lower socioeconomic status, and those living in rural areas. According to the growth incidence curves for these different demographic and socioeconomic groups (Appendix Figs. A1-A10), this rise in inequality is clearly being driven by distributional left-skewing, especially for the younger age group (20–39), rural residents and individuals with low and medium education and income.

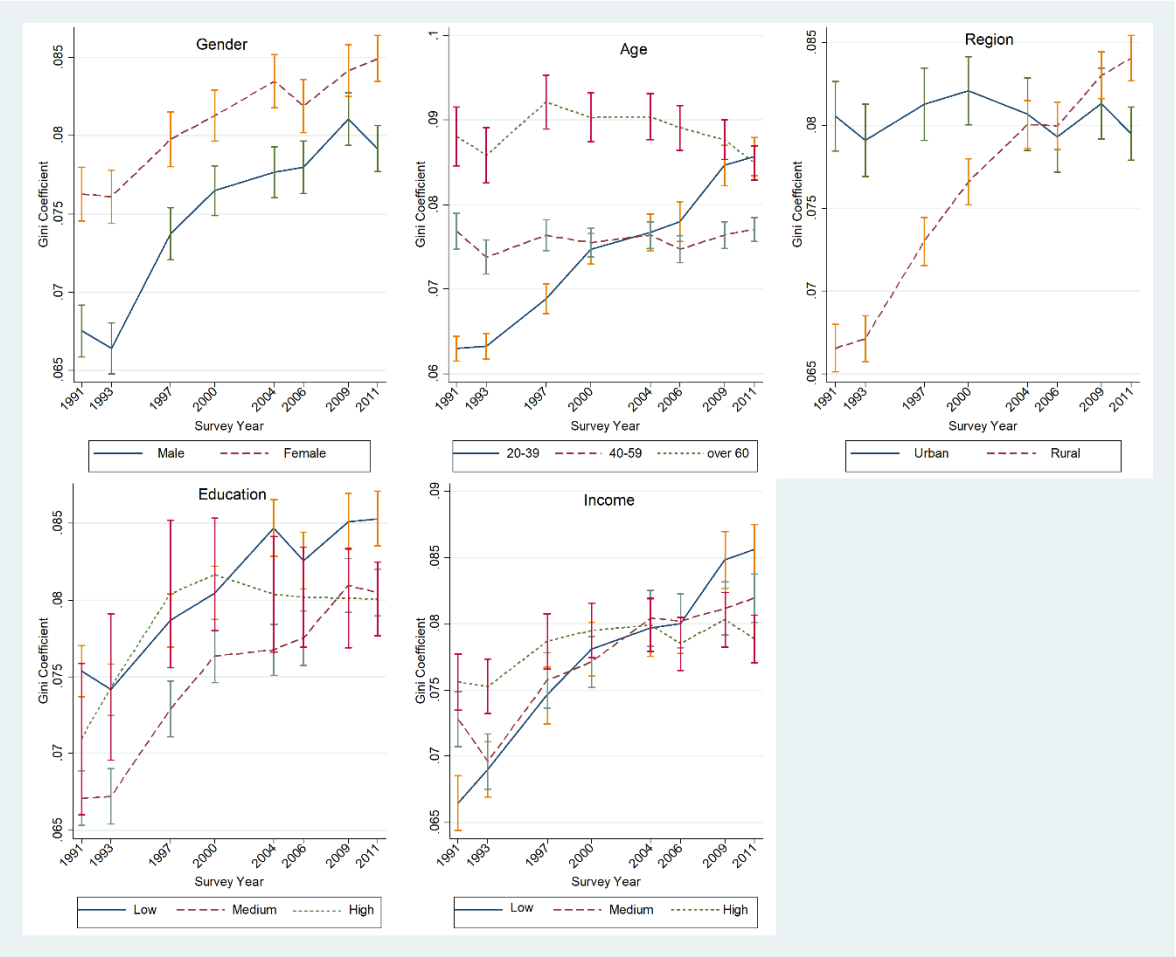

Fig. 7 Trend in general obesity inequality (Gini index) by gender, age, region, education and income, 1991–2011

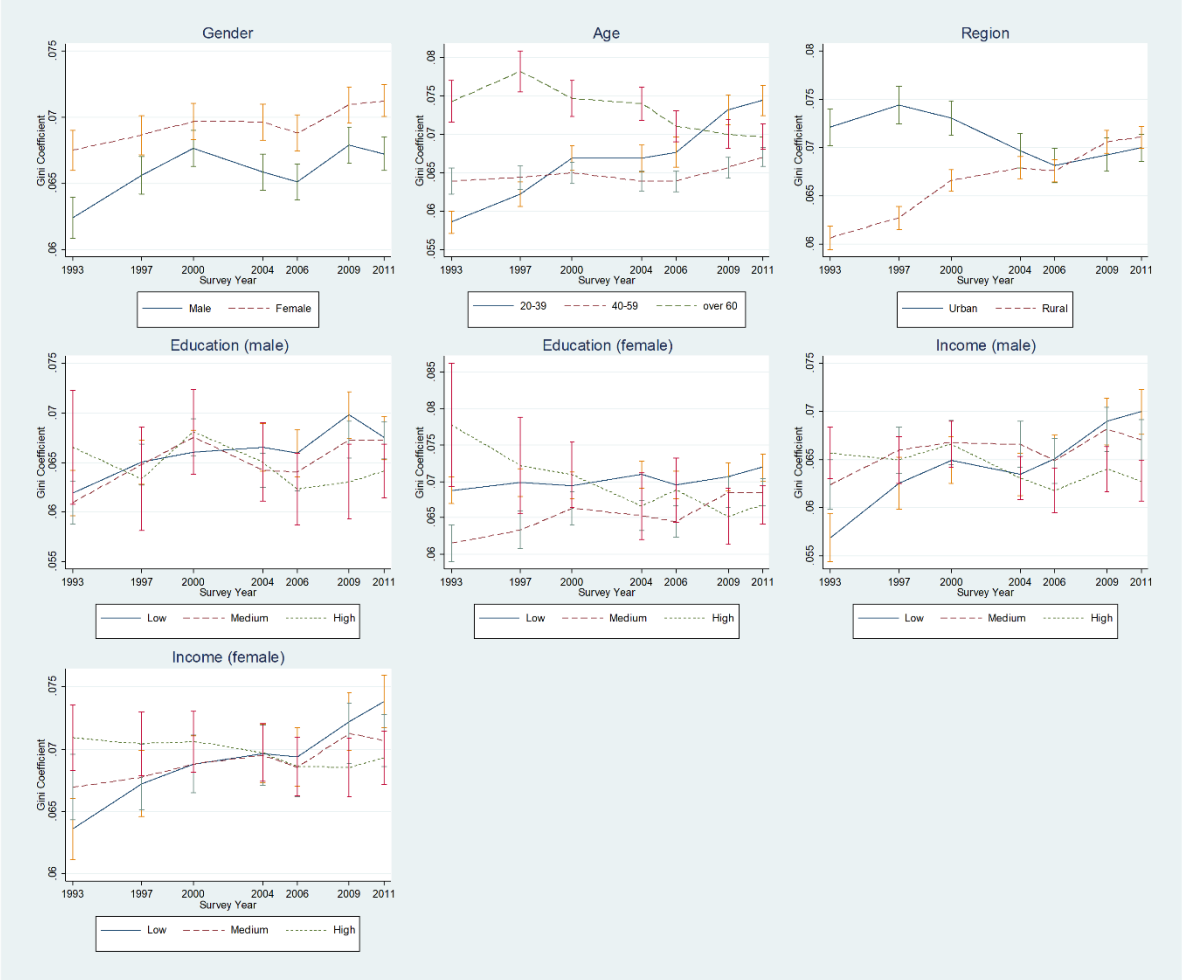

Fig. 8 Trend in central obesity inequality (Gini index) by gender, age, region, education and income, 1993–2011

Although the development of general obesity inequality is somewhat similar to that of central obesity inequality, both inequality and growth rates are larger in the former than in the latter (see Figs. 7 and 8, respectively). Hence, to throw more light on the drivers of general obesity inequality, Table 5 decomposes it into within-group and between-group components. Because Table 4 indicates no significant discrepancy between GE(0) and GE(2), we adopt the Theil index (GE(1)) to decompose obesity inequality by gender, age, education, household income, and region (urban vs. rural), as well as combinations of these characteristics. After adjusting for gender, age, region, education and income, general obesity inequality is mostly attributable to within-group inequality, whose degree – at between 91.1% and 94.0% – remains reasonably stable during the period studied. Relative to within-group inequality, the contribution of between-group inequality to total inequality is small, accounting for 6.0-9.0% of total obesity

inequality once gender, age, education, household income and region are controlled for. Of these latter characteristics, region and income account for most of the between-group inequality (0.3%-3.0% and 0.4%-2.7%, respectively). Overall, relative to between-group inequality, the dominance of within-group inequality to total obesity inequality over time suggests that this disproportionate shift in the BMI distribution is not mainly due to a changing demographic and socioeconomic composition of the population, but rather to a population-wide pattern. This conclusion also applies to central obesity inequality (Table 6), although the contribution of between-group inequality to total inequality is slightly higher, ranging from 11.75% to 13.73%.

Table 5 Within-group and between-group general obesity inequality, GE (1)

Survey year	GE(1)		Gender	Age	Region	Income	Education	Gender/age/ region/income/ education
1991	0.0084	Within	0.9948	0.9842	0.9761	0.9733	0.9957	0.9106
		Between	0.0052	0.0158	0.0239	0.0267	0.0043	0.0894
1993	0.0082	Within	0.9958	0.9822	0.9817	0.9890	0.9983	0.9270
		Between	0.0042	0.0178	0.0183	0.0110	0.0017	0.0730
1997	0.0093	Within	0.9978	0.9879	0.9706	0.9826	0.9975	0.9144
		Between	0.0022	0.0121	0.0294	0.0174	0.0025	0.0856
2000	0.0097	Within	0.9987	0.9821	0.9851	0.9817	0.9994	0.9171
		Between	0.0013	0.0179	0.0149	0.0183	0.0006	0.0829
2004	0.0103	Within	0.9993	0.9813	0.9899	0.9823	0.9996	0.9184
		Between	0.0007	0.0187	0.0101	0.0177	0.0004	0.0816
2006	0.0101	Within	0.9999	0.9846	0.9932	0.9894	0.9994	0.9222
		Between	0.0001	0.0154	0.0068	0.0106	0.0006	0.0778
2009	0.0107	Within	0.999993	0.9771	0.9960	0.9904	0.9997	0.9272
		Between	0.000007	0.0229	0.0040	0.0096	0.0003	0.0728
2011	0.0107	Within	0.9997	0.9825	0.9970	0.9962	0.9982	0.9403
		Between	0.0003	0.0175	0.0030	0.0038	0.0018	0.0597

Note: Age groups = 20–39, 40–59, 60 and over; gender = male, female; region = urban, rural; income = low, middle and high; education = low (illiterate/primary school), medium (middle school/ high school) and high (technical or vocational degree /university/master's degree or higher).

Table 6 Within-group and between-group central obesity inequality, GE (1)

Survey year	GE(1)		Gender	Age	Region	Income	Education	Gender/age/ region/income/ education
1993	0.0068	Within	0.9922	0.9413	0.9740	0.9896	0.9909	0.8734
		Between	0.0078	0.0587	0.0260	0.0104	0.0091	0.1266
1997	0.0072	Within	0.9787	0.9579	0.9669	0.9884	0.9959	0.8685
		Between	0.0213	0.0421	0.0331	0.0116	0.0041	0.1315
2000	0.0075	Within	0.9749	0.9571	0.9794	0.9858	0.9984	0.8627
		Between	0.0251	0.0429	0.0206	0.0142	0.0016	0.1373
2004	0.0074	Within	0.9724	0.9593	0.9916	0.9848	0.9997	0.8636
		Between	0.0276	0.0408	0.0084	0.0152	0.0003	0.1364
2006	0.0072	Within	0.9716	0.9652	0.9921	0.9895	0.9999	0.8753
		Between	0.0284	0.0348	0.0079	0.0105	0.0001	0.1247
2009	0.0077	Within	0.9762	0.9581	0.9945	0.9888	0.9989	0.8809
		Between	0.0238	0.0419	0.0055	0.0111	0.0011	0.1191
2011	0.0079	Within	0.9614	0.9702	0.9954	0.9970	0.9993	0.8825
		Between	0.0387	0.0299	0.0046	0.0030	0.0007	0.1175

Note: Age groups = 20–39, 40–59, 60 and over; gender = male, female; region = urban, rural; income = low, middle and high; education = low (illiterate/primary school), medium (middle school/ high school) and high (technical or vocational degree /university/master's degree or higher).

4. Conclusions

Even though knowing how bodyweight distributions have changed over time is crucial to understanding the nature of the rising obesity prevalence, this present study is the first to examine such changes in China's adult population. This knowledge is vital because, just as the social welfare implications of rising national income differ greatly dependent on whether induced by rapid income growth among the rich (i.e., rising income inequality) or across the entire population, so policy responses to rising obesity must vary according to whether driven by rapid growth at the upper ends of the bodyweight distribution or a general rightward distributional shift. In addition, although obesity inequality is generally recognized as an important indicator of well-being – a multidimensional domain that at minimum encompasses not only income but health, nutrition and education – measures of social inequality still focus almost exclusively on income or expenditure. Obesity inequality is thus empirically interesting as a measure capable of capturing the allocation of resources (primarily food) across individuals relative to their individual needs (Sahn, 2009).

Overall, by using 20 years of CHNS data (1991–2011), our study sheds valuable light on the exact nature of the rise in China of both central and general obesity. In particular, our results clearly demonstrate a significant rightward shift in both the BMI and WC distributions, with first-order stochastic dominance for all wave-to-wave comparisons. Over the two decades under analysis, about 90% of the rise in both general and central obesity is attributable to this rightward shift. On the other hand, the analysis also reveals a certain degree of distributional left-skewing, which reflects increased obesity inequality, about a 14% and 8% increase in the Gini coefficient for general and central obesity, respectively. Nonetheless, the 2011 Gini coefficients of 0.08 and 0.07 for general and central obesity, respectively, suggest that although obesity inequality had risen, it is still much lower than in the U.S., whose general obesity coefficient that year was about 0.13 (Pak et al., 2016). As in the U.S., however, the rise in obesity inequality in China has been particularly large among younger age groups and women. We also document a very strong increase in obesity inequality among rural residents and individuals with lower socioeconomic status (low education and income). Nevertheless, the rise in aggregate inequality is not being driven by changes in the demographic structure but rather by a population-wide increase across all subpopulations.

When comparing our results with those of Pak et al. (2016) for the U.S., we observe an interesting similarity in the transition from the early to later stages of the obesity epidemic (i.e., from low to high obesity prevalence); that is, in the early years, obesity inequality rose quite rapidly due primarily to a disproportionate rise at the upper end of the bodyweight distribution. This pattern is also evident in Sahn's (2009) analysis of over 70 nationally representative surveys from developing countries. Once the epidemic has broadened, however, the growth in inequality declines. To some extent, this development parallels the evolution of infectious diseases: at its onset, the epidemic disproportionally affects the most vulnerable, which in the case of obesity are those already at the upper ends of the BMI distribution. Given a broad body of evidence that these individuals are particularly susceptible to peer effects (e.g., Nie et al., 2015), bodyweight increases among this group tend to spread quickly. As this process continues and the condition spreads, then all portions of the population become affected and "inequality" becomes less of an issue.

This transitional pattern from low to high obesity has important implications for obesity's consequences: First, rising inequality levels in the early transition can have a particularly strong effect on the well-being of individuals at the right tail of the bodyweight distribution whose

bodyweight tends to increase more quickly than the population average and is thus more likely to deviate from the socially perceived ideal. Indeed, much evidence exists that obesity's negative effects on well-being depend on the extent of the deviation from peer bodyweights (Wadsworth and Pendergast, 2014). Thus, policy interventions to combat obesity during the early transition should primarily target the groups experiencing the most rapid growth in inequality. Focusing on such groups is also important to avoid spill-overs from strong peer effects at the upper end of the bodyweight distribution that could lead to rising obesity levels (i.e., a rightward distributional shift). Targeted policy interventions could thus profit from the so-called social multiplier effect (Fletcher, 2011); that is, the externality inherent in peer effects. As the epidemic spreads and obesity becomes a population-wide phenomenon, however (represented mainly by a rightward distributional shift), norms and ideals begin to change, making higher bodyweight levels more socially acceptable and even desirable. Then, not only do obesity's stigmatizing effects become less of an issue, but the changing norms and ideals contribute strongly to its persistency, making policy interventions less effective.

According to our analysis, China is well into the transition phase: obesity prevalence has risen substantially (especially in the case of central obesity), and, after a rapid rise, inequality growth is declining. The time has thus come to implement interventions targeted at specific groups whose obesity inequality is still growing as a particularly rapid pace; most notably, women, youth, rural residents, and individuals with lower socioeconomic status.

Conflict of interest

None.

Funding source

None.

Acknowledgments

This research uses data from China Health and Nutrition Survey (CHNS). We thank the National Institute for Nutrition and Health, China Center for Disease Control and Prevention,

Carolina Population Center (P2C HD050924, T32 HD007168), the University of North Carolina at Chapel Hill, the NIH (R01-HD30880, DK056350, R24 HD050924, and R01-HD38700) and the NIH Fogarty International Center (D43 TW009077, D43 TW007709) for financial support for CHNS data collection and analysis files from 1989 to 2015 and future surveys, as well as the China-Japan Friendship Hospital, Ministry of Health for support for CHNS 2009, Chinese National Human Genome Center at Shanghai since 2009, and Beijing Municipal Center for Disease Prevention and Control since 2011. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. All errors are our own.

References

Blanchflower, D.G., van Landeghem, B., Oswald, A.J., 2009. Imitative obesity and relative utility Journal of the European Economic Association 7, 528-538.

Burke, M.A., Heiland, F.W., 2018. Evolving societal norms of obesity: What is the appropriate response? JAMA 319, 221-222.

Burkhauser, R.V., Cawley, J., 2008. Beyond BMI: The value of more accurate measures of fatness and obesity in social science research. Journal of Health Economics 27, 519-529.

Christiaensen, L.D.L.P.S., 2002. Growth, Distribution and Poverty in Africa. The World Bank, Washington, D.C.

Contoyannis, P., Wildman, J., 2007. Using relative distributions to investigate the body mass index in England and Canada. Health Economics 16, 929-944.

Cowell, F.A., Flachaire, E., 2015. Chapter 6 - Statistical Methods for Distributional Analysis, in: Atkinson, A.B., Bourguignon, F. (Eds.), Handbook of Income Distribution. Elsevier, pp. 359-465.

Datt, G., Ravallion, M., 1992. Growth and redistribution components of changes in poverty measures: A decomposition with applications to Brazil and India in the 1980s. Journal of Development Economics 38, 275-295.

Davidson, R., Duclos, J.-Y., 2003. Statistical inference for stochastic dominance and for the measurement of poverty and inequality. Econometrica 68, 1435-1464.

Davidson, R., Duclos, J.-Y., 2013. Testing for restricted stochastic dominance. Econometric Reviews 32, 84-125.

Dhongde, S., 2007. Measuring the impact of growth and income distribution on poverty in India. Journal of Income Distribution 16, 25-48.

Fletcher, I.M., 2011. Peer effects and obesity, in: Cawley, J. (Ed.), The Oxford Handbook of the Social Science of Obesity. Oxford University Press, New York, pp. 303-312.

Gordon-Larsen, P., Wang, H., Popkin, B.M., 2014. Overweight dynamics in Chinese children and adults. Obesity Reviews 15, 37-48.

Hill, J.O., Peters, J.C., 1998. Environmental contributions to the obesity epidemic. Science 280, 1371.

Jain, L.R., Tendulkar, S.D., 1990. Role of growth and distribution in the observed change in headcount ratio measure of poverty: a decomposition exercise for India. Indian Economic Review, 165-205.

Jenkins, S.P., Kerm, P.V., 1999. sg107: Generalized Lorenz curves and related graphs. Stata Technical Bulletin 48, 25–29.

Kakwani, N., 1997. On measuring growth and inequality components of changes in poverty with application to Thailand. School of Economics, The University of New South Wales, Sydney.

Katsaiti, M.S., 2012. Obesity and happiness. Applied Economics 44, 4101-4114.

Lu, J., Bi, Y., Ning, G., 2016. Curbing the obesity epidemic in China. The Lancet Diabetes & Endocrinology 4, 470-471.

Madden, D., 2011. A profile of obesity in Ireland, 2002–2007. Journal of the Royal Statistical Society: Series A (Statistics in Society) 175, 893-914.

Ng, M., Fleming, T., Robinson, M., Thomson, B., Graetz, N., Margono, C., Mullany, E.C., Biryukov, S., Abbafati, C., Abera, S.F., Abraham, J.P., Abu-Rmeileh, N.M.E., Achoki, T., AlBuhairan, F.S., Alemu, Z.A., Alfonso, R., Ali, M.K., Ali, R., Guzman, N.A., Ammar, W., Anwari, P., Banerjee, A., Barquera, S., Basu, S., Bennett, D.A., Bhutta, Z., Blore, J., Cabral, N., Nonato, I.C., Chang, J.-C., Chowdhury, R., Courville, K.J., Criqui, M.H., Cundiff, D.K., Dabhadkar, K.C., Dandona, L., Davis, A., Dayama, A., Dharmaratne, S.D., Ding, E.L., Durrani, A.M., Esteghamati, A., Farzadfar, F., Fay, D.F.J., Feigin, V.L., Flaxman, A., Forouzanfar, M.H., Goto, A., Green, M.A., Gupta, R., Hafezi-Nejad, N., Hankey, G.J., Harewood, H.C., Havmoeller, R., Hay, S., Hernandez, L., Husseini, A., Idrisov, B.T., Ikeda, N., Islami, F., Jahangir, E., Jassal, S.K., Jee, S.H., Jeffreys, M., Jonas, J.B., Kabagambe, E.K., Khalifa, S.E.A.H., Kengne, A.P., Khader, Y.S., Khang, Y.-H., Kim, D., Kimokoti, R.W., Kinge, J.M., Kokubo, Y., Kosen, S., Kwan, G., Lai, T., Leinsalu, M., Li, Y., Liang, X., Liu, S., Logroscino, G., Lotufo, P.A., Lu, Y., Ma, J., Mainoo, N.K., Mensah, G.A., Merriman, T.R., Mokdad, A.H., Moschandreas, J., Naghavi, M., Naheed, A., Nand, D., Narayan, K.M.V., Nelson, E.L., Neuhouser, M.L., Nisar, M.I., Ohkubo, T., Oti, S.O., Pedroza, A., Prabhakaran, D., Roy, N., Sampson, U., Seo, H., Sepanlou, S.G., Shibuya, K., Shiri, R., Shiue, I., Singh, G.M., Singh, J.A., Skirbekk, V., Stapelberg, N.J.C., Sturua, L., Sykes, B.L., Tobias, M., Tran, B.X., Trasande, L., Toyoshima, H., van de Vijver, S., Vasankari, T.J., Veerman, J.L., Velasquez-Melendez, G., Vlassov, V.V., Vollset, S.E., Vos, T., Wang, C., Wang, X., Weiderpass, E., Werdecker, A., Wright, J.L., Yang, Y.C., Yatsuya, H., Yoon, J., Yoon, S.-J., Zhao, Y., Zhou, M., Zhu, S., Lopez, A.D., Murray, C.J.L., Gakidou, E., 2014. Global, regional, and national prevalence of overweight and obesity in children and adults during 1980-2013: A systematic analysis for the Global Burden of Disease Study 2013. The Lancet 384, 766-781.

Nie, P., Sousa-Poza, A., He, X., 2015. Peer effects on childhood and adolescent obesity in China. China Economic Review 35, 47-69.

OECD, 2012. OECD Obesity Update 2012. OECD, Paris.

Pak, T.-Y., Ferreira, S., Colson, G., 2016. Measuring and tracking obesity inequality in the United States: evidence from NHANES, 1971-2014. Population Health Metrics 14, 12.

Pan, X.-R., Yang, W.-Y., Li, G.-W., Liu, J., 1997. Prevalence of diabetes and its risk factors in China, 1994. Diabetes Care 20, 1664.

Popkin, B.M., 2008. Will China's nutrition transition overwhelm its health care system and slow economic growth? Health Affairs 27, 1064-1076.

Qin, X., Pan, J., 2016. The medical cost attributable to obesity and overweight in China. Health Economics 25, 1291-1311.

Sahn, D.E., 2009. Weights on the rise: where and for whom? Journal of Economic Inequality 7, 351-370.

Sahn, D.E., Younger, S.D., 2005. Improvements in children's health: Does inequality matter? Journal of Economic Inequality 3, 125-143.

Shields, M., Connor, G.S., Janssen, I., Tremblay, M.S., 2011. Obesity estimates for children based on parent-reported versus direct measures. Health Reports 22, 47-58.

Shorrocks, A.F., 1984. Inequality Decomposition by Population Subgroups. Econometrica 52, 1369-1385.

Wadsworth, T., Pendergast, P.M., 2014. Obesity (sometimes) matters: The importance of context in the relationship between obesity and life satisfaction. Journal of Health and Social Behavior 55, 196-214.

WHO, 2016. Obesity and Overweight. Fact sheet N°311. World Health Organization, Geneva.

Xi, B., Liang, Y., He, T., Reilly, K.H., Hu, Y., Wang, Q., Yan, Y., Mi, J., 2012. Secular trends in the prevalence of general and abdominal obesity among Chinese adults, 1993–2009. Obesity Reviews 13, 287-296.

Yang, D.T., 1999. Urban-biased policies and rising income inequality in China. American Economic Review 89, 306-310.

Yang, W., Lu, J., Weng, J., Jia, W., Ji, L., Xiao, J., Shan, Z., Liu, J., Tian, H., Ji, Q., Zhu, D., Ge, J., Lin, L., Chen, L., Guo, X., Zhao, Z., Li, Q., Zhou, Z., Shan, G., He, J., 2010. Prevalence of diabetes among men and women in China. New England Journal of Medicine 362, 1090-1101.

Yitzhaki, S., 1983. On an extension of the Gini inequality index. International Economic Review 24, 617-628.

Zhai, F., Wang, H., Du, S., He, Y., Wang, Z., Ge, K., Popkin, B.M., 2009. Prospective study on nutrition transition in China. Nutrition Reviews 67, S56-S61.
Zhang, B., Zhai, F., Du, S., Popkin, B.M., 2014. The China Health and Nutrition Survey, 1989–2011. Obesity Reviews 15, 2-7.
Zhao, W., Zhai, Y., Hu, J., Wang, J., Yang, Z., Kong, L., Chen, C., 2008. Economic burden of obesity-related chronic diseases in mainland China. Obesity Reviews 9, 62-67.
Zhou, B.F., the Cooperative Meta-analysis Group of Working Group on Obesity in China, 2002. Predictive values of body mass index and waist circumference for risk factors of certain related diseases in Chinese adults: Study on optimal cut-off points of body mass index and waist circumference in Chinese adults. Asia Pacific Journal of Clinical Nutrition 11, S685-S693.

Appendix

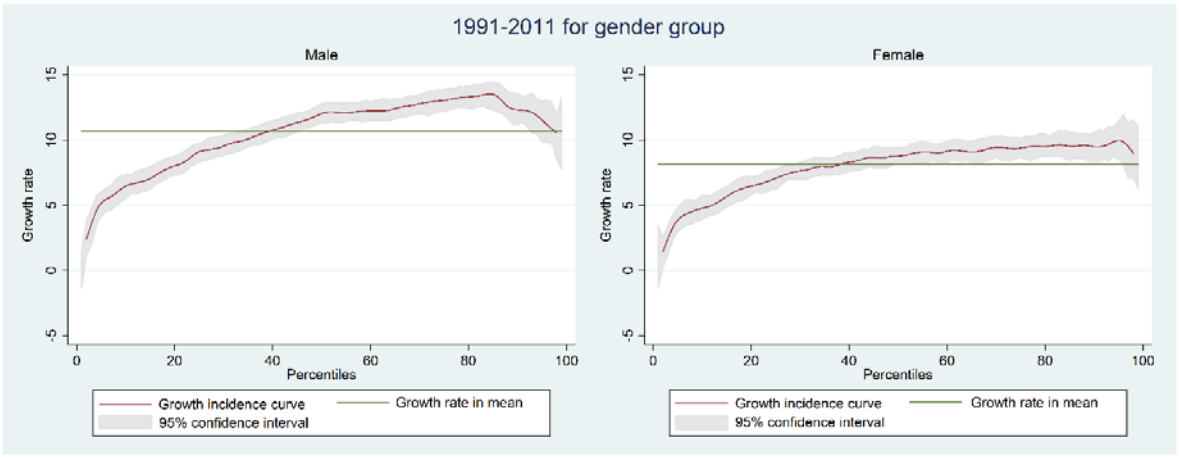

Fig. A1 BMI growth incidence curves by gender

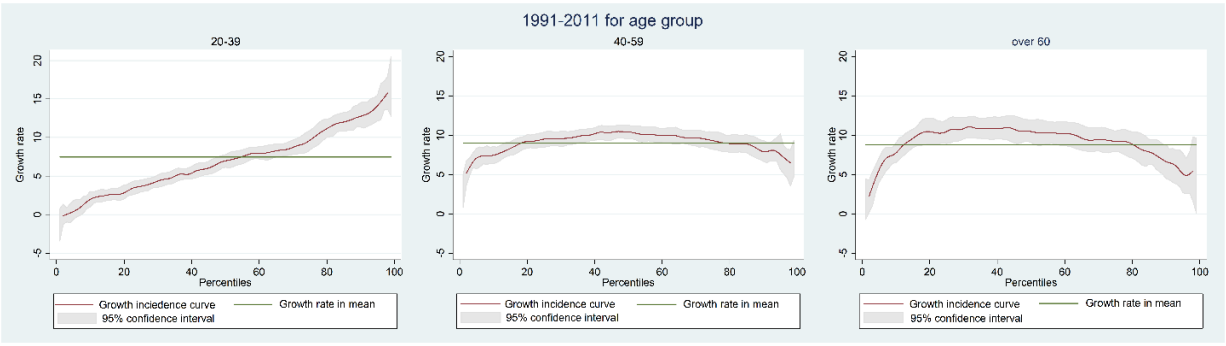

Fig. A2 BMI growth incidence curves by age groups

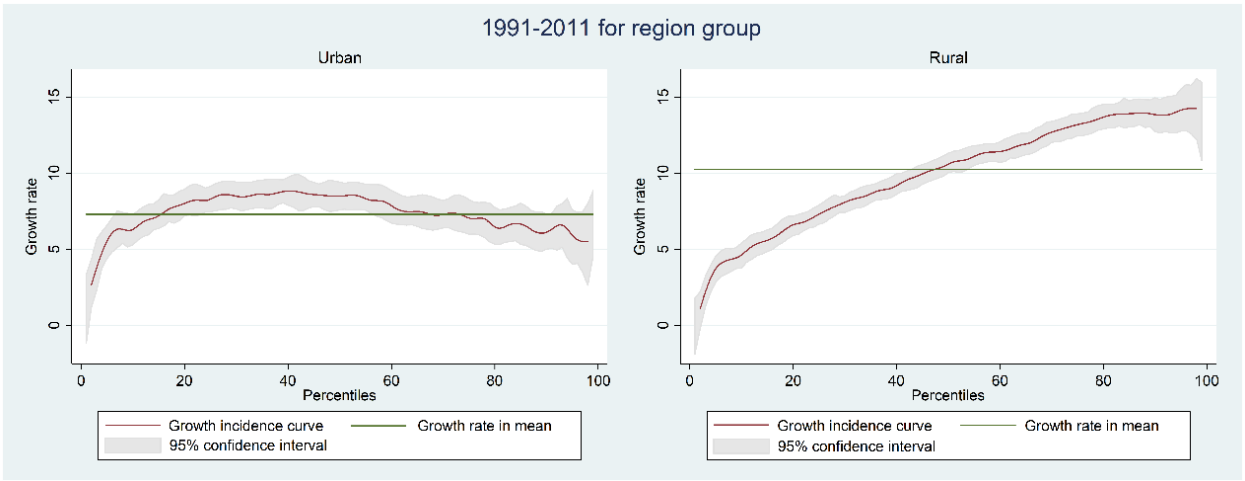

Fig. A3 BMI growth incidence curves by region

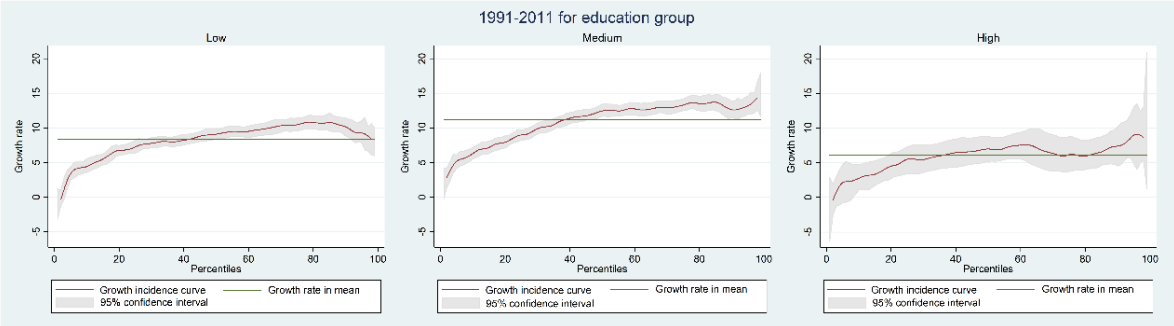

Fig. A4 BMI growth incidence curves by education

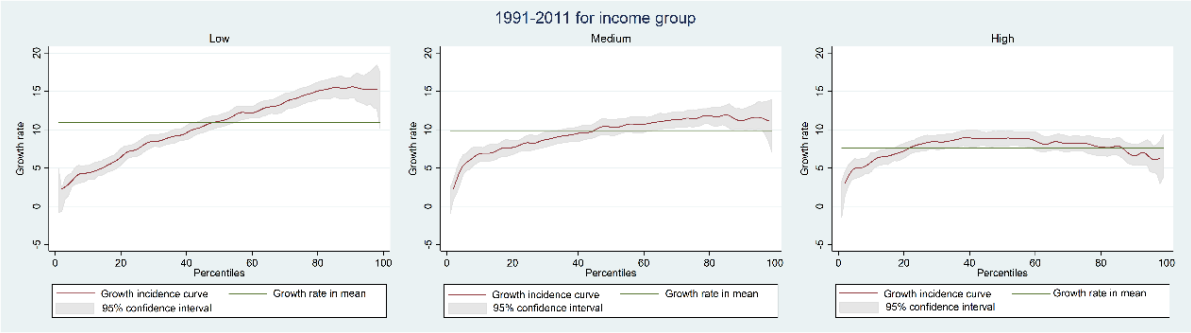

Fig. A5 BMI growth incidence curves by income

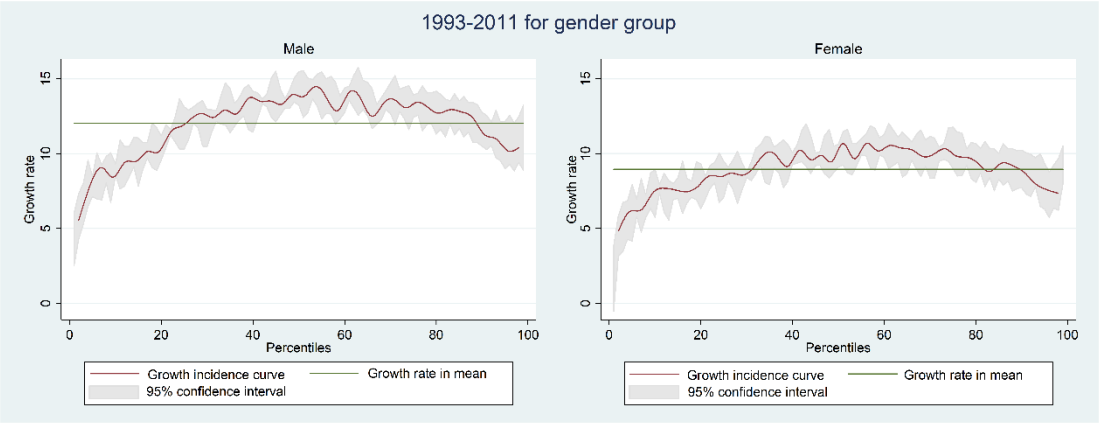

Fig. A6 WC growth incidence curves by gender

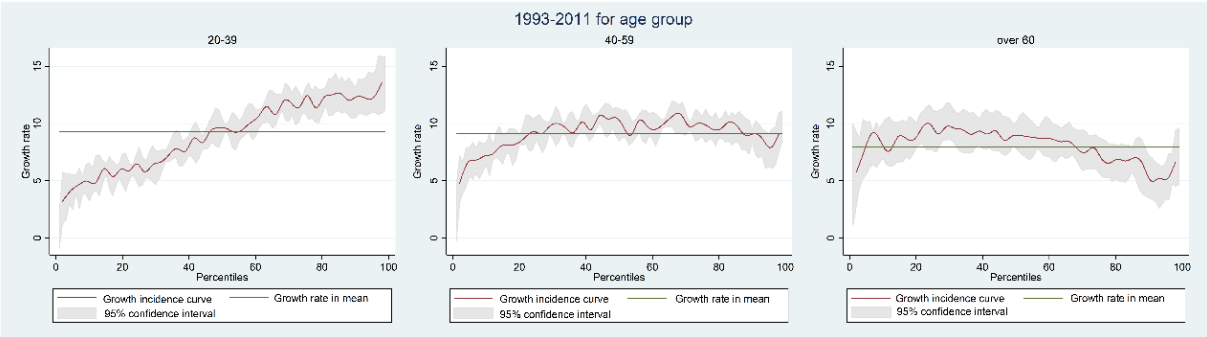

Fig. A7 WC growth incidence curves by age groups

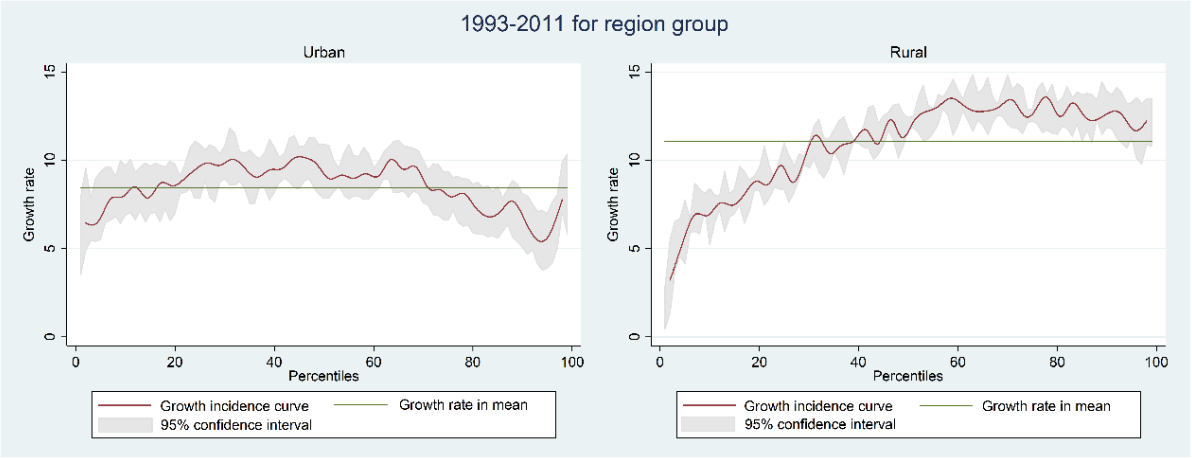

Fig. A8 WC growth incidence curves by region

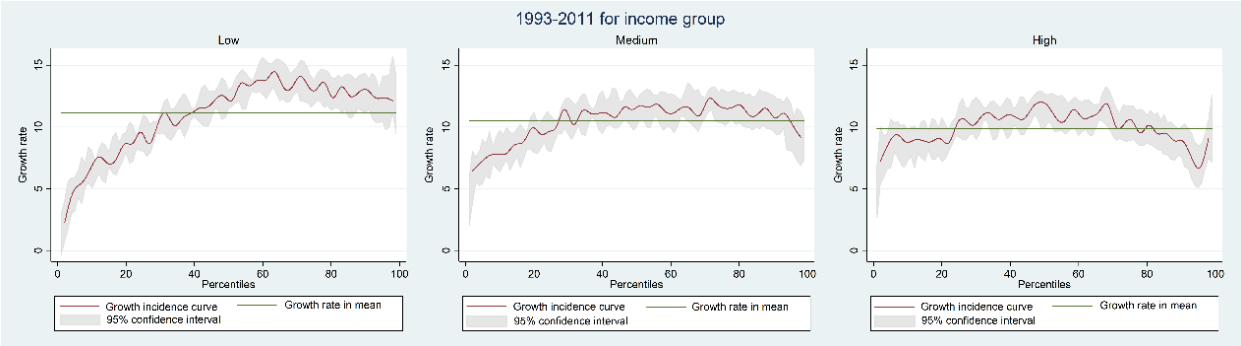

Fig. A9 WC growth incidence curves by income

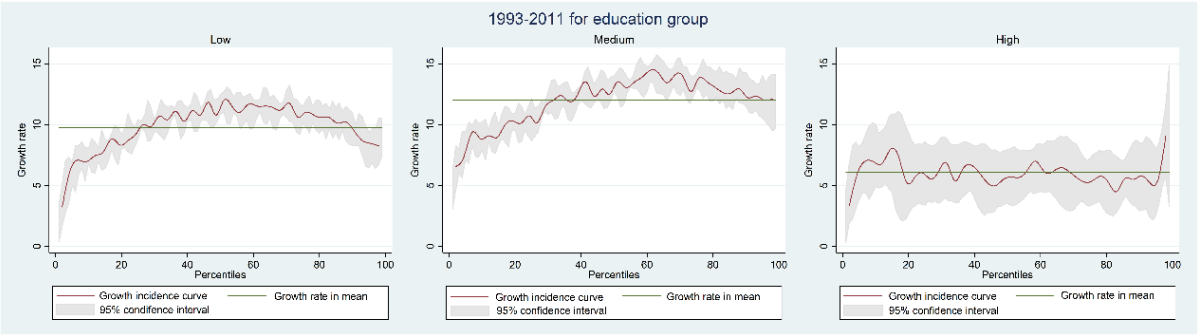

Fig.A10 WC growth incidence curves by education

Hohenheim Discussion Papers in Business, Economics and Social Sciences

The Faculty of Business, Economics and Social Sciences continues since 2015 the established “FZID Discussion Paper Series” of the “Centre for Research on Innovation and Services (FZID)” under the name “Hohenheim Discussion Papers in Business, Economics and Social Sciences”.

Institutes

510 Institute of Financial Management
520 Institute of Economics
530 Institute of Health Care & Public Management
540 Institute of Communication Science
550 Institute of Law and Social Sciences
560 Institute of Economic and Business Education
570 Institute of Marketing & Management
580 Institute of Interorganizational Management & Performance

Research Areas (since 2017)

INEPA “Inequality and Economic Policy Analysis”
TKID “Transformation der Kommunikation – Integration und Desintegration”
NegoTrans “Negotiation Research – Transformation, Technology, Media and Costs”
INEF “Innovation, Entrepreneurship and Finance”

Download Hohenheim Discussion Papers in Business, Economics and Social Sciences
from our homepage: https://wiso.uni-hohenheim.de/papers

No.	Author	Title	Inst
01-2015	Thomas Beissinger, Philipp Baudy	THE IMPACT OF TEMPORARY AGENCY WORK ON TRADE UNION WAGE SETTING: A Theoretical Analysis	520
02-2015	Fabian Wahl	PARTICIPATIVE POLITICAL INSTITUTIONS AND CITY DEVELOPMENT 800-1800	520
03-2015	Tommaso Proietti, Martyna Marczak, Gianluigi Mazzi	$\text{EURO}\text{MI}_{\text{IND}}$-D: A DENSITY ESTIMATE OF MONTHLY GROSS DOMESTIC PRODUCT FOR THE EURO AREA	520
04-2015	Thomas Beissinger, Nathalie Chusseau, Joël Hellier	OFFSHORING AND LABOUR MARKET REFORMS: MODELLING THE GERMAN EXPERIENCE	520
05-2015	Matthias Mueller, Kristina Bogner, Tobias Buchmann, Muhamed Kudic	SIMULATING KNOWLEDGE DIFFUSION IN FOUR STRUCTURALLY DISTINCT NETWORKS – AN AGENT-BASED SIMULATION MODEL	520
06-2015	Martyna Marczak, Thomas Beissinger	BIDIRECTIONAL RELATIONSHIP BETWEEN INVESTOR SENTIMENT AND EXCESS RETURNS: NEW EVIDENCE FROM THE WAVELET PERSPECTIVE	520
07-2015	Peng Nie, Galit Nimrod, Alfonso Sousa-Poza	INTERNET USE AND SUBJECTIVE WELL-BEING IN CHINA	530

No.	Author	Title	Inst
08-2015	Fabian Wahl	THE LONG SHADOW OF HISTORY ROMAN LEGACY AND ECONOMIC DEVELOPMENT – EVIDENCE FROM THE GERMAN LIMES	520
09-2015	Peng Nie, Alfonso Sousa-Poza	COMMUTE TIME AND SUBJECTIVE WELL-BEING IN URBAN CHINA	530
10-2015	Kristina Bogner	THE EFFECT OF PROJECT FUNDING ON INNOVATIVE PERFORMANCE AN AGENT-BASED SIMULATION MODEL	520
11-2015	Bogang Jun, Tai-Yoo Kim	A NEO-SCHUMPETERIAN PERSPECTIVE ON THE ANALYTICAL MACROECONOMIC FRAMEWORK: THE EXPANDED REPRODUCTION SYSTEM	520
12-2015	Volker Grossmann Aderonke Osikominu Marius Osterfeld	ARE SOCIOCULTURAL FACTORS IMPORTANT FOR STUDYING A SCIENCE UNIVERSITY MAJOR?	520
13-2015	Martyna Marczak Tommaso Proietti Stefano Grassi	A DATA–CLEANING AUGMENTED KALMAN FILTER FOR ROBUST ESTIMATION OF STATE SPACE MODELS	520
14-2015	Carolina Castagnetti Luisa Rosti Marina Töpfer	THE REVERSAL OF THE GENDER PAY GAP AMONG PUBLIC-CONTEST SELECTED YOUNG EMPLOYEES	520
15-2015	Alexander Opitz	DEMOCRATIC PROSPECTS IN IMPERIAL RUSSIA: THE REVOLUTION OF 1905 AND THE POLITICAL STOCK MARKET	520
01-2016	Michael Ahlheim, Jan Neidhardt	NON-TRADING BEHAVIOUR IN CHOICE EXPERIMENTS	520
02-2016	Bogang Jun, Alexander Gerybadze, Tai-Yoo Kim	THE LEGACY OF FRIEDRICH LIST: THE EXPANSIVE REPRODUCTION SYSTEM AND THE KOREAN HISTORY OF INDUSTRIALIZATION	520
03-2016	Peng Nie, Alfonso Sousa-Poza	FOOD INSECURITY AMONG OLDER EUROPEANS: EVIDENCE FROM THE SURVEY OF HEALTH, AGEING, AND RETIREMENT IN EUROPE	530
04-2016	Peter Spahn	POPULATION GROWTH, SAVING, INTEREST RATES AND STAGNATION. DISCUSSING THE EGGERTSSON-MEHROTRA-MODEL	520
05-2016	Vincent Dekker, Kristina Strohmaier, Nicole Bosch	A DATA-DRIVEN PROCEDURE TO DETERMINE THE BUNCHING WINDOW – AN APPLICATION TO THE NETHERLANDS	520
06-2016	Philipp Baudy, Dario Cords	DEREGULATION OF TEMPORARY AGENCY EMPLOYMENT IN A UNIONIZED ECONOMY: DOES THIS REALLY LEAD TO A SUBSTITUTION OF REGULAR EMPLOYMENT?	520

No.	Author	Title	Inst
07-2016	Robin Jessen, Davud Rostam-Afschar, Sebastian Schmitz	HOW IMPORTANT IS PRECAUTIONARY LABOR SUPPLY?	520
08-2016	Peng Nie, Alfonso Sousa-Poza, Jianhong Xue	FUEL FOR LIFE: DOMESTIC COOKING FUELS AND WOMEN'S HEALTH IN RURAL CHINA	530
09-2016	Bogang Jun, Seung Kyu-Yi, Tobias Buchmann, Matthias Müller	THE CO-EVOLUTION OF INNOVATION NETWORKS: COLLABORATION BETWEEN WEST AND EAST GERMANY FROM 1972 TO 2014	520
10-2016	Vladan Ivanovic, Vadim Kufenko, Boris Begovic Nenad Stanisic, Vincent Geloso	CONTINUITY UNDER A DIFFERENT NAME. THE OUTCOME OF PRIVATISATION IN SERBIA	520
11-2016	David E. Bloom Michael Kuhn Klaus Prettner	THE CONTRIBUTION OF FEMALE HEALTH TO ECONOMIC DEVELOPMENT	520
12-2016	Franz X. Hof Klaus Prettner	THE QUEST FOR STATUS AND R&D-BASED GROWTH	520
13-2016	Jung-In Yeon Andreas Pyka Tai-Yoo Kim	STRUCTURAL SHIFT AND INCREASING VARIETY IN KOREA, 1960–2010: EMPIRICAL EVIDENCE OF THE ECONOMIC DEVELOPMENT MODEL BY THE CREATION OF NEW SECTORS	520
14-2016	Benjamin Fuchs	THE EFFECT OF TEENAGE EMPLOYMENT ON CHARACTER SKILLS, EXPECTATIONS AND OCCUPATIONAL CHOICE STRATEGIES	520
15-2016	Seung-Kyu Yi Bogang Jun	HAS THE GERMAN REUNIFICATION STRENGTHENED GERMANY'S NATIONAL INNOVATION SYSTEM? TRIPLE HELIX DYNAMICS OF GERMANY'S INNOVATION SYSTEM	520
16-2016	Gregor Pfeifer Fabian Wahl Martyna Marczak	ILLUMINATING THE WORLD CUP EFFECT: NIGHT LIGHTS EVIDENCE FROM SOUTH AFRICA	520
17-2016	Malte Klein Andreas Sauer	CELEBRATING 30 YEARS OF INNOVATION SYSTEM RESEARCH: WHAT YOU NEED TO KNOW ABOUT INNOVATION SYSTEMS	570
18-2016	Klaus Prettner	THE IMPLICATIONS OF AUTOMATION FOR ECONOMIC GROWTH AND THE LABOR SHARE	520
19-2016	Klaus Prettner Andreas Schaefer	HIGHER EDUCATION AND THE FALL AND RISE OF INEQUALITY	520
20-2016	Vadim Kufenko Klaus Prettner	YOU CAN'T ALWAYS GET WHAT YOU WANT? ESTIMATOR CHOICE AND THE SPEED OF CONVERGENCE	520

No.	Author	Title	Inst
01-2017	Annarita Baldanzi Alberto Bucci Klaus Prettner	CHILDRENS HEALTH, HUMAN CAPITAL ACCUMULATION, AND R&D-BASED ECONOMIC GROWTH	INEPA
02-2017	Julius Tennert Marie Lambert Hans-Peter Burghof	MORAL HAZARD IN VC-FINANCE: MORE EXPENSIVE THAN YOU THOUGHT	INEF
03-2017	Michael Ahlheim Oliver Frör Nguyen Minh Duc Antonia Rehl Ute Siepmann Pham Van Dinh	LABOUR AS A UTILITY MEASURE RECONSIDERED	520
04-2017	Bohdan Kukharskyy Sebastian Seiffert	GUN VIOLENCE IN THE U.S.: CORRELATES AND CAUSES	520
05-2017	Ana Abeliansky Klaus Prettner	AUTOMATION AND DEMOGRAPHIC CHANGE	520
06-2017	Vincent Geloso Vadim Kufenko	INEQUALITY AND GUARD LABOR, OR PROHIBITION AND GUARD LABOR?	INEPA
07-2017	Emanuel Gasteiger Klaus Prettner	ON THE POSSIBILITY OF AUTOMATION-INDUCED STAGNATION	520
08-2017	Klaus Prettner Holger Strulik	THE LOST RACE AGAINST THE MACHINE: AUTOMATION, EDUCATION, AND INEQUALITY IN AN R&D-BASED GROWTH MODEL	INEPA
09-2017	David E. Bloom Simiao Chen Michael Kuhn Mark E. McGovern Les Oxley Klaus Prettner	THE ECONOMIC BURDEN OF CHRONIC DISEASES: ESTIMATES AND PROJECTIONS FOR CHINA, JAPAN, AND SOUTH KOREA	520
10-2017	Sebastian Till Braun Nadja Dwenger	THE LOCAL ENVIRONMENT SHAPES REFUGEE INTEGRATION: EVIDENCE FROM POST-WAR GERMANY	INEPA
11-2017	Vadim Kufenko Klaus Prettner Vincent Geloso	DIVERGENCE, CONVERGENCE, AND THE HISTORY-AUGMENTED SOLOW MODEL	INEPA
12-2017	Frank M. Fossen Ray Rees Davud Rostam-Afschar Viktor Steiner	HOW DO ENTREPRENEURIAL PORTFOLIOS RESPOND TO INCOME TAXATION?	520
13-2017	Steffen Otterbach Michael Rogan	SPATIAL DIFFERENCES IN STUNTING AND HOUSEHOLD AGRICULTURAL PRODUCTION IN SOUTH AFRICA: (RE-) EXAMINING THE LINKS USING NATIONAL PANEL SURVEY DATA	INEPA
14-2017	Carolina Castagnetti Luisa Rosti Marina Töpfer	THE CONVERGENCE OF THE GENDER PAY GAP – AN ALTERNATIVE ESTIMATION APPROACH	INEPA

No.	Author	Title	Inst
15-2017	Andreas Hecht	ON THE DETERMINANTS OF SPECULATION – A CASE FOR EXTENDED DISCLOSURES IN CORPORATE RISK MANAGEMENT	510
16-2017	Mareike Schoop D. Marc Kilgour (Editors)	PROCEEDINGS OF THE 17TH INTERNATIONAL CONFERENCE ON GROUP DECISION AND NEGOTIATION	NegoTrans
17-2017	Mareike Schoop D. Marc Kilgour (Editors)	DOCTORAL CONSORTIUM OF THE 17TH INTERNATIONAL CONFERENCE ON GROUP DECISION AND NEGOTIATION	NegoTrans
18-2017	Sibylle Lehmann-Hasemeyer Fabian Wahl	SAVING BANKS AND THE INDUSTRIAL REVOLUTION IN PRUSSIA SUPPORTING REGIONAL DEVELOPMENT WITH PUBLIC FINANCIAL INSTITUTIONS	520
19-2017	Stephanie Glaser	A REVIEW OF SPATIAL ECONOMETRIC MODELS FOR COUNT DATA	520
20-2017	Dario Cords	ENDOGENOUS TECHNOLOGY, MATCHING, AND LABOUR UNIONS: DOES LOW-SKILLED IMMIGRATION AFFECT THE TECHNOLOGICAL ALIGNMENT OF THE HOST COUNTRY?	INEPA
21-2017	Micha Kaiser Jan M. Bauer	PRESCHOOL CHILD CARE AND CHILD WELL-BEING IN GERMANY: DOES THE MIGRANT EXPERIENCE DIFFER?	INEPA
22-2017	Thilo R. Huning Fabian Wahl	LORD OF THE LEMONS: ORIGIN AND DYNAMICS OF STATE CAPACITY	520
23-2017	Matthias Busse Ceren Erdogan Henning Mühlen	STRUCTURAL TRANSFORMATION AND ITS RELEVANCE FOR ECONOMIC GROWTH IN SUB-SHARAN AFRICA	INEPA
24-2017	Sibylle Lehmann-Hasemeyer Alexander Opitz	THE VALUE OF POLITICAL CONNECTIONS IN THE FIRST GERMAN DEMOCRACY – EVIDENCE FROM THE BERLIN STOCK EXCHANGE	520
25-2017	Samuel Mburu Micha Kaiser Alfonso Sousa-Poza	LIFESTOCK ASSET DYNAMICS AMONG PASTORALISTS IN NORTHERN KENYA	INEPA
26-2017	Marina Töpfer	DETAILED RIF DECOMPOSITION WITH SELECTION – THE GENDER PAY GAP IN ITALY	INEPA
27-2017	Robin Jessen Maria Metzing Davud Rostam-Afschar	OPTIMAL TAXATION UNDER DIFFERENT CONCEPTS OF JUSTNESS	INEPA
28-2017	Alexander Kressner Katja Schimmelpfeng	CLUSTERING SURGICAL PROCEDURES FOR MASTER SURGICAL SCHEDULING	580
29-2017	Clemens Lankisch Klaus Prettner Alexia Prskawetz	ROBOTS AND THE SKILL PREMIUM: AN AUTOMATION-BASED EXPLANATION OF WAGE INEQUALITY	INEPA

No.	Author	Title	Inst
30-2017	Ann-Sophie Adelhelm Melanie Bathelt Mirjam Bathelt Bettina Bürkin Sascha Klein Sabrina Straub Lea Wagner Fabienne Walz	ARBEITSWELT: DIGITAL – BELASTUNG: REAL? DER ERLEBTE WANDEL DER ARBEITSWELT INNERHALB DER IT-BRANCHE AUS SICHT DER ARBEITNEHMER	550
31-2017	Annarita Baldanzi Klaus Prettner Paul Tscheuschner	LONGEVITY-INDUCED VERICAL INNOVATION AND THE TRADEOFF BETWEEN LIFE AND GROWTH	520
32-2017	Vincent Dekker Kristina Strohmaier	THE EFFECT OF TRANSFER PRICING REGULATIONS ON INTRA-INDUSTRY TRADE	520
01-2018	Michael D. Howard Johannes Kolb	FOUNDER CEOS AND NEW VENTURE MEDIA COVERAGE	INEF
02-2018	Peter Spahn	UNCONVENTIONAL VIEWS ON INFLATION CONTRAOL: FORWARD GUIDANCE, THE NEO-FISHERIAN APPROACH, AND THE FISCAL THEORY OF THE PRICE LEVEL	520
03-2018	Aderonke Osikominu Gregor Pfeifer	PERCEIVED WAGES AND THE GENDER GAP IN STEM FIELDS	INEPA
04-2018	Theresa Grafeneder-Weissteiner Klaus Prettner Jens Südekum	THREE PILLARS OF URBANIZATION: MIGRATION, AGING, AND GROWTH	INEPA
05-2018	Vadim Kufenko Vincent Geloso Klaus Prettner	DOES SIZE MATTER? IMPLICATIONS OF HOUSEHOLD SIZE FOR ECONOMIC GROWTH AND CONVERGENCE	INEPA
06-2018	Michael Trost	THE WHOLE IS GREATER THAN THE SUM OF ITS PARTS – PRICING PRESSURE INDICES FOR MERGERS OF VERTICALLY INTEGRATED FIRMS	520
07-2018	Karsten Schweikert	TESTING FOR COINTEGRATION WITH TRESHOLD ADJUSTMENT IN THE PRESENCE OF STRUCTURAL BREAKS	520
08-2018	Evanthia Fasoula Karsten Schweikert	PRICE REGULATIONS AND PRICE ADJUSTMENT DYNAMICS: EVIDENCE FROM THE AUSTRIAN RETAIL FUEL MARKET	520
09-2018	Michael Ahlheim Jan Neidhardt Ute Siepmann Xiaomin Yu	WECHAT – USING SOCIAL MEDIA FOR THE ASSESSMENT OF TOURIST PREFERENCES FOR ENVIRONMENTAL IMPROVEMENTS IN CHINA	520

No.	Author	Title	Inst
10-2018	Alexander Gerybadze Simone Wiesenauer	THE INTERNATIONAL SALES ACCELERATOR: A PROJECT MANAGEMENT TOOL FOR IMPROVING SALES PERFORMANCE IN FOREIGN TARGET MARKETS	570
11-2018	Klaus Prettner Niels Geiger Johannes Schwarzer	DIE WIRTSCHAFTLICHEN FOLGEN DER AUTOMATISIERUNG	INEPA
12-2018	Martyna Marczak Thomas Beissinger	COMPETITIVENESS AT THE COUNTRY-SECTOR LEVEL: NEW MEASURES BASED ON GLOBAL VALUE CHAINS	520
13-2018	Niels Geiger Klaus Prettner Johannes Schwarzer	AUTOMATISIERUNG, WACHSTUM UND UNGLEICHHEIT	INEPA
14-2018	Klaus Prettner Sebastian Seiffert	THE SIZE OF THE MIDDLE CLASS AND EDUCATIONAL OUTCOMES: THEORY AND EVIDENCE FROM THE INDIAN SUBCONTINENT	INEPA
15-2018	Marina Töpfer	THE EFFECT OF WOMEN DIRECTORS ON INNOVATION ACTIVITY AND PERFORMANCE OF CORPORATE FIRMS - EVIDENCE FROM CHINA –	INEF
16-2018	Timo Walter	TRADE AND WELFARE EFFECTS OF A POTENTIAL FREE TRADE AGREEMENT BETWEEN JAPAN AND THE UNITED STATES	INEPA
17-2018	Jonas Frank	THE EFFECTS OF ECONOMIC SANCTIONS ON TRADE: NEW EVIDENCE FROM A PANEL PPML GRAVITY APPROACH	INEPA
18-2018	Jonas Frank	THE EFFECT OF CULTURE ON TRADE OVER TIME – NEW EVIDENCE FROM THE GLOBE DATA SET	520
19-2018	Dario Cords Klaus Prettner	TECHNOLOGICAL UNEMPLOYMENT REVISITED: AUTOMATION IN A SEARCH AND MATCHING FRAMEWORK	INEPA
20-2018	Sibylle Lehmann-Hasemeyer Andreas Neumayer	THE PERSISTENCE OF OWNERSHIP INEQUALITY – INVESTORS ON THE GERMAN STOCK EXCHANGES, 1869-1945	INEPA
21-2018	Nadja Dwenger Lukas Treber	SHAMING FOR TAX ENFORCEMENT: EVIDENCE FROM A NEW POLICY	520
22-2018	Octavio Escobar Henning Mühlen	THE ROLE OF FDI IN STRUCTURAL CHANGE: EVIDENCE FROM MEXICO	520
23-2018	Davud Rostam-Afschar Kristina Strohmaier	DOES REGULATION TRADE-OFF QUALITY AGAINST INEQUALITY? THE CASE OF GERMAN ARCHITECTS AND CONSTRUCTION ENGINEERS	INEPA

No.	Author	Title	Inst
24-2018	Peng Nie Lanlin Ding Alfonso Sousa-Poza	OBESITY INEQUALITY AND THE CHANGING SHAPE OF THE BODYWEIGHT DISTRIBUTION IN CHINA	INEPA

IMPRINT

University of Hohenheim
Dean’s Office of the Faculty of Business, Economics and Social Sciences
Palace Hohenheim 1 B
70593 Stuttgart | Germany
Fon +49 (0)711 459 22488
Fax +49 (0)711 459 22785
wiso@uni-hohenheim.de
wiso.uni-hohenheim.de