UNIVERSITY OF WAIKATO

Hamilton
New Zealand

Poverty Measurement:

We Know Less Than Policy Makers Realize

John Gibson

Department of Economics

Working Paper in Economics 8/15

October 2015

John Gibson

Department of Economics
University of Waikato
Private Bag 3105
Hamilton
New Zealand, 3240

Tel: +64 (7) 838 4289

Email: jkgibson@waikato.ac.nz

Abstract

There is widespread policy interest in poverty estimates at both national and global level. There has been an explosion of poverty measurement in the last two decades enabled by the growing availability of household survey data. These measurements are used by policy makers to assess progress toward national and global goals for inclusive growth and poverty reduction. But the evidence base rests on shaky foundations and policy makers may have undue confidence in poverty and inequality estimates. Many household surveys are poorly designed to measure monetary living standards and poverty in an era of rising affluence and urban transition. Some key problems in measuring food consumption, housing services, and the cost of living are discussed here. Alternatives to monetary measurement, such as using questions on life satisfaction and happiness, also rest on shaky foundations.

2

1. INTRODUCTON

World leaders recently set a new goal to eradicate extreme poverty for all people everywhere by 2030, as a Sustainable Development Goal (SDG) agreed upon at the United Nations Sustainable Development Summit in September, 2015. The SDGs follow the Millennium Development Goals (MDGs), the most prominent of which was to eradicate extreme poverty and hunger. High level goals for the MDG and SDG processes are broad and generally unobjectionable, so do not attract much debate about measurement. It is the more detailed targets under the high level goals that generate debate about how progress should best be measured. For example, Target 1a for the MDGs was to 'halve, between 1990 and 2015, the proportion of people whose income is less than one dollar a day.' This was set as an income target by policy makers but global progress was measured by the World Bank mostly using household survey data on consumption. The benchmark was also moved, from $1 a day to $1.08 in 1993 purchasing power parity (PPP) terms, which was then reset to $1.25 per day in 2005 PPP prices and is likely to be reset again if the 2011 PPP estimates from the International Comparison Project are incorporated into global poverty monitoring.

These refinements to the way in which progress in meeting the poverty target is measured attract considerable academic debate (Deaton 2010, Ravallion 2015). Much of the debate is about international comparisons, where there are difficult issues of how to consistently rank the monetary welfare of a person in, say, Papua New Guinea against someone in Vietnam. Absent from these debates is much concern about the main building block for measuring poverty, both nationally and globally, which is the record of living standards given by household surveys. The explosion of poverty measurement in the last two decades has been enabled by the growing availability of these surveys. For example, the global poverty counts by Chen and Ravallion (2013) rely on a household survey database of almost 900 surveys from 125 low- and middle-income countries fielded between 1979 and 2011. In contrast, the first global poverty estimates by Ravallion, Datt and van de Walle (1991) were based on household surveys from just 22 countries, with extrapolations needed for another 64 developing countries that lacked suitable data on the distribution of living standards.

Based on this growing availability of household survey data, policy makers might assume that we know much more about poverty than we used to, and that the foundations for measuring progress towards poverty targets are getting firmer over time. The aim of this article is to argue the opposite – several factors suggest that our measures of poverty and inequality may become less reliable over time. In particular, many household surveys are poorly designed to measure living standards and poverty in an era of rising affluence and urban transition. The key problems for household surveys that I focus on in this article are problems in measuring food consumption, in measuring housing services, and in measuring the cost of living. The problems matter more as people get richer, so they apply especially in rapidly growing Asian countries, and they impede measurement of both inequality and

poverty, so they matter even to countries that escape mass poverty. In the next section I show that it is the escape from mass poverty that makes the remaining poverty more sensitive to measured inequality, and so heightens these measurement problems.

One (wrong) response to these difficulties would be to abandon attempts at measuring monetary living standards, inequality in monetary measures, and the poverty of those falling below acceptable thresholds of monetary welfare. Recent years have seen a broad movement to develop non-monetary approaches, such as measuring happiness and life satisfaction (Layard 2005). This movement gained prominent support when French President Sarkozy set up the 'Stiglitz Commission' whose mandate reflected a dissatisfaction with the present state of statistical information about the economy and society (Stiglitz, Sen and Fitoussi 2010). The last section of this article discusses why these non-monetary approaches of measuring and comparing subjective reports of happiness and life satisfaction also rest on shaky foundations.

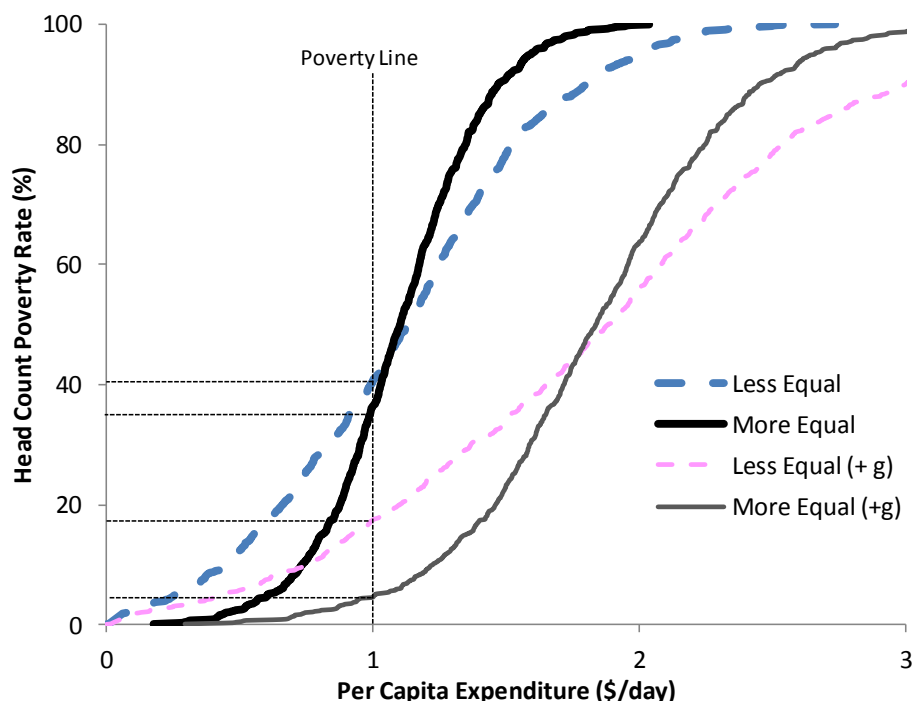## 2. THE RISING INEQUALITY-SENSITIVITY OF POVERTY

Poverty estimates can be derived with three types of information: mean living standards, inequality around that mean, and where the line dividing the poor from the non-poor is drawn. The evidence from thought experiments, as the mean is changed holding inequality constant or *vice versa* (Datt and Ravallion 1992), and also from observed changes is that poverty becomes more sensitive to inequality and less sensitive to growth as poverty falls.

The intuition behind the rising inequality-sensitivity of poverty is seen in Figure 1 using cumulative distribution functions (CDFs) of a more equal and a less equal distribution with means of $1.1 per day. The CDF is also known as the poverty incidence curve because one can directly get the head count poverty rate from where the poverty line (set here at $1 a day) cuts the CDF. When poverty is widespread, the poverty line cuts the CDF near the point of inflexion, where the CDF is almost straight, and the poverty rate is not very sensitive to inequality (shown by the curvature of the CDF). Instead, the head count poverty rate is sensitive to the location of the overall distribution (the mean), since the CDF is close to vertical where the poverty line cuts it. In the example, the gap in the poverty rate between the two distributions is just five percentage points (41% and 36%) even though the coefficient of variation (CoV) of the less equal distribution is almost double that of the more equal one (0.46 and 0.27).

The remaining curves in Figure 1 show the situation after a period of uniform growth (all consumption rises by two-thirds in the figure). A big gap in poverty rates opens up between the more equal (head count=5%) and less equal (head count=18%) distribution. Thus, as a country escapes mass poverty the sensitivity of the remaining poverty to inequality increases. If growth gave the same absolute rise in consumption for everyone (a higher growth rate for

the poor instead of the equal growth rate in Figure 1), this would just shift the CDFs in parallel and the large gap in the poverty rates under the less equal and more equal distributions still occurs.

Figure 1: Inequality Sensitivity of Poverty Increases as Countries Grow Less Poor


The heightened sensitivity of poverty to inequality as countries escape mass poverty is seen in the experience of Vietnam. At the $1 a day global poverty line, the poverty rate in Vietnam fell from 64% in 1993 to 17% in 2008 (World Bank 2012) and was down to about 5% by 2010.[1] Figure 2 shows this progress (using the left axis) and what happened to the sensitivity to growth and inequality (using the right axis). When the poverty rate was high, the elasticity with respect to inequality was little over one-half of the elasticity with respect to growth, but as the poverty rate fell the inequality elasticity rose to almost three times that of the growth elasticity. Another way to show falling growth-sensitivity is to consider the growth rate in mean living standards needed to achieve a one percentage point fall in the poverty rate; when the poverty rate was high in 2002, a growth rate of 1.6% per annum was sufficient to drop the poverty rate by a percentage point, but by 2010 it took an annual growth rate of 6% to achieve the same drop in the poverty rate.

Rising inequality-sensitivity of poverty matters to measurement because inequality data are mostly from household surveys. With mass poverty, the real growth rate matters most and this can be got without surveys, using the national accounts or proxies like night lights

---

[1] The uncertainty for 2010 is because the survey living standards indicator was revised then, to reflect Vietnam's rising affluence.

(Pinkovskiy and Sala-i-Martin 2014). But there are few alternatives to surveys for measuring inequality. Indeed, researchers such as Sala-i-Martin who argue against using surveys to estimate poverty trends still use them to measure inequality even as they obtain growth rates from other sources. The new focus by the World Bank on 'shared prosperity' also increases attention to issues with inequality data (Jolliffe *et al*. 2015). Surveys designs that let one adequately count extremely poor people may do less well at measuring more affluent living standards, but if policy makers are to judge if prosperity is being shared, it requires accurately measuring the living standards of the more prosperous.

Figure 2: Declining Effectiveness of Growth in Reducing Poverty as Poverty Falls, Vietnam 2002-2010
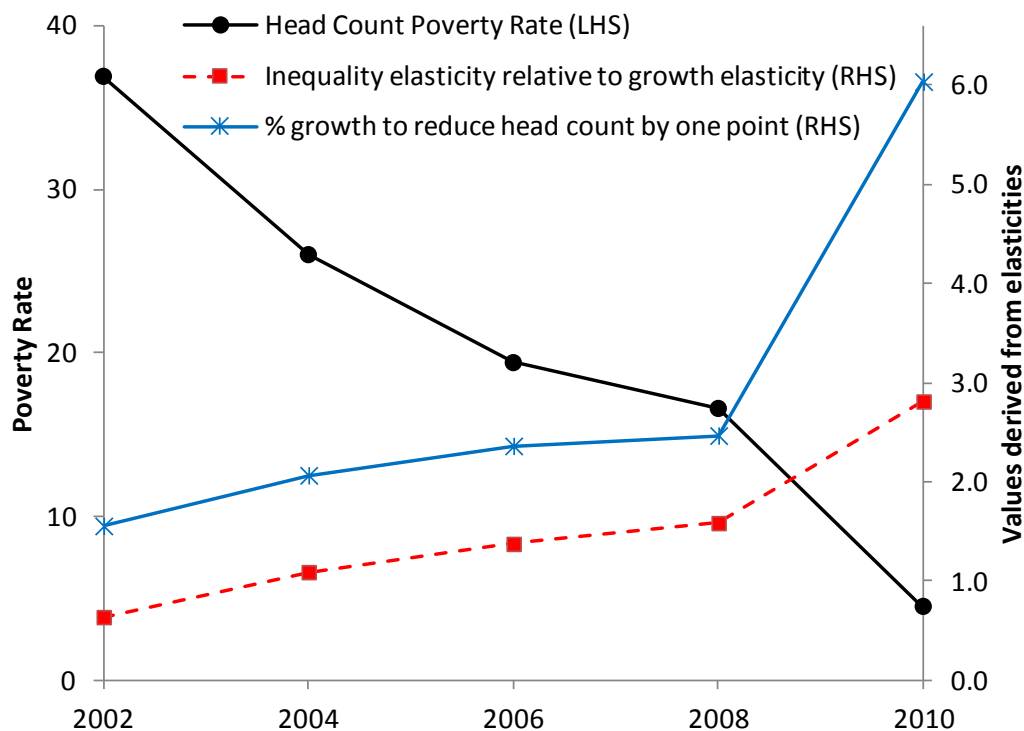
Source : Author's calculations from VHLSS data

3. PROBLEMS IN MEASURING FOOD CONSUMPTION

The data workhorse for measuring poverty in developing countries is a Household Consumption Expenditure Survey (HCES).[2] While income surveys are widely used to study poverty in rich countries, amongst developing countries only in Latin America are income surveys used more than HCES. These surveys differ along several key dimensions, such as method of data capture (diary versus recall questionnaires), the level of respondent (individual versus household), the reference period for which consumption is reported

---

[2]   The generic term HCES refers to a range of survey efforts to record total household consumption expenditures, which includes budget surveys, income and expenditure surveys, living standards surveys, and others.

(anywhere from one day to one year), and the degree of commodity detail (from less than 20 items to over 400 items).[3] Despite these differences, most HCES have an implicit aim of recording living standards of the members of a household who eat meals from a common pot, where those meals are cooked from ingredients that householders acquired by either purchase, receiving as a gift or payment, or self-production.

In recognition of this target, the food modules of these surveys are organized according to lists of ingredients such as rice, wheat flour, maize flour, and so forth. The important staples may get several lines on the list, such as for different rice varieties according to quality or season of production. Asking about ingredients makes sense for people who prepare their own meals, and thus made sense at baseline of the MDGs (1990) when most of the poor were still rural and likely ate together as a family. But this approach makes less sense for urban people who obtain food independently of other family members, in the form of prepared meals, whether as street foods, in restaurants or purchased to heat and eat at home. The poor urbanize faster than developing country populations as a whole (Ravallion *et al.* 2007) so the ingredients-based, common-pot method of measuring consumption becomes increasingly ill-suited to measuring living standards and poverty.

Consider first the problem of independent eating, or more broadly the issues for surveying urban family members who may only sleep together but not work and eat together as they did in the countryside. In a survey experiment in Tanzania, Beegle *et al.* (2012) compare two types of HCES diary surveys; in one, each adult records their own commodity acquisitions, while in the other, one respondent keeps a diary on behalf of the whole household. For rural households, there is no difference in the consumption recorded with one type of diary or the other. But urban households report 29 percent lower consumption, if surveyed with a household-level diary rather than having each adult keeping a diary. The large error when using a HCES design that seemed to cause no bias when used in the countryside (the household-level diary) shows the challenge facing HCES methods if they are to accurately measure living standards in future as poverty urbanizes and as common-pot measuring techniques become less relevant.

Asking about ingredients makes little sense for many urban people who mainly buy meals. Yet in most HCES meals eaten outside of the home are little more than an afterthought, with just a question or two about expenditures but not quantities. By ignoring eating out, policy makers may get distracted by dead-end debates, such as one in India about seemingly rising under-nutrition during the recent era of rapid economic growth. In two decades from 1987-88, mean calories per capita seemed to fall by 10 percent and the under-nourishment rate seemed to rise from one-quarter to over one-third of the population, all while India was recording some of its fastest ever economic growth rates. Hypotheses about

---

[3] See Beegle *et al.* (2012) for a discussion of these design variants and for evidence on the sensitivity of poverty and inequality estimates to variation in these design dimensions.

the puzzle include relative price changes, declining calorie needs with urbanization, dietary diversification, and a squeeze on the food budget due to rising expenditures on non-food essentials. Yet the most likely explanation is much simpler – and more troubling – the HCES evidence relied on for much of the debate increasingly understates calories because it misses the rising share of calories coming from eating out (Smith 2015). A similar data problem occurred earlier in China when the per capita quantity of meat consumed appeared almost static, despite rapidly rising incomes and rapid growth in meat supply (for example, pork supply appeared to be 45 percent higher than pork demand). At least part of this gap was due to the failure of food consumption statistics based on HCES data to account for the pork consumed as meals during eating out occasions (Ma, Huang, Fuller and Rozelle 2006).

Meals out are highly income elastic and so their budget share rises with rising affluence, and they become the most important category of food expenditure. One would not know this from looking at HCES questionnaires which have very many questions devoted to ingredients and few for meals. Figure 3 reports trends in the share of total food expenditure on eating out, for urban China and national Vietnam. The trend in this ratio is compared with the trend in the share of the food budget spent on the major ingredient – grains in urban China and rice in Vietnam. In urban China, the total for all grains, such as rice and wheat flour (in terms of what is acquired as ingredients) fell from one-seventh of all food spending in 1996 to half that level by 2011. Meanwhile eating out rose from under one-tenth of the food budget to become almost one-quarter of total food spending, with the two budget shares crossing in 1998. When the series stops, in 2011, spending on eating out was almost three times spending on grains. A similar pattern is apparent in Vietnam, where spending on rice went from being one-third of total food spending in 1998 to just one-eighth by 2012. In the other direction spending on meals went from 10 percent to 24 percent. The crossing point occurred later than in urban China, in part because the results for Vietnam include rural areas, but the pattern is the same.

Yet despite the importance of meals this form of food consumption is largely ignored in existing HCES. Dupriez *et al.* (2014) provide metadata on dimensions of HCES design related to food acquisitions and consumption from a sample of 100 low- and middle-income countries. Most of these surveys use the interview method, where a single respondent reports on the household's consumption and/or expenditure activities over some prior reference period(s). Amongst the interview surveys, the average number of groups in the food list is 110 but an average of just three of these are for meals and other forms of food eaten away from home. In contrast, ingredients categories like cereals or vegetables each have an average of 14 groups. Moreover, while most food-at-home groups have data on the quantity bought, and the quantity self-produced or consumed, in a majority of the surveys the questions about food eaten out of the home have no quantities reported. Thus it is impossible to know how many calories come from eating out of the home. In summary, HCES design is increasingly ill-suited to gathering the data needed for assessing the food consumption of a more affluent and more urban population.

Figure 3: Changing Importance of Food Ingredients and Eating Out
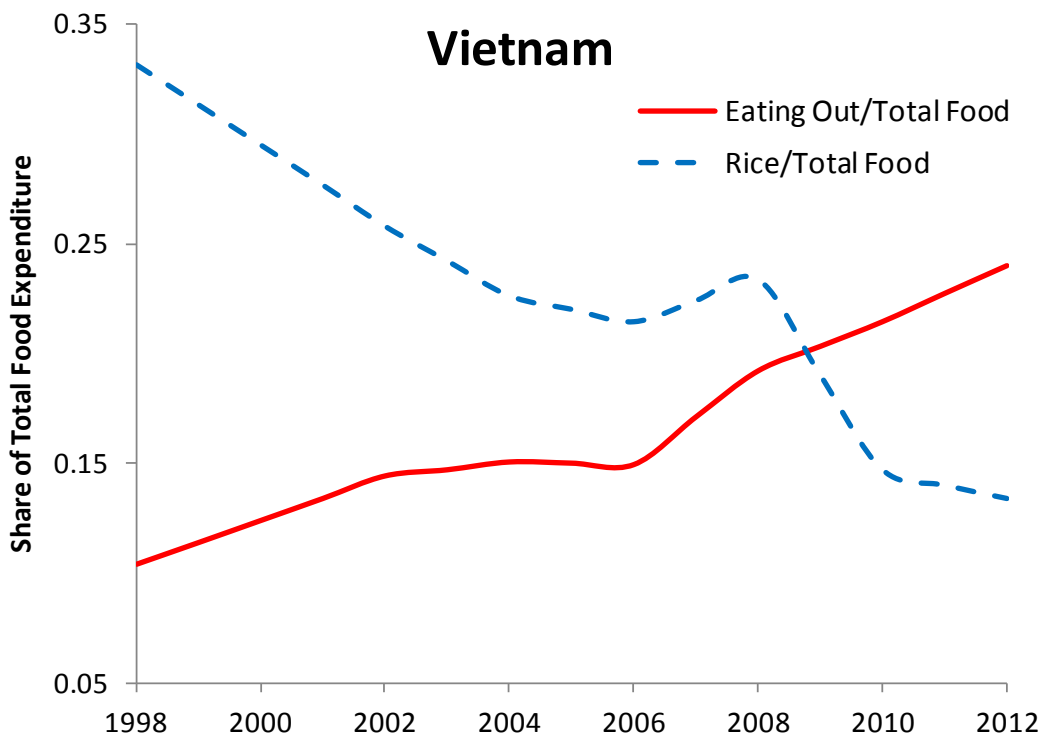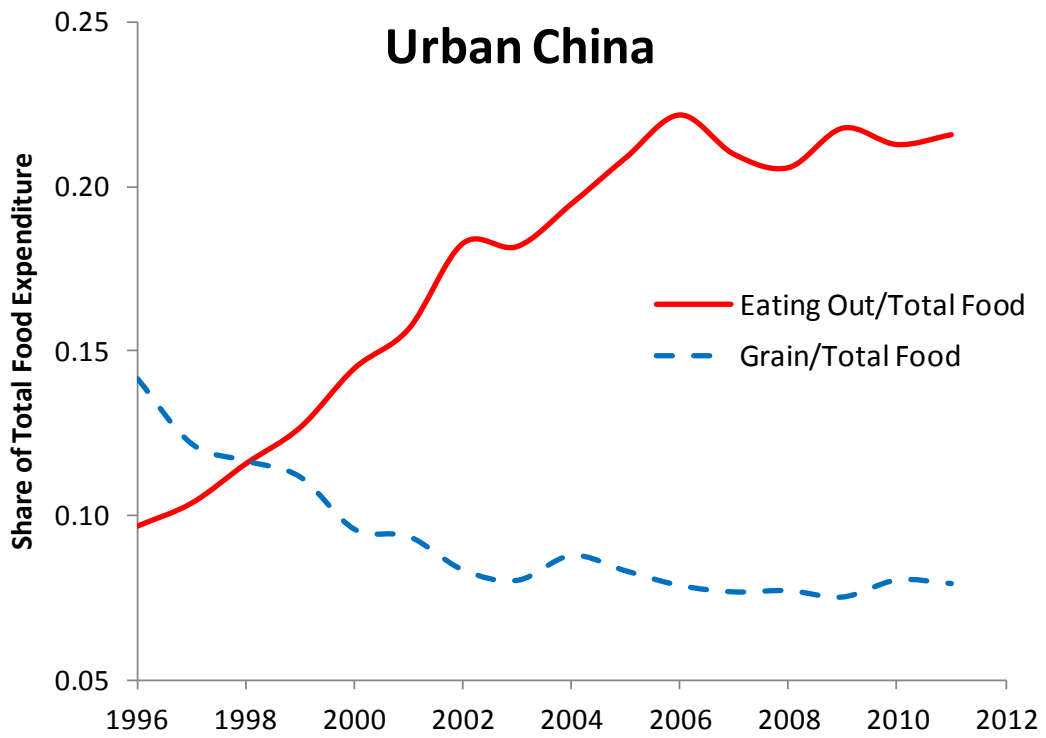
Even within ingredients lists there are problems, since rising affluence sees diets diversify away from the limited set of ingredients used when people were poorer. Thus more expenditure occurs in the catchall categories at the end of the list for types of ingredients (such as 'all meats not otherwise specified'). The foods in the catchall are too heterogeneous to allow easy recall of mixed quantities so usually just monetary values are reported. Thus, the contribution to nutrition from these income elastic catchall groups is missed. Moreover, with no quantities and prices for the catchall groups, it becomes harder to take account of spatial and temporal price variation; apparently rising inequality could just be more spending on residual category foods, which have rising prices due to the rise in their demand, and constant-price inequality may be unchanged.

4. PROBLEMS IN MEASURING HOUSING SERVICES

The other form of poorly-measured consumption whose high income elasticity makes it of growing importance is housing. With rising affluence, housing eventually becomes the largest household budget item; for example, 44 percent of a U.S. cost-of-living index is housing (Jolliffe 2006). Ideally, surveys would enable consumption of housing services to be calculated for both renters and owner-occupiers. Similarly, variation in the price of housing services over time and space would be measured so as to put consumption, poverty, and inequality estimates in real terms. While most household surveys ask for actual rents paid, in many developing countries renters are a small minority so it is hard to extrapolate from rents paid by these renters to imputed rents for others. Moreover, most surveys do not collect the data needed on either replacement costs for dwellings, or historical costs, life expectancies and depreciation rates that could enable the flow of housing services provided by the dwelling to be estimated.

Indeed, some surveys do such a poor job that consumption of housing services is dropped from analyses (Deaton and Dupriez 2011). An equivalent treatment is to assume that housing has a constant budget share so that this form of consumption can be imputed as a simple ratio to the value of consumption in the parts of the budget that are better measured by surveys. For example, poverty measurement in Vietnam from the 1990s though 2008 treated consumption of housing as a constant proportion of other non-food consumption so housing was an unchanged six percent of the total budget (World Bank 2012). When this assumption was dropped, and the estimated value of housing consumption was derived by applying the rent-to-value ratio of renters to the dwelling values that owner-occupiers reported, the average share of housing in household budgets rose to 15 percent. Moreover, housing was estimated to be 27 percent of the budget for people in the richest quintile and just eight percent for the poorest quintile, suggesting that the assumption about constant housing shares had greatly understated inequality.

Treating housing as a fixed ratio to other forms of consumption also ignores the implications of the Balassa-Samuelson effect, that prices of non-traded goods are higher in

richer areas. Housing is the quintessential non-traded so it is expected that richer areas will have higher housing prices, and that these spatial price differentials will grow over time as an economy urbanizes and becomes richer. So if housing consumption and prices are poorly measured (or not measured at all) what is interpreted as rising inequality may just be increasing spatial price differences. For example, Li and Gibson (2014) construct a spatial price index for urban China and find nominal incomes outside Beijing need to be inflated 33 percent to put them on a comparable cost-of-living basis, even allowing just housing costs to differ between Beijing and other cities.

Figure 4 shows what happens to measured inequality if no account is taken of this spatial variation in the cost of living. Inequality is overstated by up to 35 percent if one is using the Theil index and considering inter-provincial differences. Within-province heterogeneity means that there is more inequality at city level than at province level, so the relative exaggeration from not accounting for housing cost variation is slightly less – 30 percent – at city level. Also, the over-stated inequality is not as great if inequality is measured with the Gini index, where not deflating for spatial cost of living differences cases an upward bias in the Gini coefficient of 15-16%.[4]

Figure 4: Overstated spatial inequality in China's GDP per capita, 2010
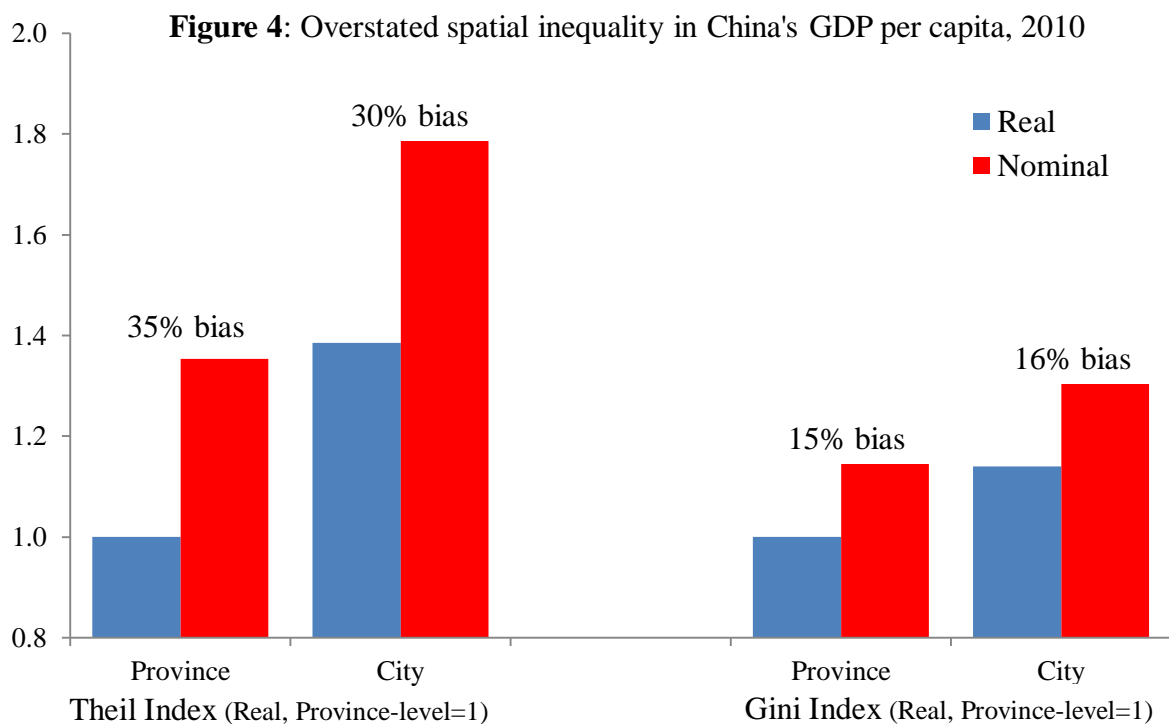
Taking an average of the results for the two inequality measures in Figure 4, in round terms approximately one-quarter of apparent spatial inequality in China disappears once account is taken of cost of living differences coming just from house prices. It will especially

---

[4]   In Figure 4, both the Theil and the Gini have been scaled to equal 1 for real inequality at provincial level.

be true for China, because of the absence of housing markets under central planning, but probably is true more generally throughout rapidly urbanizing Asia, that the spatial cost of living differentials from urban housing markets are likely to have grown from a low base. Thus, some of the apparent rise in inequality found in many countries may just be a growth in spatial price differences. Once again, the evidence base for important public policy debates about inequality, poverty, shared prosperity, and the inclusiveness of the economic growth process is much weaker than it should be, in this case because of problems with the survey data on housing consumption and prices.

5. PROBLEMS IN MEASURING FOOD PRICES

The inability of poverty estimates to account for variation in the cost of housing services may be partly excused by services being hard to measure. But there is less excuse for the fact that many surveys poorly, or do not attempt to, measure food prices. Even with changing diets as noted in Section 3, and the decline in the overall food share as people get richer (Engel's Law), food remains one of the most important items in household budgets. Moreover, the cost-of-basic-needs (CBN) method of forming poverty lines is anchored by the local cost of buying a food bundle that gives a certain level of nutrition (for example, 2000 calories per person per day). So food prices are needed to measure poverty, and policy makers might expect that these prices are straightforward to obtain by survey since there is a long history of collecting food prices for the Consumer Price Index (CPI).

In fact, few countries in Asia and the Pacific collect spatially detailed food prices. Statistics offices in China, India and Indonesia do not collect market price data to match to their rural HCES and urban food prices from the CPI are a poor proxy for prices prevailing in the countryside. Moreover, CPI prices are not designed with spatial comparisons in mind; for example, in Vietnam the particular brand or finely defined specification used to track temporal price movements for a food group can vary by province, introducing quality differences over space. Other countries either do not, or only poorly, get rural prices despite the opportunity afforded by design of their household surveys. For example, interview teams for the 2010 Household Income and Expenditure Survey in Papua New Guinea lived in villages for up to three weeks to implement a 14-day expenditure diary. Interviewers visited markets to buy their own food but no price survey was done. A slightly less egregious example is the 2008 Cambodia Socio-Economic Survey, where teams spent a month in each village for an expenditure diary and village survey; 14 percent of villages had no price data for any food (it is implausible for a month to go by without food markets operating nearby) and across all villages just one-third of the expected number of price reports were obtained.

Instead of using price surveys, the pricing of food poverty line baskets in many countries in Asia and the Pacific is based on *unit values* – the ratio of expenditures on a food group to the quantity bought. There are many problems with this, the first and most obvious from the discussion in Section 3 is that a growing share of food consumed, as meals and in the catchall

12

categories at the end of lists of types of ingredients, has no quantity data so unit values cannot be calculated. But even for food ingredient groups with quantity data, unit values are a biased measure of prices, and the bias will rise with rising affluence. Unit values can only proxy for the price level if prices of each variety within a group move in fixed proportions over time and space. But fixed relative prices within groups (known as *Hicksian separability*) violates the Alchian-Allen effect where the relative price of quality varies over space ('shipping the good apples out') and time due to the effect of fixed charges for transport, storage or processing (Gibson and Kim 2015).

An example of the Alchian-Allen effect is shown in Figure 5, where the ratio of the price of high quality rice to low quality rice in Vietnam is mapped using average prices calculated for each province from a 2010 price survey. On average, high quality rice is 40 percent dearer than low quality rice but the ratio varies widely and has a distinct geographic pattern. High quality rice is relatively cheaper in the north, where the premium averages 33 percent *versus* 47 percent in the south. The reason for this geographic pattern is that the market surplus of rice flows from the south to the north in Vietnam (and from the south to the world market). It costs the same to ship high quality rice as low quality rice, so adding a per unit transport cost lowers the relative price of high quality rice in the north, as shown in Figure 5.

The Alchian-Allen effect should get stronger over time because rising affluence sees more food transformed through time (storage), space (transport) and form (processing). The year-round availability of particular foods becomes important to consumers as they get richer, leading to more storage, while regional specialization and supply chain evolution lead to longer distance transport. For example, none of India's potato crop was cold stored in the 1980s but more than 50 percent is now, and growers in the specialized production hub around Agra cold store more than 80 percent of their crop (Reardon et al, 2012). It costs the same to store high quality and low quality potatoes, so the relative price of high quality potatoes should fall as time since harvest increases, and will also fall the further away are consumers from a production hub like Agra.

Since within-group relative prices vary, consumers can switch to relatively cheaper items within a group. So the unit value will not have the same quality mix across locations, and conflates inter-area (or inter-period) price differences with differences in quality mix in each area (or time period). These mix differences are in response to the relative price of quality varying. An example of this mix effect is from a 2012 HCES for Vietnam, which had high quality and low quality rice as separate food groups (in prior years the survey just asked about 'rice' as a food group, with all qualities lumped together).

Figure 5: Relative Price Variation Over Space: High Quality and Low Quality Rice
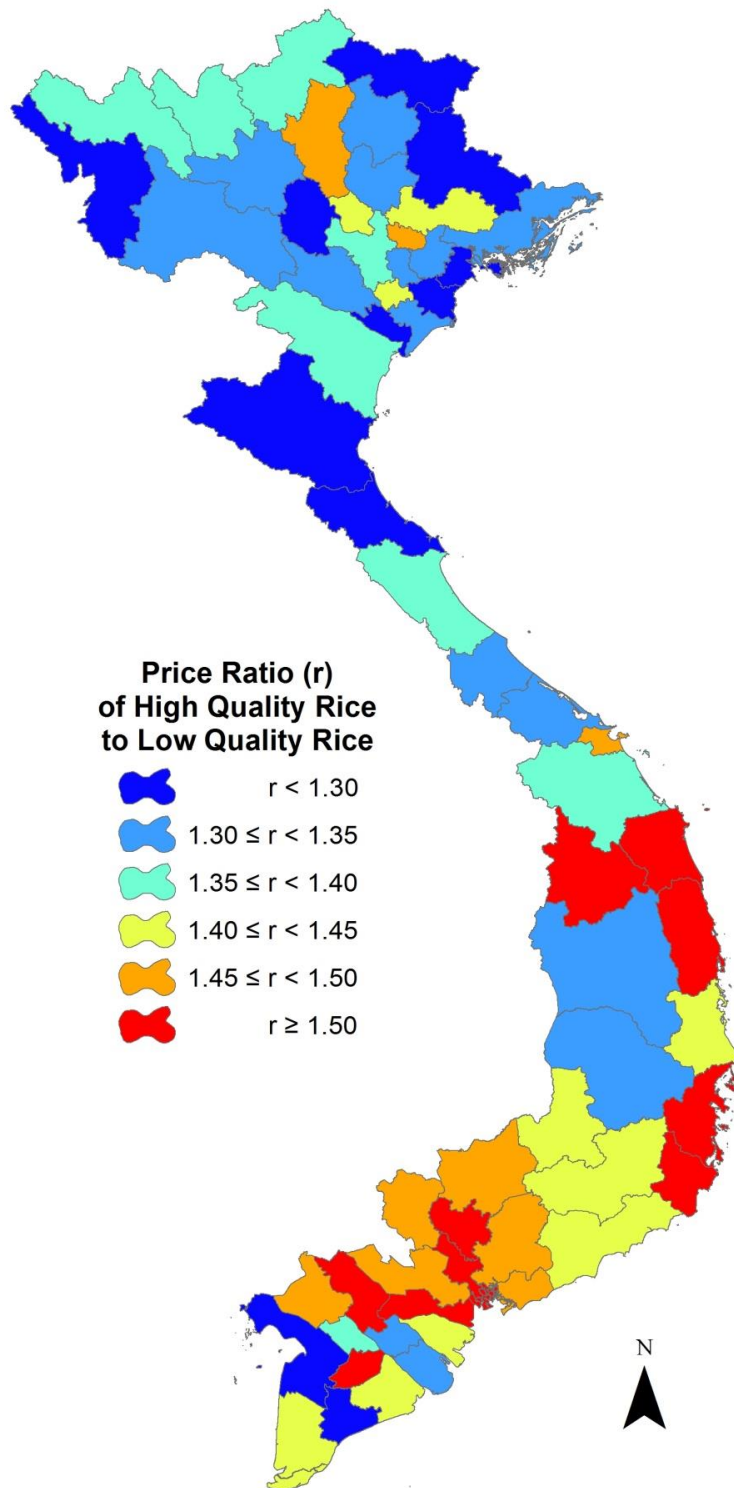
The Alchian-Allen effect means that the relative price of high quality rice should be lower, the further one is from the point of excess supply; the major city in the Mekong delta, Can Tho, is considered as the excess supply point. This effect is seen in column (1) of Table 1, which is from a regression where the independent variable is the distance from Can

Tho to each of Vietnam's provinces; the price ratio of high quality to low quality rice falls by one percentage point for every 100 kilometres. In column (2) the dependent variable is the ratio of high quality rice to low quality rice (measured in kilograms) bought in each province. On average, there is a 1:6 ratio of high quality rice to low quality rice bought, but this varies from 1:4 in Northern provinces to 1:15 in the south; the regression shows this effect with the high-to-low quality ratio rising by two percentage points for every 100 kilometres further from Can Tho. In contrast, rice from non-market sources (which is mostly from own-production) has no Alchian-Allen effect, with the distance from Can Tho statistically insignificant (column (3)).

Table 1: Effects of distance from Can Tho (as a proxy for shipping costs) on Price and Quantity Ratios for High Quality Rice and for Low Quality Rice

	Relative Price of High Quality Rice	Quantity of High Quality Rice Relative to Low Quality	
	(1)	Purchases (2)	Non-market supply (3)
Distance from Can Tho	-0.011 (4.06)**	1.886 (3.22)**	-1.697 (0.78)
Intercept	1.482 (49.74)**	2.879 (1.58)	26.781 (1.07)
R-squared	0.17	0.12	0.01

Notes: t-statistics in ( ) are from heteroscedasticity-robust standard errors, ** statistically significant at 1%. *N*=63.

How biased are unit values as a proxy for prices, due to the variation in the quality mix? If a unit value is calculated for 'rice' (as it was for surveys in Vietnam prior to 2012, with high and low quality lumped together), more high quality rice in the purchased basket of households in the north makes the unit value there six percent higher than in the south, irrespective of any actual spatial price differences. Rice was 36 percent of the value of the food basket used for the CBN poverty line prior to 2010 so this quality mix effect spuriously lifts the food poverty line by two percent in the north. In effect, a higher standard of living (eating higher quality rice) is being confused with a higher cost of living. The upward bias in the poverty line in the north due just to the rice quality mix raises the head count poverty rate there by almost five percent in 2010.

This bias is expected to rise over time as households switch away from eating their own rice, given that non-market acquisitions have no Alchian-Allen effect (as seen from column (3) of Table 1). When people eat own-grown food, the relative price of quality and the composition of demand are less affected by transport or storage costs. As people get richer they rely more on the market to obtain their food, so the column (1) pricing patterns and the within-group demand patterns in column (2) become more important. Thus, unit values will be an ever-worse proxy for prices since the Alchian-Allen effect should get stronger as countries become richer. Once again, rising affluence undermines statistical approaches that

may have worked adequately in the past, even for the simple task of measuring differences in food prices over time and space.

6. PROBLEMS IN MEASURING AND COMPARING SUBJECTIVE WELFARE

Since rising affluence creates challenges for the measurement of monetary welfare through survey, one response is to focus on alternative, non-monetary, measures of wellbeing such as happiness or life satisfaction. These type of measures are increasingly making their way into policy discussions and use of these measures is even promoted by some economists, such as Richard Layard (2005). There is also a specialized literature devoted to the empirical analysis of poverty and welfare when one uses such subjective data that includes contributions by economists who mainly work with survey measures of monetary welfare (for example, Ravallion and Lokshin 2001).

Despite the attractiveness of slogans such as 'maximizing gross national happiness' policy makers should note that welfare economics does not provide a justification for maximising either happiness or life satisfaction, since neither correspond to utility. For example, Glaeser, Gottlieb and Ziv (2014) show that many internal migrants in the United States move to less happy cities and have the lower life satisfaction of their destination. No one forces these people to move so revealed preference implies that the move makes them better off. How can this be? The answer is that unhappy cities tend to be declining cities that offer higher real incomes because of the low cost of housing. These higher real incomes partly compensate for lower reported life satisfaction, which is a trade-off that people are willing to make because they are maximising utility – of which life satisfaction may be one argument but it is not the maximand, utility is.

Another critique comes from McCloskey (2012), who discusses problems with measuring happiness from self-reported declarations that are then added up and averaged across people and eras. She describes these efforts as asking survey respondents where they fall on a three-point scale, 1-2-3: 'not too happy,' 'pretty happy,' 'very happy' which is an accurate description of the General Social Survey, although some other surveys use finer-grained 4- or 5-point scales. The problem with this effort is that when these numbers are treated as data to be used in the same way that incomes and expenditures are used, researchers are guilty of mixing up a 'non-interval scale' with an interval scale. For example, the gap between, say, a '1' and a '2' is not the same across different people, and may not be the same in different times for the same people. As McCloskey notes (2012, p.4):

> If a man tormented by starvation and civil war in South Sudan declares that he is 'happy, no, very happy, a regular three, mind you,' we have learned something about the human spirit and its sometimes stirring, sometimes discouraging, oddity. But we inch toward madness if we go beyond people's lips and claim to read objectively, or subjectively, their hearts in a 1-2-3 way that is comparable with their neighbors or comparable with the very same South Sudanese man when he wins an immigration lottery and gets to Albany.

The temptation to interpret happiness and subjective wellbeing values as cardinal measures may lead to misleading conclusions.

Bond and Lang (2014) expand upon this theme by showing that standard happiness measures cannot rank the average happiness of two groups (or the same group in two time periods), unless researchers are willing to make strong and unverifiable assumptions about the underlying (and unknown) distribution of happiness. The problem occurs because a continuous variable (life satisfaction or happiness) is being placed into discrete categories and this makes it possible to reverse the average happiness ranking between two groups (or countries or time periods) by using different monotonic transformations.

In a time series example, Bond and Lang (2014) relate mean self-reported happiness in the United States to real per capita GDP over 1972-2006, with a negative (but statistically insignificant) time trend found. However if a monotonic transformation of the distribution of happiness is sufficiently left-skewed, under what they call the 'Tolstoy Assumption' (*All happy families are alike but each unhappy family is unhappy in its own way*) then a positive and statistically significant relationship between GDP and happiness is found. Similarly, cross-country rankings from the World Values Survey are sensitive to the use of left-skew or right-skew transformations.

A left-skew suggests that the highest average happiness levels are in small, rich OECD countries like New Zealand, Sweden, Canada and Norway, while the least happy countries are in Africa (Ghana, Zambia and Ethiopia). If happiness is assumed to be normally distributed, Mexico is the happiest country and the top countries under the left-skew ranking fall to 10th place on average. If happiness is assumed to be right-skewed, Ghana becomes the happiest country and the small OECD countries that were at the top under the assumption of a left-skew distribution drop to 22nd place on average.

Of course researchers might assert that happiness is distributed in a particular way; for example, they could claim that it is normally distributed. Bond and Lang (2014) note that making such as assertion amounts to assuming the conclusion that is reached. The distribution of income is skewed to the right (that is, the mean is well above the median). Thus, if happiness is assumed to be normally distributed then, by construction, the marginal effect of income (or wealth) on happiness will tend to be strongly decreasing given the right skew in income and wealth. A large literature suggests that there are diminishing returns in the effect of income on happiness or life satisfaction (Layard 2005) but this literature rests on shaky foundations, since it depends on an assumption about the unknown functional form of the distribution of happiness. Thus, notwithstanding the problems with survey reports of monetary measures, such as consumption, there are likely to be even greater problems with measures of happiness and life satisfaction.

7. CONCLUSIONS

Rising affluence is good but it causes difficulties for survey measurement of living standards. The problems discussed in this paper – of food purchases changing from ingredients towards meals, of mismeasurement of the real value of the flow of services from housing, and of either ignoring spatial cost of living differences or measuring them with unit values that confuse a higher standard of living with a higher cost of living – are related by a common theme. This theme is the failure by the designers of most household surveys used in developing countries to adequately adapt to the generally more prosperous and more urbanized circumstances of the people whose lives they attempt to measure.

If a curious policy maker examined the household survey questionnaires used to provide the data on inequality and poverty that underpin assessment of progress toward national and global goals for inclusive growth and poverty reduction they may be surprised at how similar they are to what was used 30 to 40 years ago. The focus on food ingredients rather than prepared meals and on having a single person proxy report for the whole household ignores the enormous change in diets and eating habits bought about by rising affluence and the urban transition. The neglect of needed details for estimating the value of housing services and the variation over space in housing costs ignores the high income elasticity of housing and the emergence of spatially differentiated housing markets as countries get richer and more urban. The use of unit values as a proxy for food prices neglects the transformed supply chains with food increasingly shipped, stored and processed so that the relative price of quality varies over time and space and, thus, renders invalid the constant quality mix assumption needed if unit values are to proxy for the price level.

In fact, many policy makers seem incurious about data and so dead-end public debates, such as the Indian calorie debate (Smith, 2015), consume policy attention even if they are based on bad data. Yet without attention from policy makers it is unclear where impetus will come from for questioning if living standards are being measured in the most appropriate manner for the era that will be covered by the Sustainable Development Goals. The people of Asia and the Pacific deserve better from the statisticians and economists who supply the numbers used to gauge progress toward goals for poverty reduction and shared prosperity.

REFERENCES

Beegle, K., de Weerdt, J., Friedman, J., & Gibson, J. (2012). Methods of household consumption measurement through surveys: Experimental results from Tanzania' *Journal of Development Economics*, 98*(1)*, 3-18.

Bond, T. & Lang, K. (2014). The sad truth about happiness scales. *Working Paper* No. w19950, National Bureau of Economic Research.

Chen, S., & Ravallion, M. (2013). More relatively-poor people in a less absolutely-poor world. *Review of Income and Wealth*, *59*(1), 1-28.

Deaton, A. (2010). Price indices, inequality and the measurement of world poverty. *American Economic Review*, *100*(1), 5-34.

Deaton, A., & Dupriez, O. (2011). Purchasing power parity exchange rates for the global poor. *American Economic Journal: Applied Economics*, *3*(2), 137-166.

Dupriez, O., Smith, L., & Troubat, N. (2014). *Assessment of the Reliability and Relevance of the Food Data Collected in National Household Consumption and Expenditure Surveys*. FAO, IHSN and World Bank accessed 6 April 2014: http://www.ihsn.org/home/node/34

Gibson, J., & Kim, B. (2015). Hicksian separability does not hold over space: Implications for the design of household surveys and price questionnaires. *Journal of Development Economics*, *114*(1), 34-40.

Glaeser, E., Gottlieb, J., & Ziv, O. (2014). Unhappy cities. *Working Paper* No. w20291, National Bureau of Economic Research.

Jolliffe, D. (2006). Poverty, prices, and place: How sensitive is the spatial distribution of poverty to cost-of-living adjustments? *Economic Inquiry*, *44*(2), 296-310.

Jolliffe, D., Lanjouw, P., Chen, S., Kraay, A., Meyer, C., Negre, M., Prydz, E., Vakis, R., & Wethli, K. (2014). *A Measured Approach to Ending Poverty and Boosting Shared Prosperity: Concepts, Data and the Twin Goals* (Washington D.C.: World Bank)

Layard, R. (2005). *Happiness: Lessons from a New Science* (London: Penguin).

Li, C., & Gibson, J. (2014). Spatial price differences and inequality in the People's Republic of China: housing market evidence. *Asian Development Review*, *31*(1), 92-120.

Ma, H., Huang, J., Fuller, F., & Rozelle, S. (2006). Getting rich and eating out: consumption of food away from home in urban China. *Canadian Journal of Agricultural Economics, 54*(1), 101-119.

McCloskey, D. (2012). Happyism: The creepy new economics of pleasure. *The New Republic*, *8*.

Pinkovskiy, M., & Sala-i-Martin, X. (2014). Lights, Camera,... Income!: Estimating Poverty Using National Accounts, Survey Means, and Lights *Working Paper* No. w19831, National Bureau of Economic Research.

Ravallion, M., Chen, S., & Sangraula, P. (2007). New evidence on the urbanization of global poverty. *Population and Development Review*, *33*(4), 667-701.

Ravallion, M., Datt, G., & van de Walle, D. (1991). Quantifying absolute poverty in the developing world. *Review of Income and Wealth*, *37*(4), 345-361.

Ravallion, M., & Lokshin, M. (2001). Identifying welfare effects from subjective questions. *Economica*, *68*(271), 335-357

Ravallion, M. (2015). Toward better global poverty measures. *Journal of Economic Inequality* (forthcoming).

Reardon, T., Chen, K., Minten, B., & Adriano, L. (2012). *The Quiet Revolution in Staple Food Value Chains*. Asian Development Bank and International Food Policy Research Institute*,* Manila and Washington DC.

Smith, L. (2015). The great Indian calorie debate: Explaining rising undernourishment during India's rapid economic growth. *Food Policy*, *50*(1), 53-67.

Stiglitz, J., Sen, A., & Fitoussi, J. (2010). Report by the commission on the measurement of economic performance and social progress. *Paris: Commission on the Measurement of Economic Performance and Social Progress*.

World Bank (2012). *Well Begun, Not Yet Done: Vietnam's Remarkable Progress on Poverty Reduction and the Emerging Challenges*, World Bank: Hanoi.