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The Living Standards Dimension of the Human Development Index

Measuring Poverty with Big Data in China

This publication has been translated into Chinese. If there is any inconsistency or ambiguity between the English version and the Chinese version, the English version shall prevail. This report is published to elicit comments and further debate around the usefulness of big data for development.

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The Living Standards Dimension of the Human Development Index

Measuring Poverty with Big Data in China

United Nations Development Programme China

Foreword

Big Data continues to be one of the most discussed topics in recent years. Never before in human history has so much information been generated on a daily basis, bringing with it a whole host of new possibilities.

In 2014, UNDP published a working paper on '*Big Data for Development in China*' (2014) exploring the concept of its potential to help development practitioners. Through this new report, we hope to be able to take this concept of big data for development a step further and to promote its use for informing the work on Sustainable Development Goal 1: Eradicating poverty.

China has achieved unprecedented success in bringing a total of 700 million people out of poverty since 1978. Despite these staggering achievements there are still around 56 million people living below China's national poverty line today. Last year, the government announced its commitment to lift the remaining poor out of poverty by the year 2020. To achieve this ambitious goal it will require targeted solutions addressing the root causes of poverty.

In order to identify the causes of poverty, the definition and measurement of poverty must reflect its complex, multifaceted nature beyond only income and consumption based measures. Through this report, UNDP aims to develop a Living Standards Index with a multi-dimensional approach in mind, combining eight different indicators.

The use of big data for measuring poverty has the opportunity to play an increasing role to inform poverty alleviation policies. Turning insights collected from big data to complement official statistics and survey data, adding depth and nuances with more recent data, and thereby narrowing both information and time gaps.

It is important to recognize that big data is no modern cure-all for development challenges. Several challenges and considerations with big data must be kept in mind. With the speed and the dynamic sources of data we are aware of a possibility of an increasing margin of error. This report touches on some of them but hopes to illustrate that despite its limitations it serves to complement existing data and promote discussion.

This report is only the beginning, future research is already in the works to consider other dimensions such as health, education, public services and transportation with possibly in depth looks at specific provinces or counties. Our partnership with Baidu, which provided us with data, has helped us to appreciate the potential of big data to complement current strategies and information.

These are our first steps in using big data to measure poverty with new and more recent data and we hope that this work will be interesting and useful for everyone working on poverty alleviation, as we strive to work together to make the world a better place.

Patrick Haverman

Deputy Country Director

UNDP China

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This report has benefited from valuable comments from: Mr. Wang Xiaolin, Deputy Director-General of Information Centre of the State Council Leading Group Office of Poverty (LGOP) Alleviation and Development; Prof. Wang Sangui, Department of Agriculture and Rural Development, Renmin University of China; Ms. He Xiaojun, Former Deputy Director of the International Poverty Reduction Centre of China (IPRCC); Prof. Liu Jianjin, Senior Research Fellow at the Rural Development Institute, Chinese Academy of Social Sciences (CASS); Mr. Song Fuli, Vice President of The Institute of City and Government Affairs, the Economic Observer; Dr. Shen Yangyang, Postdoctoral fellow at the Oxford Poverty and Human Development Initiatives (OPHI).

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This report has also benefitted from an internal peer review process. Many thanks to colleagues in the Poverty, Equity and Governance Team (PEG), Policy and Partnership Unit (PPU), Environment and Energy (EE) and Communications team; special thanks to Ms. Samantha Anderson, Senior Adviser PEG for her useful comments and language editing. Thanks to Ms. Zhang Wei, Assistant Country Director; Ms. Li Xi, Communications and Innovation Officer; Ms. Nicole Huxley, International Communications Consultant; Ms. Li Liping, Program Associate PEG; Ms. Zhou Shuwen, National Consultant PEG; Mr. Niels Knudsen, Assistant Country Director; Mr. Wang Dong, Program Manager PPU; Dr. Zheng Yuan, National Economist PPU; Mr. Carsten Germen, Assistant Country Director; Ms. Zhu Ruoqi, Communications Assistant EE, and many thanks also go to Ms. Camille White and Mr. Chi Man Cheung who provided substantial inputs and support to the research team.

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List of Abbreviations

ADB	Asian Development Bank
Baidu	Baidu, Inc.
DMSP-OLS	Defense Meteorological Satellite Program Operational Linescan System
HDI	Human Development Index
HOI	Human Opportunities Index
MDG	Millennium Development Goals
NGDC	National Geophysical Data Centre
OPHI	Oxford Poverty and Human Development Initiatives
POI	Points of Interest
PPP	Purchasing Power Parity
SDK	Software Development Kit
SDG	Sustainable Development Goals
UN	United Nations
UNDP	United Nations Development Programme
UGC	User Generated Content
WHO	World Health Organization

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Executive Summary

KEY MESSAGES

- UNDP considers poverty to be a multifaceted phenomenon and is dedicated to measuring poverty beyond only the economic dimension. The Living Standards Dimension of the Human Development Index (Living Standards Index) offers an alternative perspective from which to review and track poverty. In collaboration with Baidu Big Data Laboratory, UNDP has developed this index as a tool, which harnesses unconventional sources of data to measure certain living standards linked to poverty at the county level across China.
- The dynamic, convenient and cost-effective information provided by big data analysis can improve poverty alleviation programmes by helping to locate poor communities, inform effective poverty alleviation programmes, monitor the progress and develop a better understanding of the root causes of poverty. These factors complement traditional household survey data, which furthers our identification and understanding of the conditions of the poor.
- The Living Standards Index, which is composed of eight indicators, gives insight into the availability of some public services in each of China's 2,284 counties. These can help provide detailed information for government, social organizations and the private sector to better allocate resources for poverty alleviation as well as help measure progress in combatting poverty.
- UNDP appreciates the important and scientific foundation of traditional poverty data analysis based on household survey, and considers big data to be a useful tool in informing poverty alleviation and other development efforts from a different timely perspective to follow the dynamic nature of poverty.
- The findings and analysis suggest that the Living Standards Index should be seen as a complementary measurement to income-based measures of poverty.

Due to rapid and continuous economic development and an increased number of poverty reduction programmes, China has achieved remarkable poverty alleviation progress during the past three decades. In order to achieve its stated policy to eradicate extreme poverty by the year 2020 as outlined in the 13th Five-Year Plan (2016-2020), the Chinese government must target its poverty alleviation programmes for maximum effectiveness.

UNDP considers poverty to be a multifaceted phenomenon and is dedicated to measuring poverty beyond only the economic dimension. In collaboration with Baidu Big Data Laboratory, UNDP has developed the Living Standards Dimension of the Human Development Index (otherwise called the Living Standards Index). The Living Standards Index, which harnesses unconventional sources of data to measure poverty at the county level across China, offers an alternative perspective from which to review and track poverty. The eight indicators that make up the Index combine three from census data and five from Baidu's big data sets. The census indicators are: access to piped water, access to sanitary toilets, and access to indoor kitchens. The indicators from Baidu's big data sets are: access to living services, access to financial services access to roads, mobile internet coverage and nighttime light density. This tool can help to give insight into the provision of public services, and private amenities in each of China's counties. Together, it can help to provide detailed information for government, social organizations and the private sector to better allocate resources to poverty alleviation as well as be able to measure the progress of poverty alleviation efforts.

The findings and analysis suggest that the Living Standards Index should be seen as a complementary measurement instead of a replacement to income-based measures of poverty. Income measured poverty does capture the economic aspects of poverty but cannot accurately reflect the social aspects of poverty. In order to measure the economic and living conditions aspects of poverty, taking into consideration both income measured poverty and the Living Standards Index will help develop more comprehensive policy responses. Our findings are summarized in the form of poverty maps and poverty dashboards, which give detailed information on living conditions in all counties across China.

First, the Living Standards Index finds that there are gaps in the living standards between eastern and western counties, and between coastal and inland counties. These measures confirm the existing view that western and mountainous counties are among the poorest areas in China.

Second, the Living Standards Index supplements analysis based on conventional data with a more detailed understanding of the variation in living standards in these impoverished areas. The Living Standards Index poverty map suggests that counties in the eastern part of China have more access to services and amenities than western counties. Furthermore, for coastal counties, the northeast does not perform as well as the south. In the centre of China, counties in the plain areas have higher living standards than mountainous counties. We also compare the bottom Living Standards Index poor counties with National Poor Counties as defined by the Central Government. The overlap rate is 63%.

Third, unsurprisingly, the Living Standards Index dashboard shows that the most economically developed counties, particularly those along the coast of China, also perform best in terms of living standards. Yet this does not mean they all have achieved sustainable and equitable development across the different aspects of the Living Standards Index. By uncovering the particular areas of strengths and weaknesses in each county, we hope that this information can be helpful for future programmes to strengthen access to the services and amenities identified in the Index. The findings suggest significant variation in living standards within poor regions, indicating that different programmes could target the particular needs of each county.

Our findings support the existing policy of focusing the majority of poverty alleviation resources on western and inland areas. Our analysis complements this approach by uncovering and underscoring the differences between poor counties. As is evident in the poverty maps and poverty dashboard, each province and county has its own strengths and weaknesses in terms of poverty reduction and sustainable development. Therefore, poverty reduction policies and programs can become more effective if we develop better understandings of the sources of poverty in each case.

By using new sources of data to measure poverty in China, this report demonstrates how big data may be used for development. This research demonstrates that big data is a promising source of information for reviewing and tracking poverty and development. The dynamic, convenient and cost-effective information provided by big data analysis can complement traditional approaches such as household survey data. It can help improve or refine poverty alleviation programmes by helping locate poor communities and provide an additional monitoring tool. This could support the identification of new effective poverty alleviation programmes and develop further understanding of the root causes of poverty.

However, as our understanding of big data is just a first step, we realize some shortcomings of the research. The data comes from different sources, the analysis is not able to maintain a consistent observation period across indicators due to data availability. The total number of observations in this study is 2,284 counties which deviates from official statistics. The analysis based on poverty mapping takes place at the county level. The research does not consider individual or household-level indicators, which means that there may be intra-county variation that is not captured by the research.

With the publication of this report, the UNDP seeks to embrace these new sources of data and encourage our partners and other parties to harness the potential of big data for development.

ONE
INTRODUCTION

1. Introduction

KEY POINTS

- Since 1978, China has made significant progress towards reducing poverty.
- The current commitment to eradicate extreme poverty by the year 2020 will require that resources are directed to the areas most in need to target the root causes of poverty.
- In order to identify the causes of poverty, we recommend a multidimensional approach to poverty reduction. This report presents the new Living Standards Index, which combines eight indicators related to poverty.
- This report aims to show how big data can complement conventional data sources and serve as a convenient, dynamic and economic way of tracking poverty alleviation progress.

1.1 Poverty in China

Due to rapid and continuous economic development and an increased number of poverty reduction programmes, from 1978 to 2014, China successfully lifted a total of 700 million poor rural people out of poverty (Yearbook of China's Poverty Alleviation and Development, 2015). This achievement made China the first developing country in the world to achieve the poverty reduction target of the Millennium Development Goals (MDGs) making a remarkable contribution to global poverty reduction efforts.

However, in 2015, China still had approximately 56 million people living under the national poverty line of RMB 2,300 (2010 PPP) annual net income per capita for rural residency (UNDP, 2016). In September 2015, the 193 United Nations member states adopted the 2030 Agenda for Sustainable Development, including the 17 Sustainable Development Goals (SDGs) which set targets for development over the next 15 years. The SDGs take eliminating poverty as their primary goal (SDG1) and call for an end to poverty in all forms everywhere by 2030. Echoing this, at the 2015 Global Poverty Reduction and Development Forum, Chinese President Xi Jinping stated that China would intensify its poverty reduction efforts and lift all remaining poor out of poverty by the year 2020 (Fang, 2015). This commitment was reinforced and extended in China's 13th Five-Year Plan (2016-2020) on National Economic and Social Development, which endeavours to eradicate extreme poverty in China by 2020 (Ma and Xiao, 2016).

In order to achieve this ambitious target, poverty alleviation efforts must be informed and guided by increasingly accurate data. While the 56 million people living in extreme poverty in China today face common disadvantages, their experiences of poverty are diverse. The remaining poor are largely clustered in remote and isolated rural areas– especially in mountainous areas in China's central and western provinces, and they have been excluded from the fast-paced growth of economic development in China's eastern and urban areas.

To ensure effective and sustainable poverty alleviation, we need to understand these diverse experiences. Poverty cannot be understood simply in terms of income and consumption; conversely, it is a multifaceted reality. Since the 1990s, the UNDP has sought to better reflect this reality by adopting a human development approach, which encompasses health, education, access to knowledge and communications technology, human and political rights, dignity, confidence, and self-respect (UNDP, 1997). Using this comprehensive conception of poverty, we can better reflect the lived experience of poverty and identify its root causes to target areas of greatest need.

With a better understanding of poverty comes a need for better measurements of poverty. Equipped with a multidimensional view of poverty, our report collates nation-wide data to capture the different facets of life for poor communities. Our findings are summarized in national poverty maps and a poverty dashboard displaying the Living Standards Index, revealing differences in the causes and circumstances of poverty in China.

The Living Standards Index is intended to supplement existing income-based measure of poverty. Taken together, these measures can help target poverty alleviation. By harnessing the power of big data, we can further understand the sources of poverty to eradicate extreme poverty by 2020.

In this report, Chapter One discusses existing measures of poverty and outlines the benefits of supplementing these with the Living Standards Index. This also gives an overview of big data and its uses in development. Chapter Two introduces the data sources, indicators, and the Living Standards Index. The eight indicators are: access to sanitary toilets, access to indoor kitchens, and access to piped water, mobile internet coverage, living services coverage, road coverage, nighttime light density, and financial services coverage. The first three of the indicators are assessed using a conventional data source, the 2010 Chinese Census, while the other 5 indicators comes from satellite imagery, mobile phone usage data, and Baidu Points of Interest data.

As this is the first research done by UNDP China using big data and given that big data is fast, dynamic and cost effective, there may be more issues with accuracy or the margin of error, therefore the discussions about the index and an explanation of the methodology and especially the limitations of the research can be found in Chapter Three. Chapter Four considers the findings of the research for each of the eight different indicators in turn. For each indicator, findings are presented in national "poverty maps" and analysed at the provincial and county level. Chapter Five combines these indicators into the new Living Standards Index. The findings are presented in poverty maps and a poverty "dashboard" for further analysis. In addition, the Living Standards Index is used to evaluate the National Poor Counties as defined by the Chinese government. As part of the analysis, the Living Standards Index is used to identify counties that perform poorly with regards to living standards and examine the root causes of poverty in each province. Chapter Six provides the conclusions and recommendations based on the findings.

1.2 Defining and measuring poverty

The definition of poverty usually refers to deprivations in well-being that result in an inability to meet basic needs due to insufficient income or wealth of individuals or families (World Bank, 2000). This 'basic needs' approach is one of the major approaches to the measurement of absolute poverty in developing countries. The measurement of poverty is a type of measurement of the income or consumption necessary to meet certain basic needs (poverty line), including food and nonfood needs (Haughton and Khandker, 2009). While the most commonly used measures of poverty are based on income or consumption, more and more research indicates that poverty is a multifaceted problem (UNDP, 2010).

According to Nobel Laureate Amartya Sen, poverty is not captured by the mere lack of income to meet basic needs, but deprivations in basic human capabilities (Sen, 1992). Poverty can be understood as the deprivations in basic capabilities of individuals or families; the deprivation is multidimensional and includes premature death, obvious malnutrition, persistent disease and widespread illiteracy, etc. (Sen, 2000). The United Nations defines poverty as "a condition characterized by severe deprivation of basic human needs, including food, safe drinking water, sanitation facilities, health, shelter, education and information." (UN, 1995).

Therefore, poverty is closely related to income, but also to access to social services and other "opportunities of living" that may not be captured by an exclusive focus on income. For example, an increase in income might obscure a decrease in the quality of facilities or services. Moreover, according to the Oxford Poverty & Human Development Initiative, poor people themselves describe their experience of poverty as multidimensional. Our definition and measurement of poverty must reflect this reality in order to address it. Thus, in addition to economic growth as measured by GDP, success in poverty alleviation also requires taking transformational solutions in scale, whether in terms of programs to improve sanitation in burgeoning cities, projects to ensure more efficient use of water for farming and other purposes, or expansion of health coverage for lower-income people (World Bank Group, 2014).

For this reason, multidimensional poverty measures have been applied in Sub-Saharan Africa, Columbia, China, Germany, Iran, Sudan, and elsewhere (Alkire and Haosseini, 2014; Suppa, 2015; amongst others). For example, in Latin America and the Caribbean, the World Bank Group and its partners use the Human Opportunity Index to measure how equitably basic services are distributed among different segments of the population, in order to pinpoint where gaps persist (World Bank, 2014).

The Chinese government's conception of poverty has considered poverty primarily in terms of income, i.e. "the cost of a basic minimum subsistence package of food plus a proportionate amount for essential non-food items." The government classifies individuals as poor "if either their annual per capita net income or their annual per capita consumption expenditure is below the official poverty line." (ADB, 2004). However, in its Opinions on Establishing the Poverty Exit Mechanism in 2016, the Chinese government proposes to guarantee the basic needs of those living in poverty with enough food and clothes, and ensure that they have adequate access to education, medical services and housing, whilst working on raising their income above the poverty line. With the multidimensional measure of poverty, about 20% of urban and rural families in China are experiencing multidimensional poverty according to research conducted in 2009 (Yearbook of China's Poverty Alleviation and Development, 2015), which makes it more meaningful to study poverty with a multidimensional approach. In light of these findings, this report adopts a multidimensional measure of poverty.

Since China's rural poverty is still significant, the remaining poor population has obvious regional characteristics (Liu et al., 2014). Therefore, the targeted poverty alleviation programme in China still needs to give priority to specific regions for some time (Liu and Xu, 2015). As well, in its Outline of Poverty Alleviation and Development in Rural Areas of China 2011-2020, particularly under the section of poverty alleviation in concentrated contiguous destitute areas, the Chinese Government states that each province needs to develop and implement Poverty Alleviation Project Planning at the county level under the guidance from the Central Government. This report adopts analysis units at the county level.

Since 2010, the UNDP has also adopted a multidimensional measure poverty as part of its Human Development Index analysis. The Human Development Index, first created in recognition that development means more than only increased income, has measured country performance on indicators of health, education, and income since 1990, while the Global Multidimensional Poverty Index, first applied in 2010, measures performance through an expanded set of indicators grouped under similar dimensions as the HDI: health, education, and standard of living. This report follows the living standards dimension of the Multidimensional Poverty Index in constructing a new measure for poverty in China. There are two reasons for the report's focus on living standards. First, there is a gap in the literature on poverty in China vis-à-vis living standards, which we hope this report will help address. Second, countrywide data on health and education available were not analysed at the same level of detail as the living standards indicators. For now, this research will focus on living standards, but it is anticipated that future research will extend this approach to the areas of health and education.

To assess the living standards dimension of poverty, we have selected eight indicators encompassing key determinants of an individual's quality of life. For the purposes of analysis and comparison, we aggregate the eight indicators into one compound index, which we have termed "the Living Standards Dimension of the Human Development Index (Living Standards Index)".

The Living Standards Index measures people's living standards in a way that can complement income-based measurements of poverty. Conventional unidimensional measures of poverty are easy to understand and to compare, but they overlook interrelated features of poverty, and underestimate the importance of trends in these other dimensions. Multidimensional measures of poverty like the Living Standards Index can provide decision-makers with more policy-relevant information.

However, without accurate and comprehensive data, it can be very difficult to operationalise multidimensional conceptions of poverty. In order to measure living standards, this research draws on innovative sources of big data, thereby yielding a picture of poverty based on living standards in China.

1.3 Using big data for development

According to the Gartner IT Glossary, a widely-accepted definition of big data refers to high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation. Using big data for development purposes requires that we turn imperfect, complex and often unstructured data into actionable information that can unveil trends and patterns within and between these datasets (UNDP, 2012). Big data has been used intensively in industry to help companies make more informed business decisions, and it also shows potential in the field of international development (UN Pulse, 2012).

In recent years, more and more development projects have used big data to solve development issues in many different ways all around the world. The use of big data has been championed by the UN Global Pulse, an initiative launched by the UN Secretary-General in 2009. Some of the projects conducted under the auspices of the UN Global Pulse include the use of nighttime satellite images of the globe in 2009 to estimate poverty, the use of cellphone records to draw poverty maps in 2013-14 in Cote d'Ivoire, and the use of internet-based data to estimate the consumer price index and poverty rate in Argentina in 2013 (Letouze, 2015). The UNDP in Sudan has used nighttime light data and household electricity consumption to construct a poverty index (Thapa, 2016).

Internet usage data was also used in Argentina to design a price index and cellphone usage data has been used to study migration in Rwanda and Afghanistan (BPP, 2014; Blumenstock and Donaldson, 2013). In Rio de Janeiro, satellite imagery has been used to forecast weather patterns (Treinish, 2014). These are just a few examples of the variety of ways in which big data has been used to inform development.

Extensive academic research, including research undertaken by Bundervoet and Maiyo (2015), Thapa (2016), and Cheng (2014), has further discussed and demonstrated the benefits of big data for development, particularly for better understanding and mapping poverty.

From all these examples, it is clear that big data can be of service to development programs by serving as a proxy for, and a complement to, conventional official statistics. Compared with the onerous and costly conventional methods of poverty mapping using periodic social surveys and censuses, big data is a relatively quick, economical, and dynamic source of information on people's well-being.

In this report, we use big data to measure living conditions in more detail by filling gaps in official statistics, including mobile usage and financial development. In addition to enlarging the scope of research, big data can also enable analysis at different regional levels. In this report we focus on the county level.

TWO
THE LIVING STANDARDS INDEX

2. The Living Standards Index

KEY POINTS

- The Living Standards Index is a measure of poverty that combines eight indicators of living standards, drawing on the Living Standards Dimension of the Human Development Index.
- The eight indicators are: access to sanitary toilets, access to indoor kitchens, and access to piped water, access to living services, access to financial services, access to roads, mobile internet coverage and nighttime light density.
- The living standards indicators are measured using a combination of conventional and new big data sources.

Following the HDI framework and existing literature on the uses of big data for development purposes, we select eight indicators of living standards: toilets, kitchens, water, mobile internet, living services, road infrastructure, nighttime light density, and financial services. Three of the indicators are assessed using a conventional data source, the 2010 Chinese Census, while evidence for the remainder of the indicators comes from satellite imagery, mobile phone usage data, and Baidu Points of Interest data. These data sources are all commonly used in big data literature and have been found to be feasible and reliable. However, no other literature concerning Chinese poverty has used such data to the best of our knowledge. We hope that, by combining new data and a solid theoretical framework, this research can contribute to the tracking and review of poverty alleviation in China and may serve as a reference point for the use of big data for development.

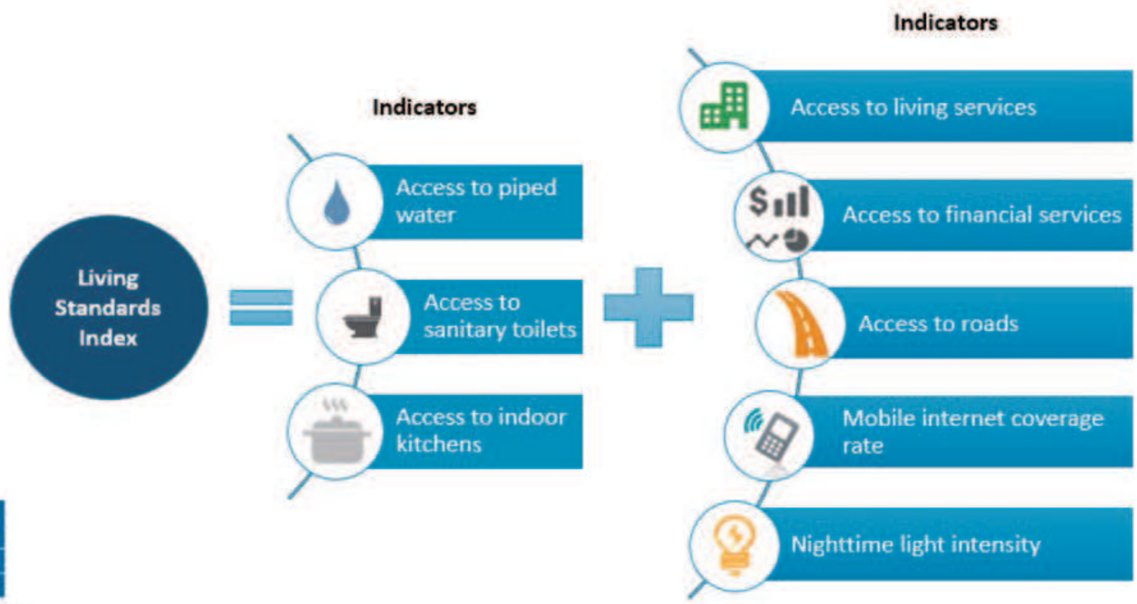

Figure 1 The Living Standards Index and Indicators

2.1 Eight indicators of living standards

In order to measure people's living conditions, we select eight indicators that cover important elements of well-being.

The indicators measured are in line with the Human Development Index. The report uses the percentage of households with access to piped water, kitchen facilities, and toilets as indicators of access to piped water and sanitation. For electricity, this is measured using nighttime light density (labelled "night light") to serve as a proxy indicator for electricity use, which is a measure both of living standards and economic activity.

In addition to these conventional indicators, the report also proposes several indicators that capture new aspects of living conditions: availability of local services, financial services coverage, road infrastructure and mobile internet coverage. The addition of these indicators distinguishes the Living Standards Index from the HDI and may provide further information for policy-makers on the availability of important facilities in poor communities.

2.2 Combining conventional and big data

The report uses conventional data, namely the 2010 Chinese Census, where this data is available and reliable. This is complemented by the use of big data to measure the remaining indicators. A detailed list of the sources of data for each indicator is presented below:

Indicator	Source	Year
1. Access to piped water	China Sixth Census Data	2010
2. Access to sanitary toilets	China Sixth Census Data	2010
3. Access to indoor kitchens	China Sixth Census Data	2010
4. Access to living services	Baidu POI Data*	2015
5. Access to financial services	Baidu POI Data*	2015
6. Access to roads	Baidu Map Road Network Data*	2015
7. Mobile internet coverage	Baidu positioning data*	2013
8. Nighttime light density	Defense Meteorological Satellite Program– Operational Linescan System (DMSP-OLS) dataset NOAA*	2013

Table 1 Living standards indicators and data sources *Indicates new data source

2.3 Conventional data

Indicators 1, 2 and 3 are measured using China's Sixth Population Census conducted in 2010. Despite the six years that have passed since this data was collected and the rapid pace of change in China, this remains the most current and comprehensive source of data for these indicators.

By using new sources of data to measure poverty in China, this report demonstrates how big data may be used for development. This research demonstrates that big data is a promising source of information for reviewing and tracking poverty and development. The dynamic, convenient and cost-effective information provided by big data analysis can complement traditional approaches such as household survey data. It can help improve or refine poverty alleviation programmes by helping locate poor communities and provide an additional monitoring tool. This could support the identification of new effective poverty alleviation programmes and develop further understanding of the root causes of poverty.

However, as our understanding of big data is just a first step, we realize some shortcomings of the research. The data comes from different sources, the analysis is not able to maintain a consistent observation period across indicators due to data availability. The total number of observations in this study is 2,284 counties which deviates from official statistics. The analysis based on poverty mapping takes place at the county level. The research does not consider individual or household-level indicators, which means that there may be intra-county variation that is not captured by the research.

With the publication of this report, the UNDP seeks to embrace these new sources of data and encourage our partners and other parties to harness the potential of big data for development.

dung and poor living standards, including respiratory problems and increased child mortality. (Balakrishnan et al., 2004; Boadi and Kuitunen, 2005; amongst others) Goal 7.1 of the SDGs aims for affordable and reliable modern energy sources to be adopted globally, which may be understood to include cooking fuels. Access to indoor kitchen facilities is a proxy measure for the use of safe fuels as families can be supposed to prefer modern fuels when cooking indoors. Thus, in addition to the added convenience of cooking indoors, indoor kitchens also indicate increased use of modern fuels, and thus improved living standards.

2.4 New data sources

Indicators 4, 5, 6 and 7 are measured using data from Baidu. One of the biggest Chinese digital services providers, Baidu is particularly well known for its search engine, which as the most popular in China, occupies 78% of the search engine market share as of 2015 (Stat Counter, 2016). Baidu also offers many other online services, including Baidu Maps, which will be our focus. Most of the data we consider here was generated by Baidu users map services.

Indicators 4 and 5 are measured using Baidu Points of Interest (POI) data. Baidu POIs are specific point locations that are classified into different categories by Baidu. Each data is labelled with different tags after duplicates removal and data verification. Each POI data bears coordinate and category information. The whole dataset comprises about 50 million POIs, which are sorted into 30 categories and 240 subcategories. In the report we use POIs from the living facilities and financial services categories. We can obtain the numerators for living services and financial services by counting the number of POI categories for each county.

To measure access to living services in a given area, we use the density of POIs in the relevant category within that region. Living services are herein defined as newsstands, funeral services, lottery stands, pet services, real estate agencies, public utilities (electricity company, gas company and water supply company), housekeeping, ticket offices, telecommunication business halls, express printing services, repair services, logistics companies, laundry shops, post offices, photo studios, etc.

The living services indicator is a new indicator of living standards based on a new source of data that has not previously been used in China. Nonetheless, this indicator is supported by current thinking on how to best conceive of living standards. For example, living facilities can be included under Goal 1.4 of the SDGs, which states, "By 2030, ensure that all men and women, in particular, the poor and the vulnerable, have equal... access to basic services." (UN, 2016). The density of living facilities can be understood as an indicator of the ease of access to these facilities, and, indirectly, as an indicator of the improvements in quality of life brought about by such facilities. For example, a person's quality of life will be improved if they can easily access a post office. Clearly, ease of access to such services suggests that a person will benefit from improved sanitation, mobility, and community life.

To measure access to financial services within a given region, we used the density of POIs in the banks, ATM and credit cooperatives category. Access to financial services is a key element of living standards which is included in both Goal 1.4 (equal access to services) and Goal 2.3 (doubling agricultural productivity) of the SDGs. It is also relevant to a variety of other SDGs including Goal

5.a (gender equality), Goals 8.3 and 8.10 (sustainable, inclusive growth) and Goal 9.3 (infrastructure and industrialisation). This is supported by a review of the existing research conducted at the University of London in 2012, which found that improving people's access to banking services can raise incomes and help people work their way out of poverty (Pande et al., 2012).

Indicator 4: Access to living services

Number of living services per km^2 per capita = $\frac{Number\ of\ living\ services\ POIs\ in\ one\ county}{County\ area\ (km^2) * County\ population}$

Indicator 5: Access to financial services

Number of ATMs & banks per km^2 per capita = $\frac{Number\ of\ ATMs\ and\ bank\ POIs\ in\ one\ county}{County\ area\ (km^2) * County\ population}$

Moving to the sixth indicator, access to good quality roads enhances both Goal 9.1 of the SDGs regarding quality, reliable, sustainable infrastructure, and Goal 11.2 concerning access to safe, affordable, accessible and sustainable transport systems for all. The Asian Development Bank's 2002 analysis of the impact of rural roads on poverty reduction confirmed that roads are "a critical enabling condition for improvement of living conditions in rural areas" in Asia (ADB, 2002). Road quality affects the living standards of the poor because their journeys are primarily for subsistence tasks and they lack time and energy, so improvements in road quality help them save valuable time and energy in accessing essential services.

Investment in transport infrastructure can also create economic opportunities indirectly by "improving the conditions and opportunities for marketing goods and services, reducing input prices, opening opportunities in new markets, and offering seasonal migration opportunities for work"(ADB, 2002).

Other studies have confirmed that better roads improve living standards (Khandker et al., 2006). However, it should be noted that this is only one indicator of the transport aspect of living standards, which is also affected by access to "wheeled or motorized transport to utilize a road". (Bryceson et al., 2006).

The cumulative length of the roads per km^2 per capita is calculated by using Baidu Maps Road Network Data from 2015. These suppliers obtain raw data through mapping. The dataset accounts for variation in the quality of roads by assigning to each a score from 1 to 5: the higher the number, the better the roads. In particular, national roads are assigned higher values than provincial roads. When calculating the total length of roads at the county level, Baidu applies weights according to the quality of the road (higher quality scores imply higher weights). After the weighted length of the roads within each county is obtained, the road indicator is calculated using the following formula:

Indicator 6: Access to roads

Cumulative length of roads per km^{2}per capita = $\frac{Total\ length\ of\ road}{County\ area\ (km^2) * County\ population}$

Goal 9.c of the SDGs concerns access to information and communications technology and commits member states to "strive to provide universal and affordable access to internet in least developed countries by 2020" (UN, 2016). Goals 17.6 and 17.8 regarding the Global Partnership for Sustainable Development also consider indicators based on the proportion of individuals using the internet. Mobile internet coverage represents an important indicator of these goals.

Access to mobile phones "may reduce information asymmetries, enabling users to access arbitrage, market or trade opportunities that they otherwise would have missed out on." (Bhavnani et al., 2008; Side et al., 2010) Improved information and access to market opportunities, thanks to mobile phones, can increase the capacity of individuals to earn their way out of poverty and help lift living standards in impoverished communities. (Aker and Mbiti, 2010). Mobile phones can also improve living standards by aiding in disaster relief and facilitating the dissemination of education and health information (Guerriero, 2015).

Internet access, in particular, has been found to have a positive effect on educational attainment (Chowdry, 2010) which is positively correlated with living standards. Therefore, mobile internet coverage is an important indicator of individuals' economic and educational opportunities and access to mobile internet brings with it many additional benefits for living standards.

This indicator uses scaled Baidu users as the numerator divided by county population. Since Baidu assumes users account for 80% of the total number of mobile internet users in a given year, the number of mobile internet users in a county is equal to its number of Baidu users multiplied by 1.25, an estimated index. Given that either the numerator or the denominator keeps changing, the index estimates will not affect the ranking of the indicator.

As one of the most popular online map service providers in China, Baidu Maps provides positioning services for hundreds of millions of users, generating tens of billions of location requests every day. The rate of mobile internet coverage uses geo-positioning data. Users use the Software Development Kit (SDK) service based on Baidu's geo-positioning and the SDK will propagate the corresponding positioning data. Each location point includes an anonymized user ID, a coordinate (longitude and latitude) and a timestamp.

Calculating mobile internet coverage requires determining which county a user lives in. For this report, the number of mobile internet users is calculated through identifying the name of the county in which the users use the maximum number of mobile geo-positioning services in the fourth quarter of 2013, excluding weekends and festivals, in order to focus on typical usage at home and work. The users are assigned to a particular county based on their most common locations according to their geo-positioning records. By summing up the number of users within one county and scaling the total number of mobile users to 500 million, Baidu generated an estimate for the total number of mobile internet users in each county. To calculate the coverage rate, the number of users within each county is divided by the county population:

Indicator 7: Mobile internet coverage

Mobile internet coverage = $\frac{\textit{Number of users of Baidu location services}}{\textit{County population}}$

Nighttime light density has been commonly used as a proxy measure of economic growth at the national and subnational level (Chen and Nordhaus, 2011). For example, a 2015 World Bank study of Kenya and Rwanda found a "strong and robust link between growth in night lights and growth in GDP" (Bunderviet et al., 2015). Conversely, UNDP Sudan has found that nighttime lights are a good proxy for poverty (Thapa, 2016). Similar research has been conducted in China comparing nighttime light and multidimensional poverty indexes (Wen et al., 2012).

Besides serving as an indicator of growth and poverty, nighttime lighting relate directly to Goal 7.1 of the SDGs, which commits to providing access to affordable, reliable and modern energy services to all by 2030. Nighttime lights therefore serve as an indirect indicator of living standards both in terms of economic development and access to modern energy services.

The night light data are obtained from the Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS) dataset NOAA 2013. The National Geophysical Data Centre (NGDC) process imaging data were collected by DMSP-OLS, removing intense sources of natural light to leave mostly man-made light. The data from every orbit of a given satellite in a given year is averaged over all valid nights to produce a satellite-year dataset. The data used in this report is a satellite-year dataset from 2013. This is the most recent yearly data available. Each satellite-year dataset is a grid reporting the intensity of lights as an integer between 0 and 63. We calculate the sum of the light intensity within one region and divide by the area and population:

Indicator 8: Nighttime light density

Night light per km^2 per capita = $\frac{\textit{Sum of nighttime light intensity within one county}}{\textit{County area } (km^2) * \textit{County population}}$

In using the datasets and methodologies described above, the research team looked at the aggregate picture for each county. It did not examine or retain information about individual users.

THREE
METHODOLOGY

3. Methodology

KEY POINTS

- In order to consolidate the eight indicators of living standards into the Living Standards Index, we
    1. Performed statistical tests for normality and scale transformation;
    2. Normalized the scores to 0-100;
    3. Aggregated the indicators.
- The data sources used in this report cover different time periods, but each source provides the most recent available data. The different data collection methods used may lead to some biases in the data.
- Our findings may differ from other sources due to the units we consider and our selection methods.

3.1 Statistical tests and scale transformation

Before the indicators were normalized, statistical tests were conducted to check the distribution of each indicator. The normal distribution hypothesis was rejected for all indicators at a 5% significance level. Some of the indicators have a very wide range and are positively skewed due to the considerably unbalanced development between rural and urban areas. To reduce the positive skew of the data, we applied a log transformation to the following indicators: mobile coverage rate, number of living services, number of ATMs & banks, length of roads and night light density. We were concerned about these positively skewed indicators because the normalization method used in the second step is sensitive to extreme values. Log transformation helps shrink the heavy right tail of the distribution and thus diminishes the effect of extreme values.

3.2 Normalization using the min-max method

Since the indicators are measured in different units, in order to aggregate them as a composite index, we first needed to normalize the data. An often-used method for normalization is to transform the data linearly along a range of 0-1 by subtracting the minimum value and dividing by the range of the indicator values (OECD, 2008). For the index, we followed this method but with a small adjustment for the purposes of our research, i.e., the data was transformed to a range of 0-100 instead of 0-1 to allow for a better comparison between counties and a more straightforward interpretation. One can consider this 0-100 range to be analogous to a test score, where 0 denotes the worst performance and 100 denotes the best.

In the aggregation stage, we calculated the geometric mean of the eight indicators to produce the final index. Using the geometric mean implies that a value of 0 on any indicator would lead to a 0 in the final index, which would over-penalize counties with poor performance on a single indicator. To avoid scores of 0 after normalization, we add two hypothetical counties to the data. One is assigned to be the "best-performing" county, with values greater than each indicator's upper bound. The second is constructed as the "worst-performing" county, with values lower than the lower bounds for each distribution. These hypothetical counties automatically receive the 0 and 100 scores, leaving the real counties within the range of 0-100 (not inclusive). With this small change, we ensure that no (real) county is penalized in the final index.

Indicator score = $\frac{(x-min)*100}{max-min}$

3.3 Aggregating the indicators

Each of the eight indicators is assigned an equal weight in the index. While the indicators may not represent equally important determinants of living standards, the choice was made to weigh them equally in the Living Standards Index, rather than seek to assign subjective weights to each.

The method used to aggregate indicators is geometric aggregation. This method is preferred to additive aggregation, as the latter would allow for poor performance on some indicators to be compensated for by high values in other indicators. Given that all eight indicators attempt to describe different (but equally important) aspects of living standards, it would not be appropriate for high values on one indicator to balance low values on another, as they are not substitutable. Instead, we chose to use geometric aggregation, which penalizes counties where the scores were not balanced across all indicators. Finally, when calculating the geometric mean, all eight variables are assigned equal weight.

After aggregation, the Living Standards Index takes values from 0-100, where a score of 70, for example, signifies that on average the county stands 70% of the way from worst to best across the indicators.

Index value=$\sqrt[8]{(indicator1 * indicator2 \dots indicator8)}$

3.4 Disclaimers

First, the data comes from different sources: China's Sixth Census, Baidu and NOAA. The analysis uses the most recent available data for each indicator but is not able to maintain a consistent observation period across indicators due to data availability. These datasets may also differ in their inherent sampling biases. For example, data collected from Baidu users may not be representative of the general population.

Second, the base map of China is from Baidu Big Data Lab which has been generated based on World Bank Puma Data in 2010-2013. The analysis based on poverty mapping takes place at the county level. The total number of observations in this study is 2,284 counties. This number deviates from official statistics. This is because the analysis merges all districts located within the same city into a single unit, rather than distinguishes them, as the focus is primarily on comparing counties in rural areas. For example, official statistics regard Beijing as 14 separate districts and 2 counties. In this analysis, they are considered as three county-level administrative areas.

Third, bias may arise in measuring certain indicators, such as the number of living services or financial services per square kilometer per capita. This choice was based on previous research and our own preliminary findings, which showed that scoring these indicators using population data overestimates their accessibility in sparsely populated counties, erroneously suggesting high living standards in these areas or using geographic density data underestimates their accessibility in sparsely populated counties, suggesting low living standards in these areas. Therefore, the geographic area, multiplied by the population, was used as the denominator rather than the sole population density or geographic area in order to ensure that living standards were not overestimated or underestimated on these indicators.

Fourth, the selection method for identifying poor counties is not the same as the method adopted by government agencies in identifying National Poor Counties and it may therefore lead to some differences in the findings.

Fifth, the research does not consider individual, or household-level, indicators, which means that there may be intra-county variation that is not captured by the research. Taking counties as the unit of analysis also represents a break with the Capability Approach to poverty, which focuses on individual- or household-level deprivation.

Finally, this study is not able to analyze living standards in Hong Kong, Taiwan and Macao due to data constraints.

In addition, three caveats should be stated before proceeding with the report. First, the analysis in the report is conducted at the county level instead of at the household level or individual level in order to better address the general provision of services. Thus, the target audience for the report does not include poverty reduction programs targeting specific groups of poor people, which operate with a different perspective and from a different level of analysis.

Second, when conducting horizontal comparisons between different counties using the data provided, we caution against the use of the data without consideration of particular local contexts. Policies should be formulated with attention to additional local factors that may not have been controlled for in our analysis. For example, if County A falls below County B on the road coverage indicator, this only means that County A has fewer roads than County B, but not necessarily that County A needs more roads.

Third, the focus here is on the living standards dimension of poverty, for two reasons. First, there is a gap in the literature on poverty in China regarding living standards, which we hope this report will help address; second, we were not able to acquire countrywide data on health and education at the same level of detail and analysis as on the living standards indicators. For the time being, we focus on the living standards dimension of the Human Development Index, but we anticipate that future research will extend our approach to the areas of health and education.

FOUR
FINDINGS BY INDICATORS

4. Findings by Indicators

While the Living Standards Index provides a concise summary of living standards across China, we will first consider our findings for each of the eight indicators that make up the index. The Living Standards Index can be a powerful tool for targeting poverty alleviation, but each indicator also contains valuable information that can be used to understand and address people's living conditions. In the following section, we will consider each of the indicators, using maps and charts to present our findings at three administrative levels: national, provincial, and county.

In the map, we divided the 2,284 counties into seven equal parts according to the size of each indicator, and mark each part with a different shade of blue. The darker the blue, the greater value of the indicator, which means that the county had better performance for the indicator, and that it ranked higher.

4.1 Access to piped water

4.1.1 Analysis at the National Level

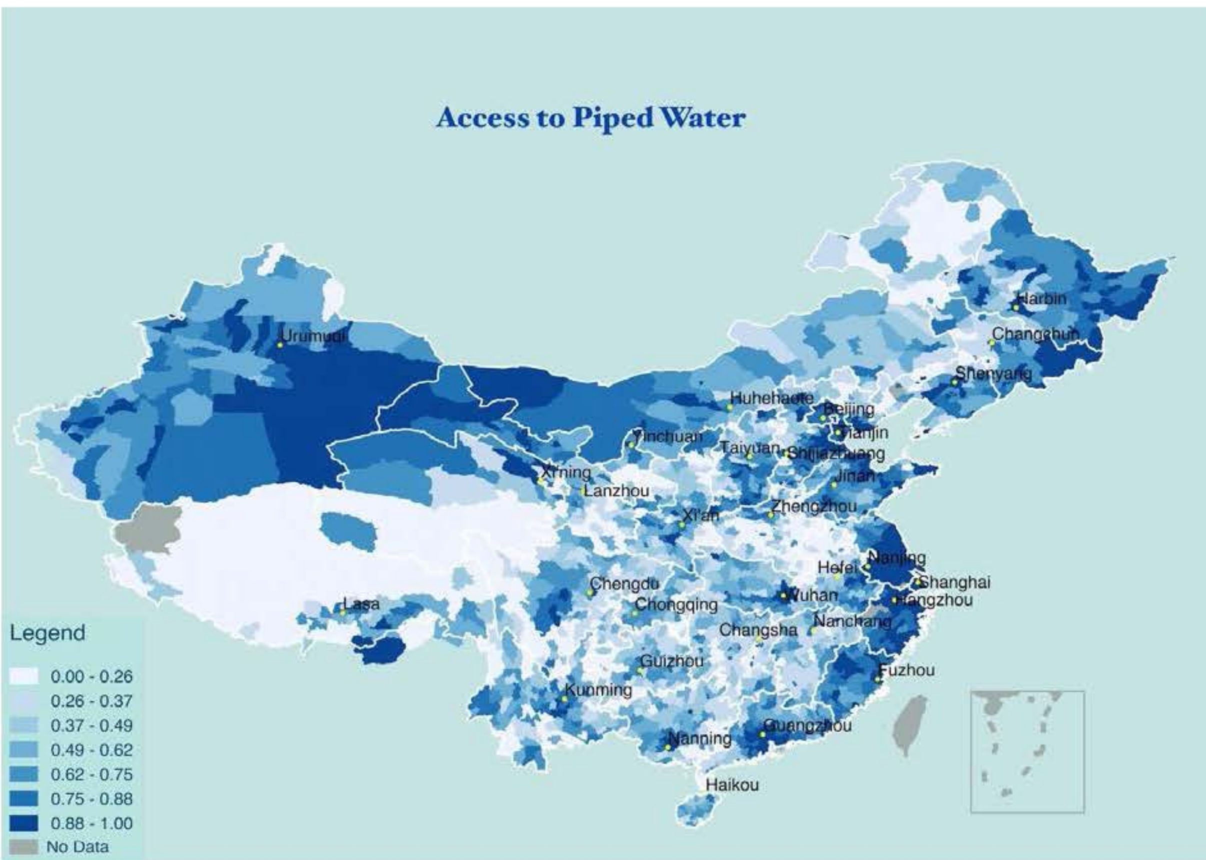

Figure 2 Map based on access to piped water

Based on this map, it can be concluded that the areas with the highest percentage of houses that have piped water are mostly concentrated along the coast. Among all the coastal provinces, Zhejiang and Jiangsu are the darkest colour, which indicates that people in these two provinces have higher living conditions in terms of access to piped water. Besides coastal areas, another dark area is visible across eastern Xinjiang, western Gansu and western Inner Mongolia. This is surprising since western China is usually considered to suffer from a lack of water. The high scores on this indicator in those areas suggest that they benefit from a good water supply system. The light colour, indicating that few houses have piped water, is distributed mostly in inland provinces. Tibet has the lightest colour, which suggests there is a need for improved water supply in this region in order to improve people's living conditions. Besides the autonomous region of Tibet, Guizhou and Henan provinces also have many light coloured areas.

4.1.2 Analysis at the Provincial Level

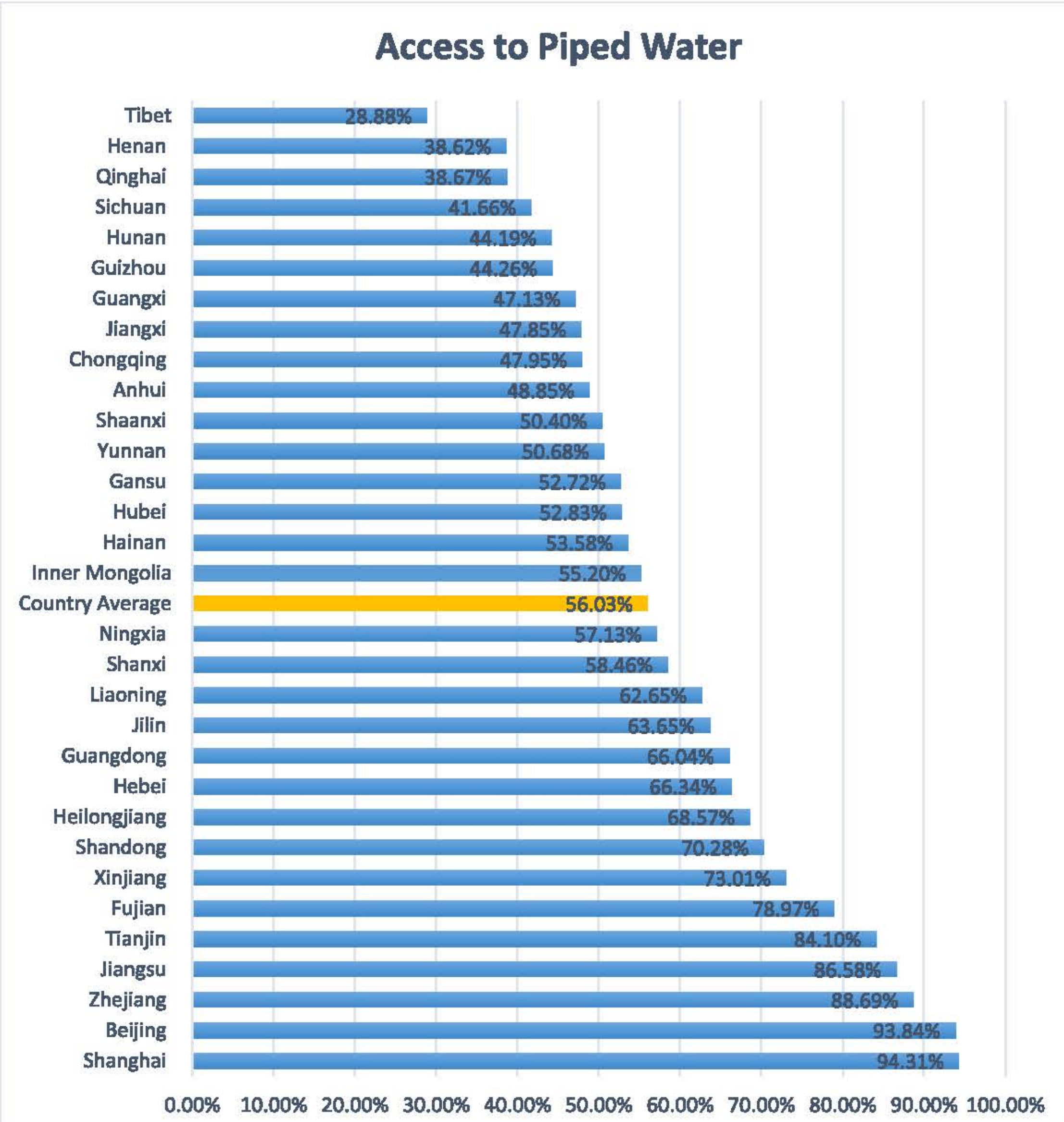

Figure 3 Ranking of provinces based on access to piped water

Figure 3 (above) ranks the provinces using their scores on the first indicator. The minimum, average and maximum values of the indicator are 28.9% (Tibet), 56.0% and 94.3% (Shanghai) respectively. The five highest ranked province-level administrative areas are Shanghai, Beijing, Zhejiang, Jiangsu and Tianjin. This ranking is consistent with the conclusion derived from the map above, whereby Zhejiang and Jiangsu constitute the most prominent dark areas. Looking towards the western regions, Xinjiang is ranked 7th out of all 31 provinces and has a value of 0.73, which exceeds the country average by 30%. The autonomous region of Inner Mongolia is just below the country average. One possible reason why western regions have higher values on this indicator may be related to topography. Due to complex topographical and geological conditions, it is costly for some areas in the southwest, south and centre of China to establish water supply systems. Finally, the above analysis of the lightest areas in the map concurs with the ranking of Tibet, Henan, Qinghai, Sichuan and Hunan at the bottom of the table.

4.1.3 Analysis of the 100 Lowest-Ranked Counties

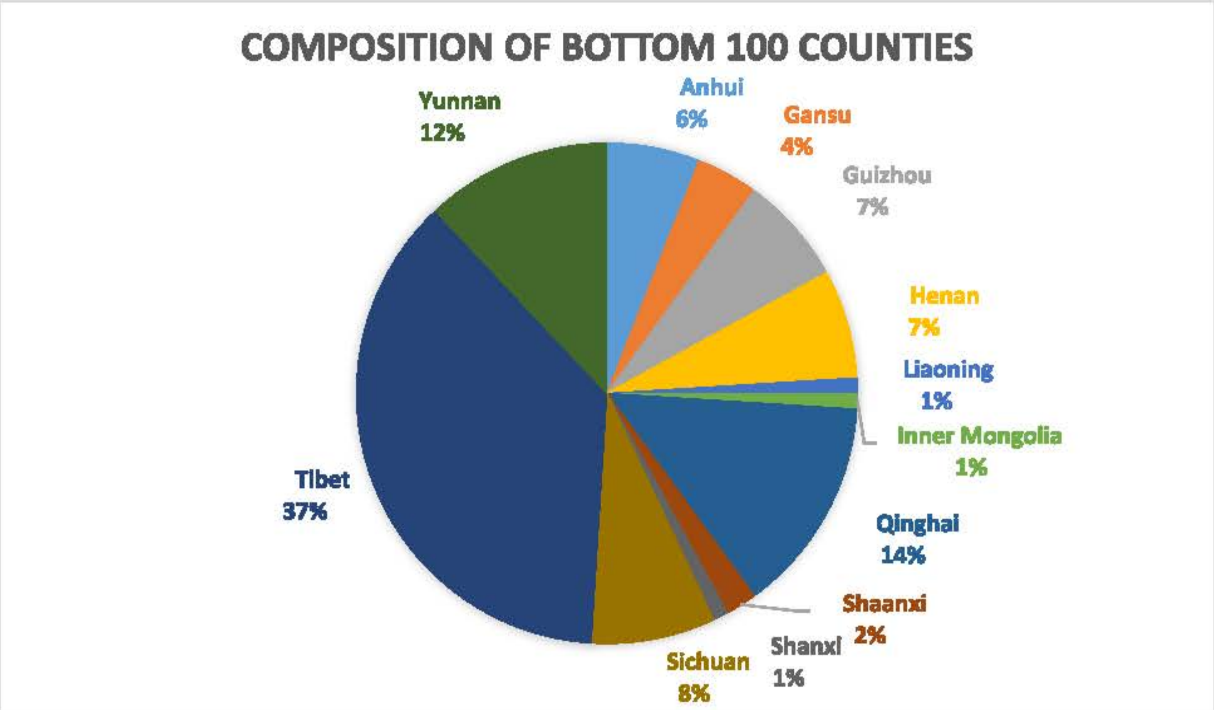

Figure 4 Distribution of the bottom 100 counties ranked by access to piped water

Of the bottom 100 counties in the ranking, 37% of them come from Tibet, which explains the large white area in the map of the Tibet Autonomous Region. Aside from Tibet, 14% of the lowest ranking counties are in Qinghai; Yunnan accounts for another 12%.

4.2 Access to sanitary toilets

4.2.1 Analysis at the National Level

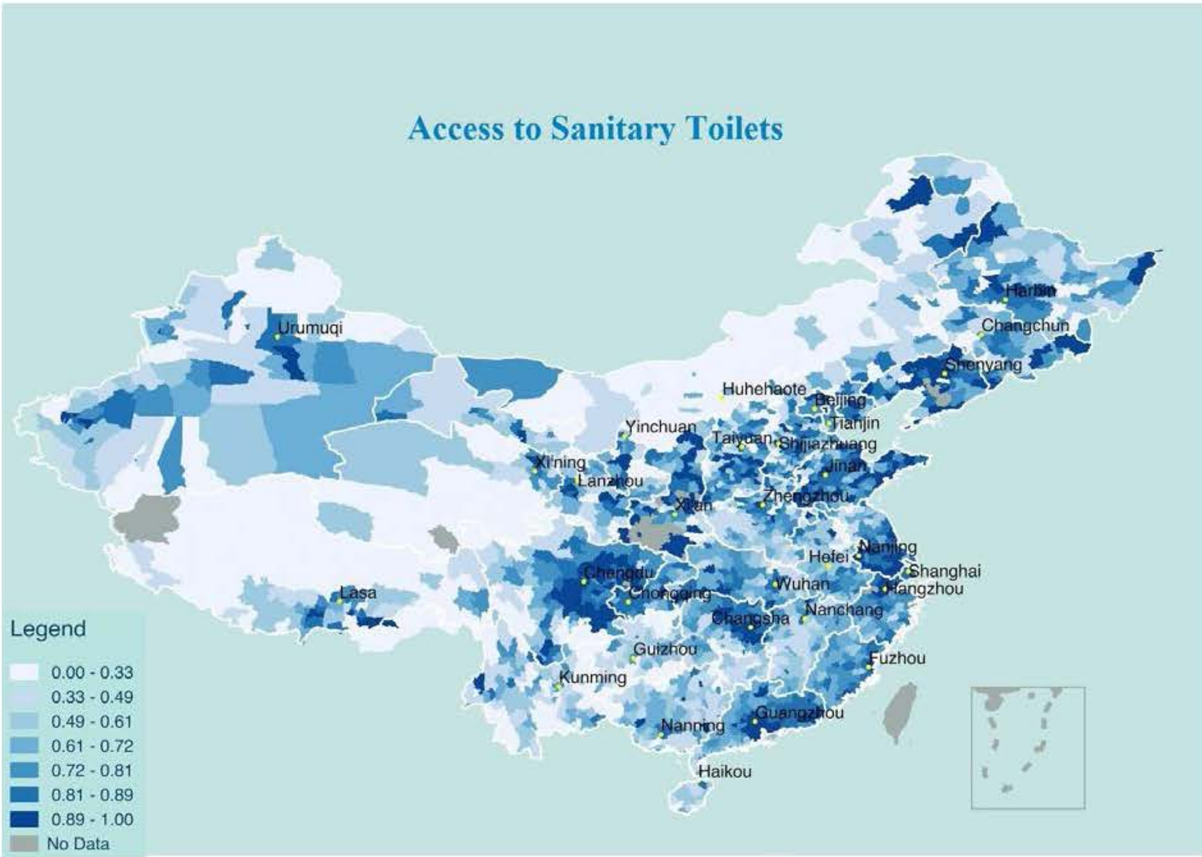

Figure 5 Map based on access to toilets

Here we measure the percentage of households that have access to modern toilets. While the previous indicator portrayed an imbalance in the access to piped water between coastal areas and inland areas, the indicator for access to toilets does not suggest a big coastal-inland gap. Instead, the dark colour (indicating a high percentage of houses with sanitary toilets) is widespread throughout all regions. Out of the provinces that perform most strongly on this indicator, Sichuan and Shandong provinces have the most concentrated dark colour, whereas Inner Mongolia and Tibet have the lightest colour, representing poor performance on this indicator.

4.2.2 Analysis at the Provincial Level

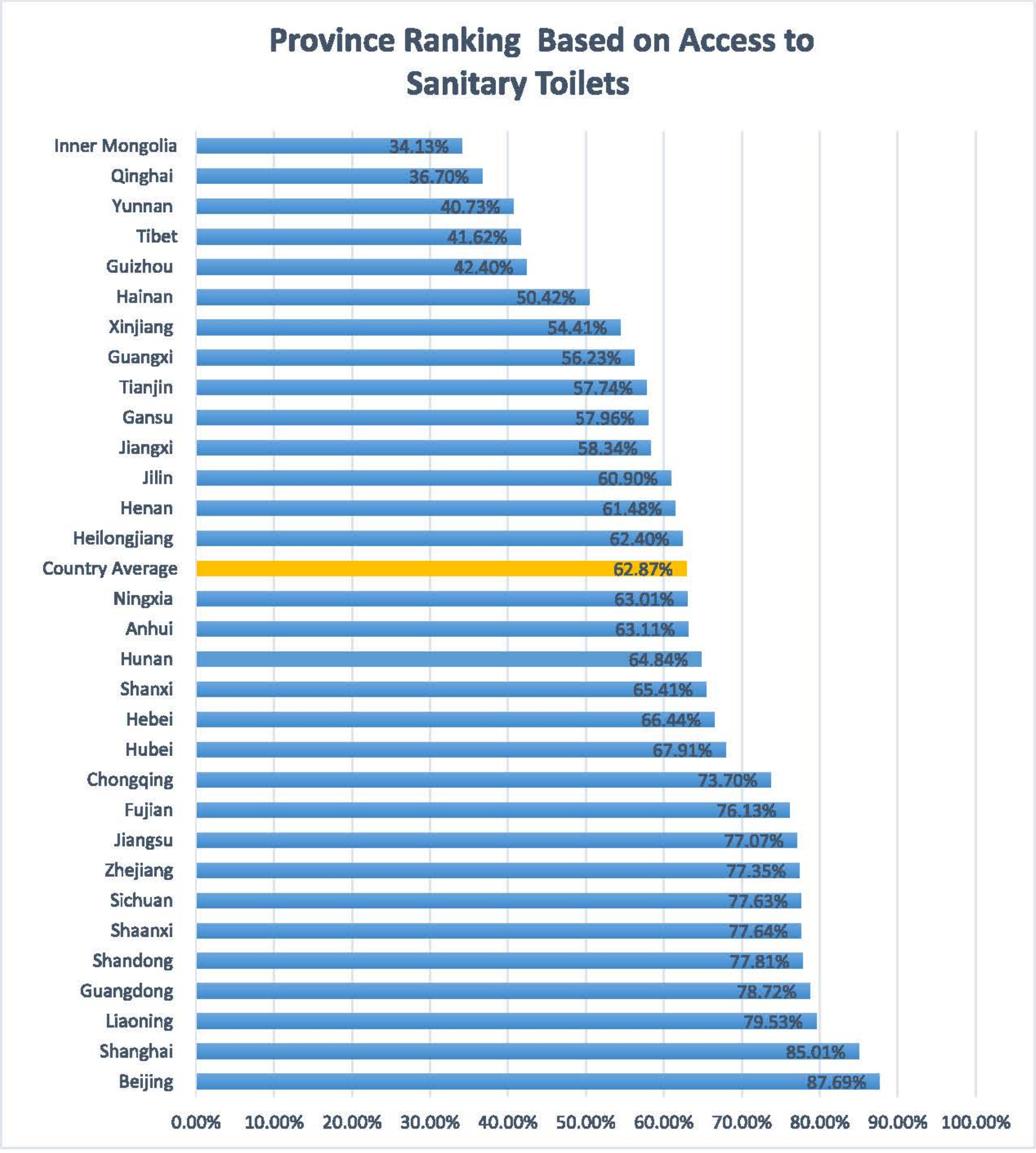

Figure 6 Ranking of provinces based on access to toilets

We find that, across the country, 63% of households have access to toilets on average. The minimum and maximum values of the indicator are 34.1% (Inner Mongolia) and 87.7% (Beijing) respectively. The five provinces that have the lowest rate of access to toilets are Inner Mongolia, Qinghai, Yunnan, Tibet and Guizhou. The five provinces or municipalities that have the highest rates are Beijing, Shanghai, Liaoning, Guangdong and Shandong.

4.2.3 Analysis of the 100 Lowest-Ranked Counties

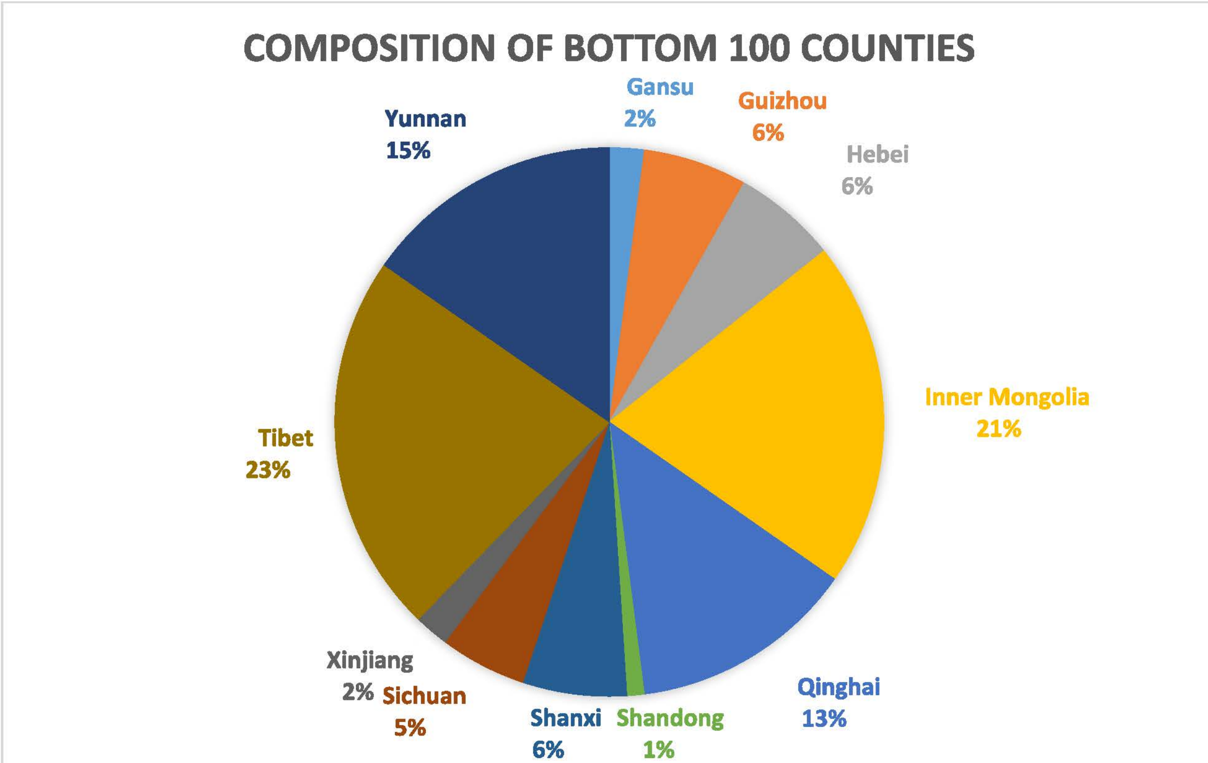

Figure 7 Distribution of the bottom 100 counties ranked by access to toilets

Focusing on the lowest ranked provinces, we can see that Tibet and Inner Mongolia perform far below the average in access to toilets not only in terms of the provincial average but also in terms of the number of low performing counties. Together, they account for nearly half of the bottom 100 counties, with 22% of the bottom 100 counties coming from Tibet and 20% of them coming from Inner Mongolia.

4.3 Access to indoor kitchens

4.3.1 Analysis at the National Level

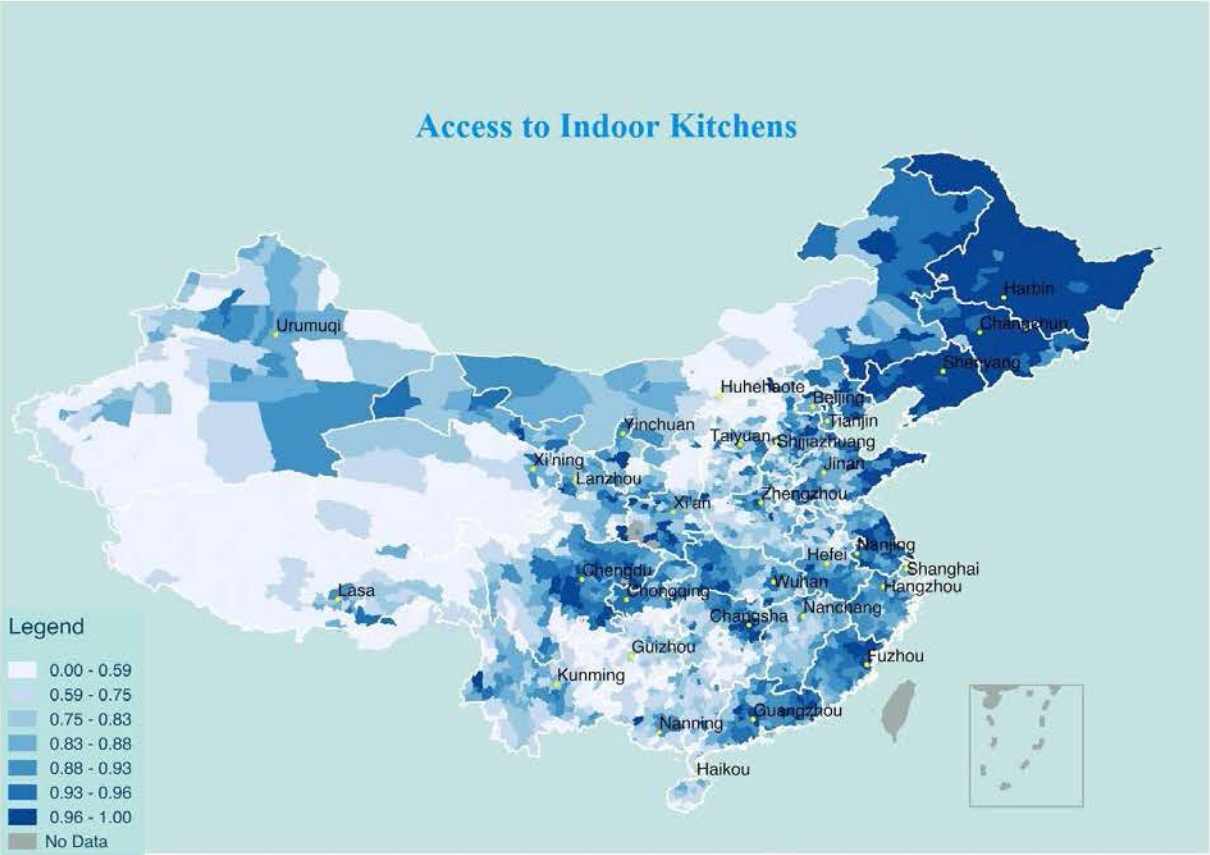

Figure 8 Map based on access to kitchens

The third indicator is access to kitchens, which we measure as the percentage of households that have access to a kitchen inside their own homes. Although this indicator does not directly provide information about cooking fuel use, having access to a kitchen inside one's home implies the use of improved cooking fuels. From the map, one can observe a clear regional imbalance in access to kitchen facilities. The northeast of China, including Liaoning, Jilin and Heilongjiang provinces, has a higher rate of access to kitchens. Guizhou and Tibet constitute areas with the lightest colour, indicating more limited access to kitchens. It should be noted that this indicator may not correlate with economic development as more developed areas may also be more densely populated and thus have fewer kitchens as a result.

4.3.2 Analysis at the Provincial level

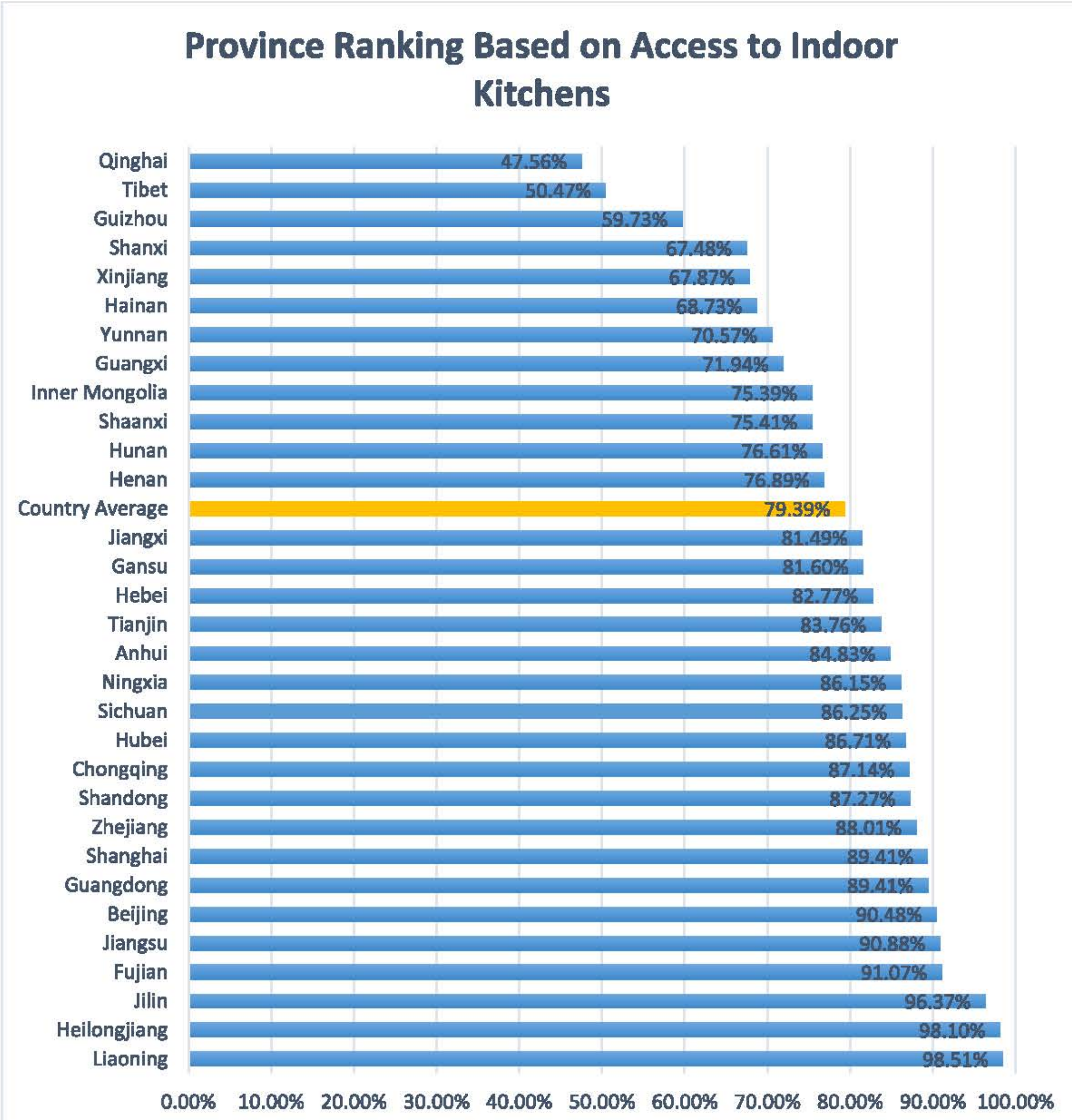

Figure 9 Ranking of provinces based on access to kitchens

The table indicates high rates of access to kitchens across the country, with an average national rate of 79%. The five provinces with the best access to kitchens are Liaoning, Heilongjiang, Jilin, Fujian and Jiangsu, which confirms the pattern shown in the map. This is the first indicator discussed of which both Beijing and Shanghai do not rank in the top five. Qinghai ranks last on this indicator, together with Tibet, Guizhou, Shanxi and Xinjiang.

4.3.3 Analysis of the 100 Lowest-Ranked Counties

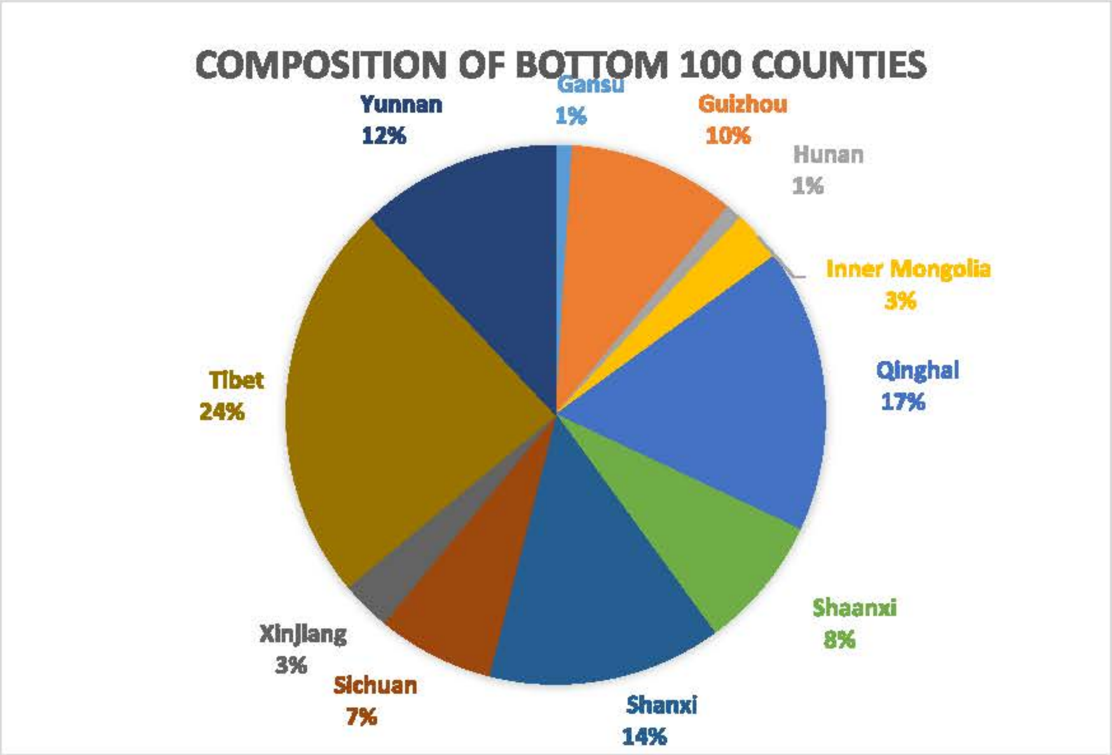

Figure 10 Distribution of the bottom 100 counties ranked by access to kitchens

Among the 100 counties with the lowest rate of access to kitchen facilities, 24 of them are in Tibet and 17 are in Qinghai. Besides these two provinces, Shanxi, Yunnan and Guizhou also account for around 10% each.

4.4 Access to living services

4.4.1 Analysis at the National Level

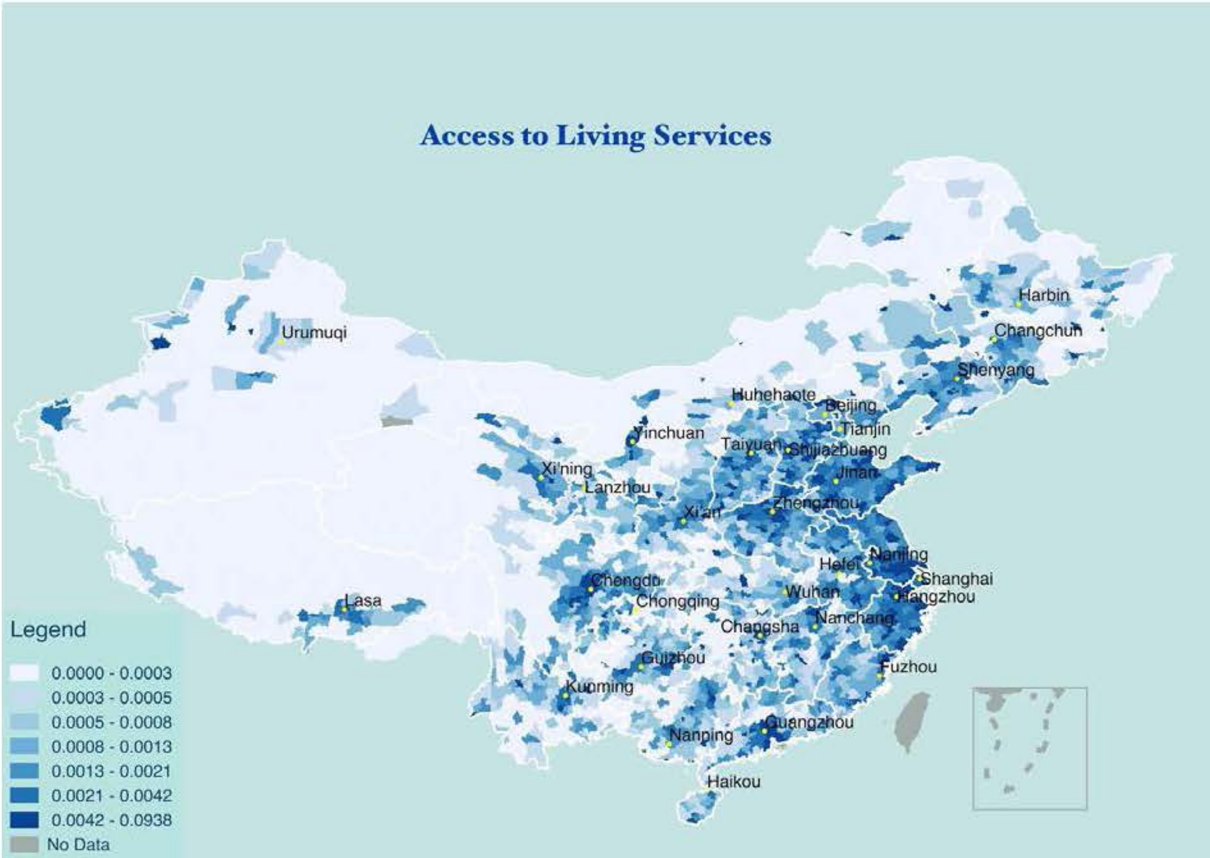

Figure 11 Map based on access to living services

In order to measure the ease of access to living facilities, we calculated the number of living facilities per square kilometer per capita. These services include communication businesses, post offices, logistics companies, ticket offices, launderettes, printers, photography studios, real estate agencies, utilities companies, household management services, veterinarians, newsstands and public toilets. Among the best performing provinces, Shandong, Jiangsu and Zhejiang have the most concentrated dark colour. Western parts of China, such as Xinjiang, Tibet, Qinghai and Inner Mongolia, have a very light colour, which indicates reduced access to living facilities in those areas. This indicator reveals a large difference between living standards in western and eastern areas.

4.4.2 Analysis at the Provincial Level

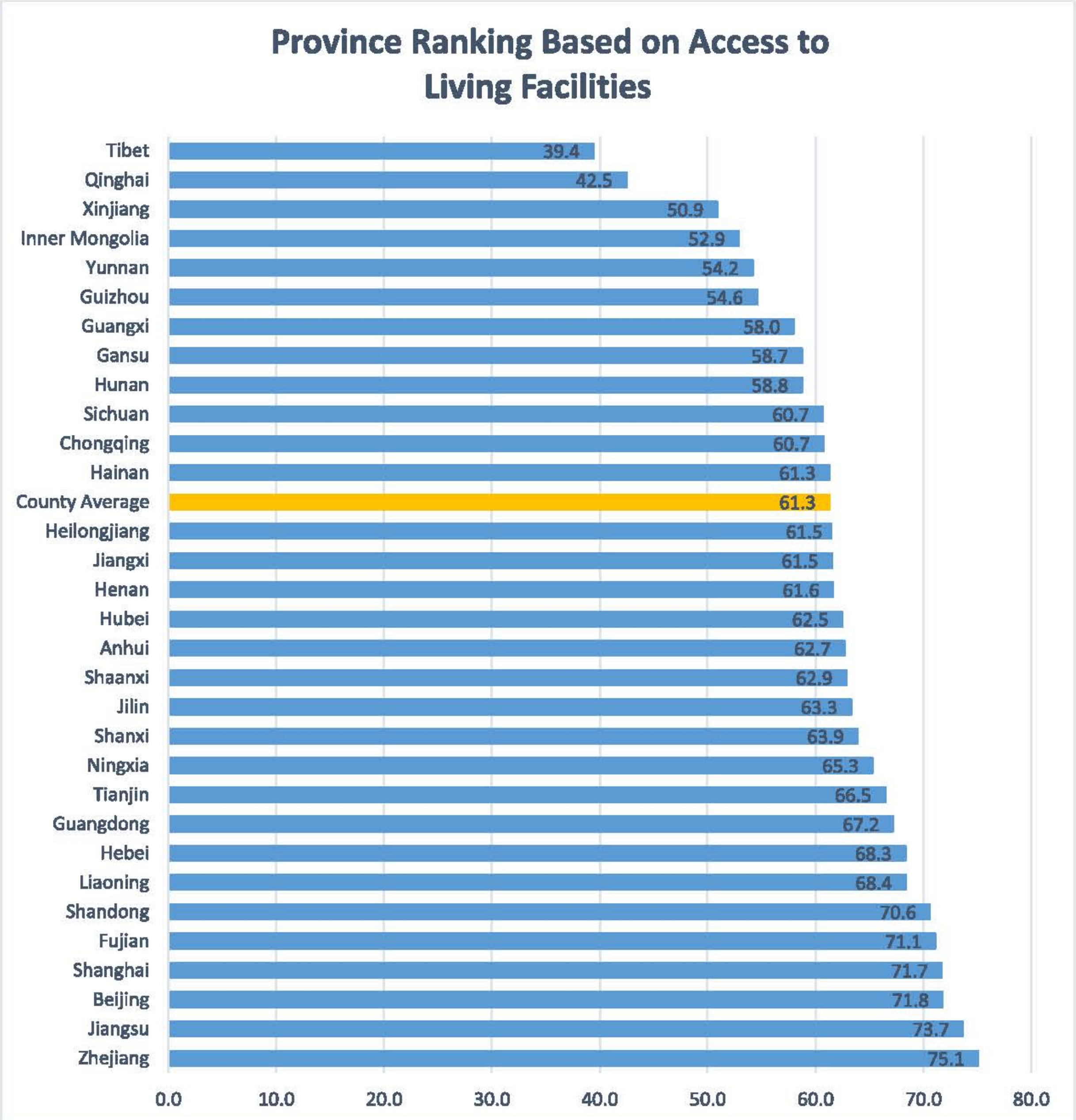

Figure 12 Ranking of provinces by living facilities

The national average for this indicator is 61.3. Zhejiang is the best performer at the provincial level with a value of 75.1; Tibet has the lowest score of 39.4. Of all 31 provinces, only 12 provinces are below the national average, which also suggests an imbalanced distribution at the provincial level. The top-ranked provinces' high performance is enough to outweigh the majority's low performance and leads to a comparatively high national average. Beijing, Shanghai and Fujian province also have a high density of living facilities and rank just behind Jiangsu and Zhejiang.

Tibet, Qinghai, Xinjiang, Inner Mongolia and Yunnan have few living facilities and rank at the bottom. Tibet and Qinghai have values of only 39.4 and 42.5 respectively.

4.4.3 Analysis of the 100 Lowest-Ranked Counties

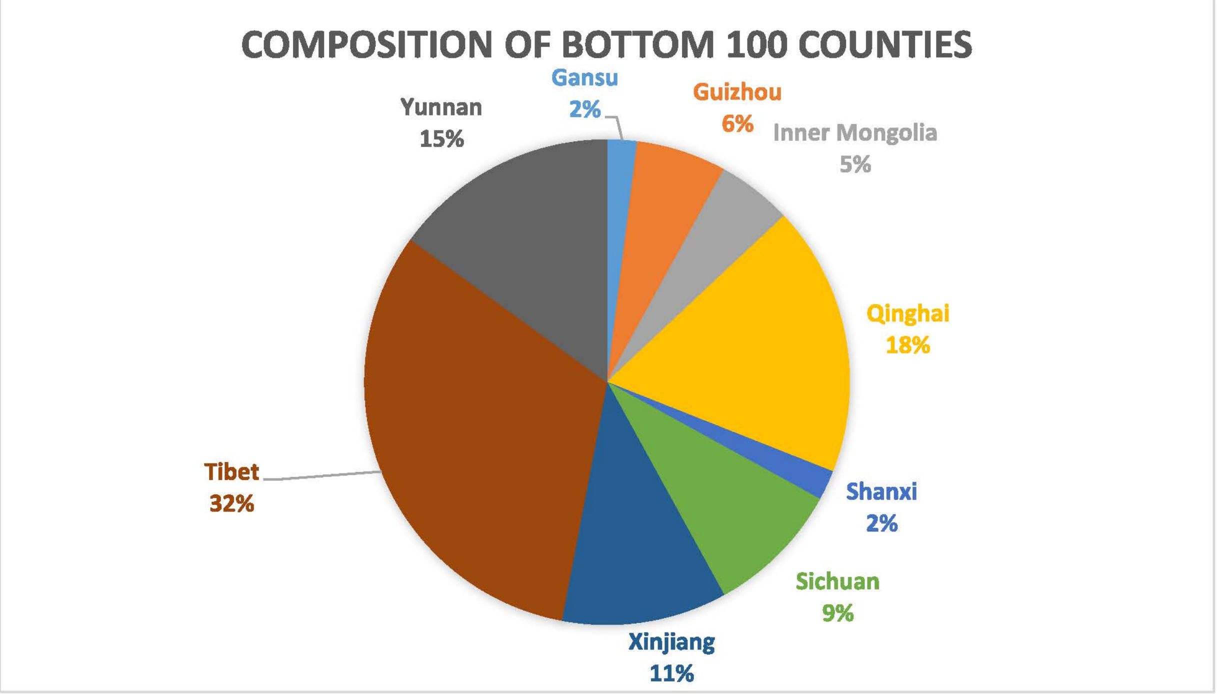

Figure 13 Distribution of the bottom 100 counties ranked by access to living services

The bottom 100 counties are quite concentrated in nine provinces in western China. Nearly half of the bottom counties are from Tibet and Qinghai. On the other hand, Yunnan accounts for nearly 15%.

4.5 Access to financial services

4.5.1 Analysis at the National Level

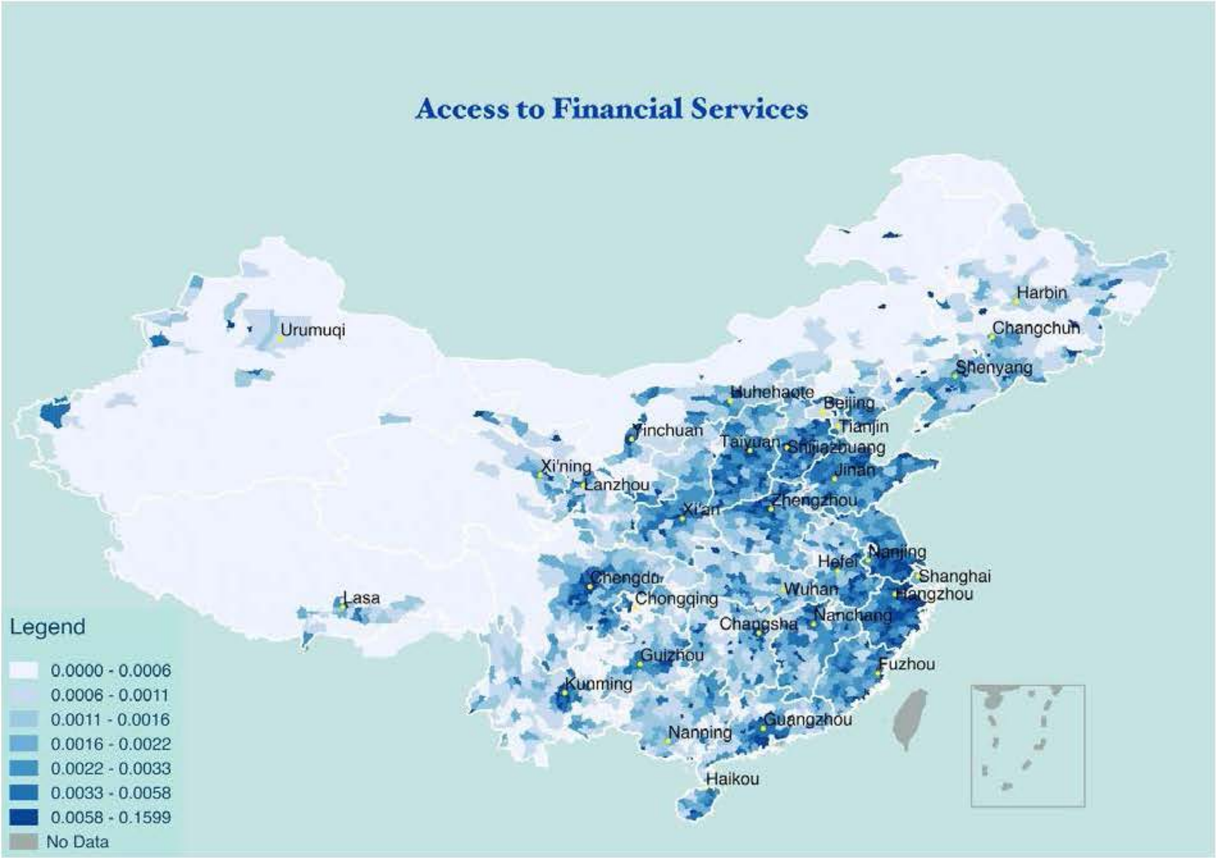

Figure 14 Map based on access to financial services

One simple way to measure people's access to financial services is to see how many financial institutions are present within a given area. Here we calculate the number of ATMs, banks and credit cooperatives per square kilometer per capita. From the map, we can clearly observe similar patterns as with previous indicators. Coastal provinces, such as Shandong, Jiangsu, and Zhejiang, all receive high indicator values, suggesting good access to financial service. The west of China, including Xinjiang, Tibet, Qinghai and Inner Mongolia, is very light in colour, which depicts limited access to financial services in these areas. However, due to smaller population numbers in the west, this does not necessarily mean financial services coverage in western areas is necessarily worse than eastern areas.

4.5.2 Analysis at the Provincial Level

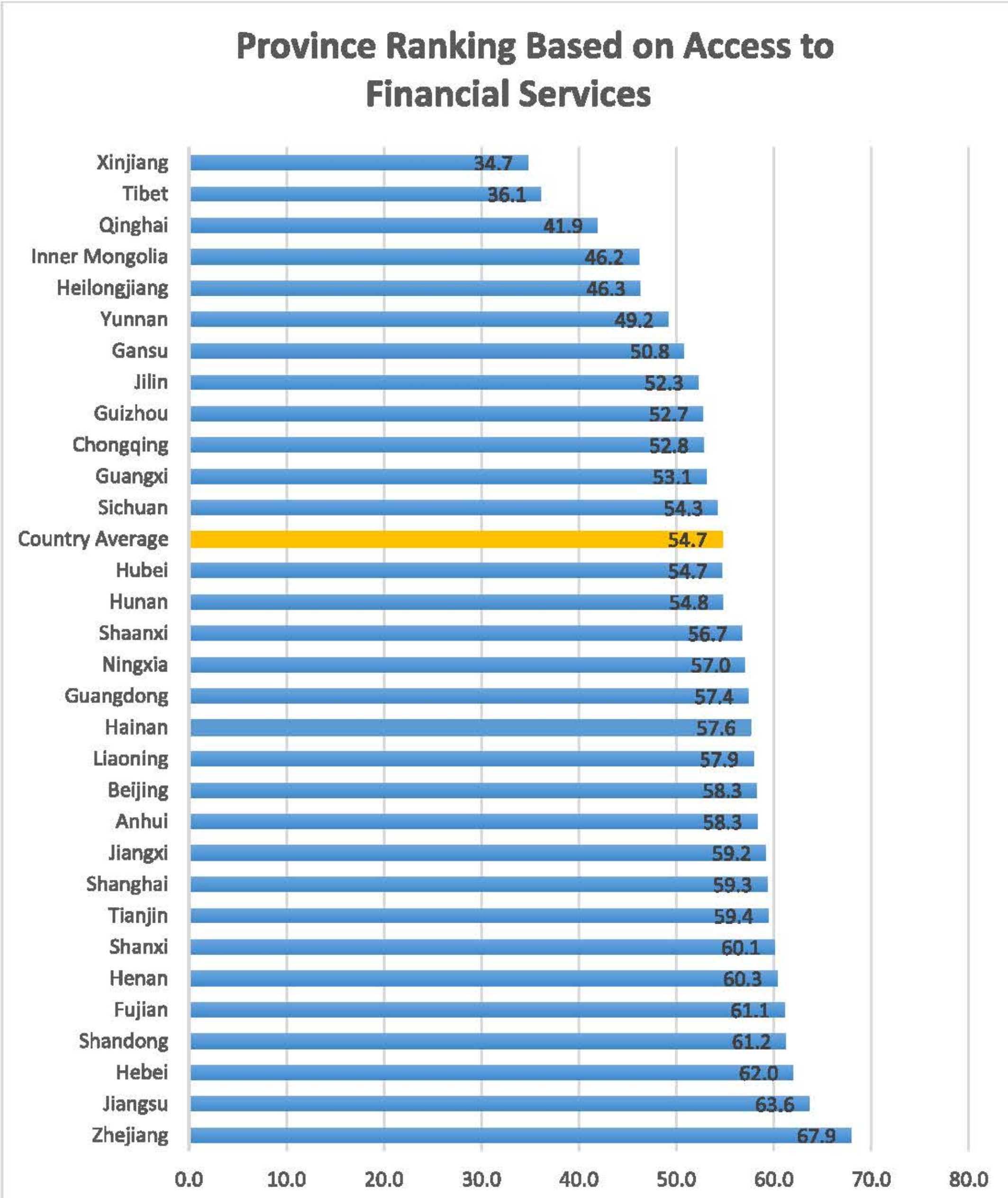

Figure 15 Ranking of provinces based on financial services

The minimum, country average and maximum values of the indicator are 34.7 (Xinjiang), 54.7 and 67.9 (Zhejiang) respectively. The top five provinces and municipalities in terms of financial development are Zhejiang, Jiangsu, Hebei, Shandong and Fujian. They overlap with the Yangtze River Delta, one of the biggest economic zones in China. This reflects a correlation between financial development and economic development. The five lowest-ranked provincial level of administration areas are Xinjiang, Tibet, Qinghai, Inner Mongolia and Heilongjiang and their values are all below 47.

4.5.3 Analysis of the 100 Lowest-Ranked Counties

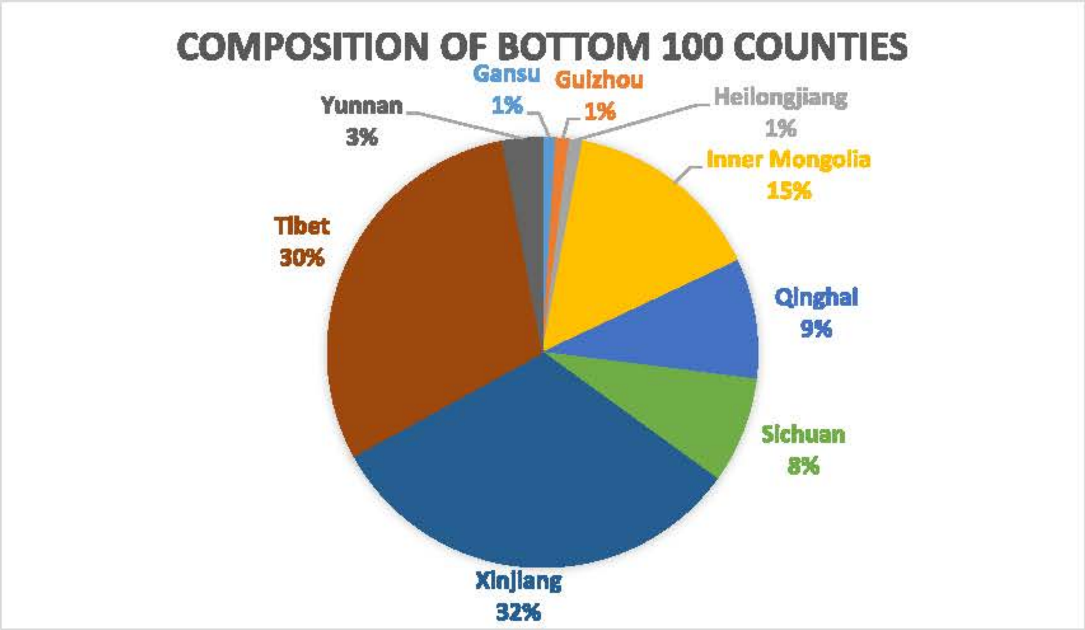

Figure 16 Distribution of the bottom 100 counties ranked by access to financial services

The bottom 100 counties on the financial services indicator are concentrated in five provinces. Tibet, Xinjiang, Inner Mongolia account for 30%, 32% and 15% of the bottom 100 counties respectively. This fact again confirms the underdevelopment of financial services in western areas.

4.6. Access to roads

4.6.1 Analysis at the National Level

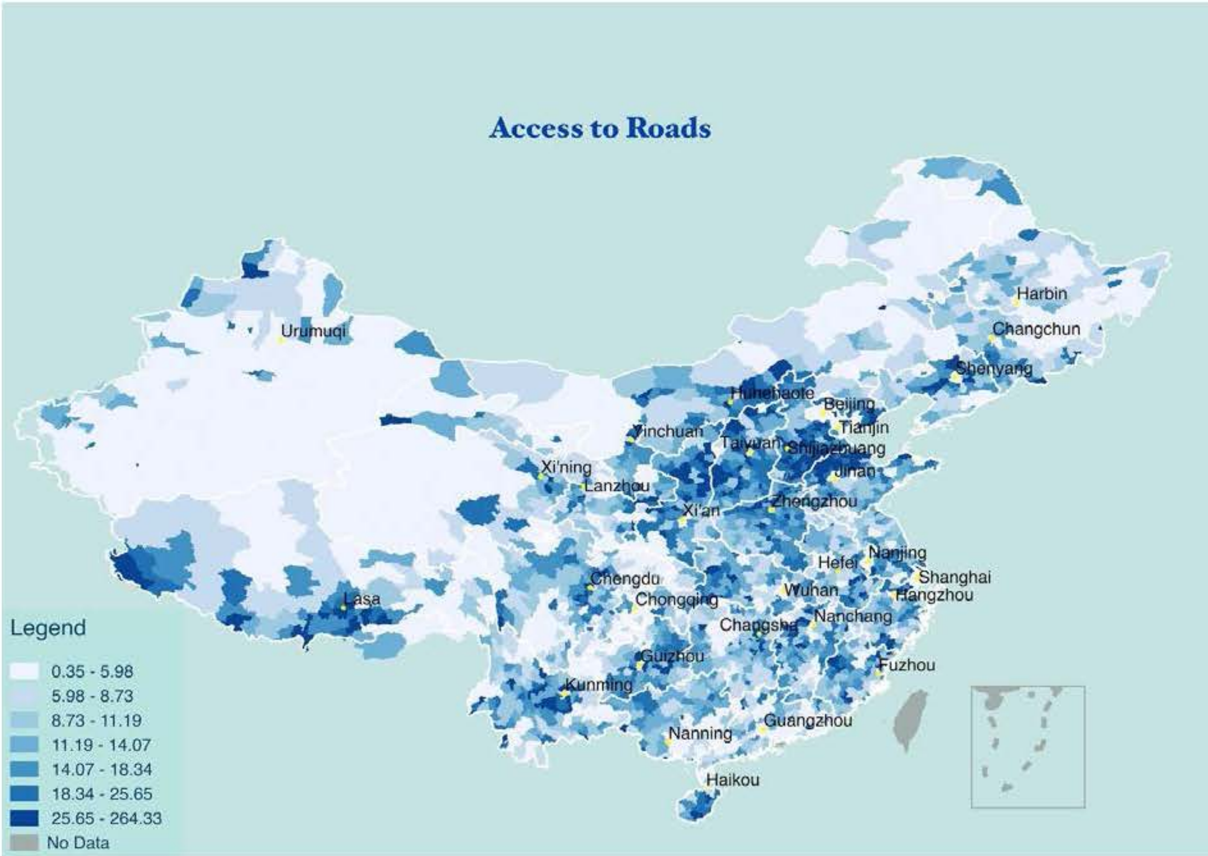

Figure 17 Map based on access to roads

The road coverage was measured using the cumulative length of roads per square kilometer per capita, adjusted for the quality of the roads. One can clearly observe a considerable difference in the provision of roads between the west and the east of China. While provinces in eastern China have clear advantages over those in western China, there are also differences within eastern China. Provinces located in the northern part, such as Hebei, Henan, and Shanxi, have higher values than provinces in the southern part, such as Guangdong, Guangxi and Fujian.

4.6.2 Analysis at the Provincial Level

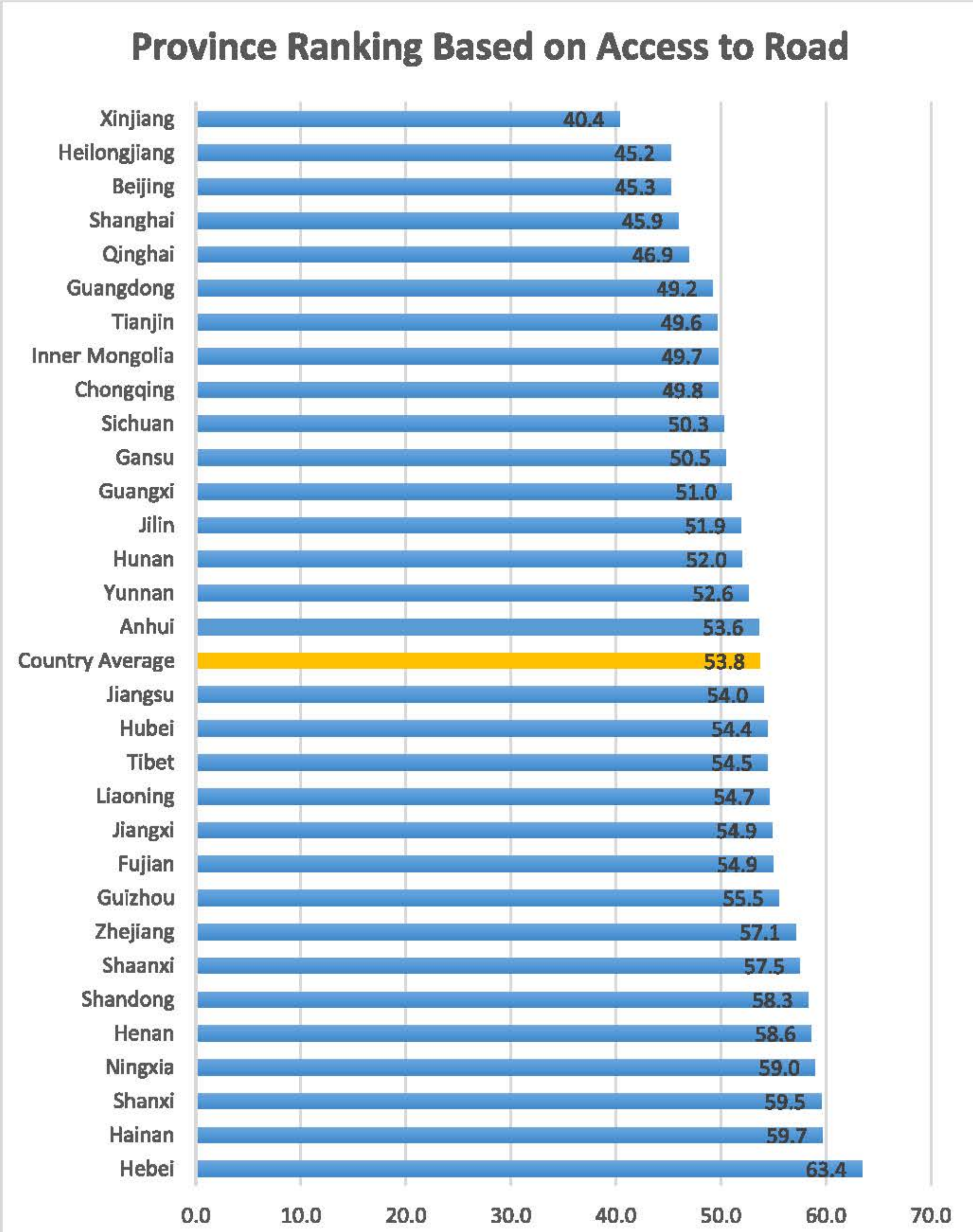

Figure 18 Ranking of provinces by access to roads

The minimum, country average and maximum values of the indicator are 40.4 (Xinjiang), 53.8 and 63.4 (Hebei) respectively. The top five provincial level administration areas on this indicator are Hebei, Hainan, Shanxi, Ningxia and Henan. The provincial averages confirm the conclusion drawn from the previous map: nearly all the above average provinces are from eastern China. The below average provinces are from the western part of China; some are located in the south. One interesting finding for this indicator is Beijing, Shanghai, Tianjin and Chongqing. These directly-administered municipality cities have been ranked in the bottom 10, with Beijing in the bottom three. The big cities with scaling effects have dramatic impacts on the performance of big cities under this indicator.

4.6.3 Analysis of the 100 Lowest-Ranked Counties

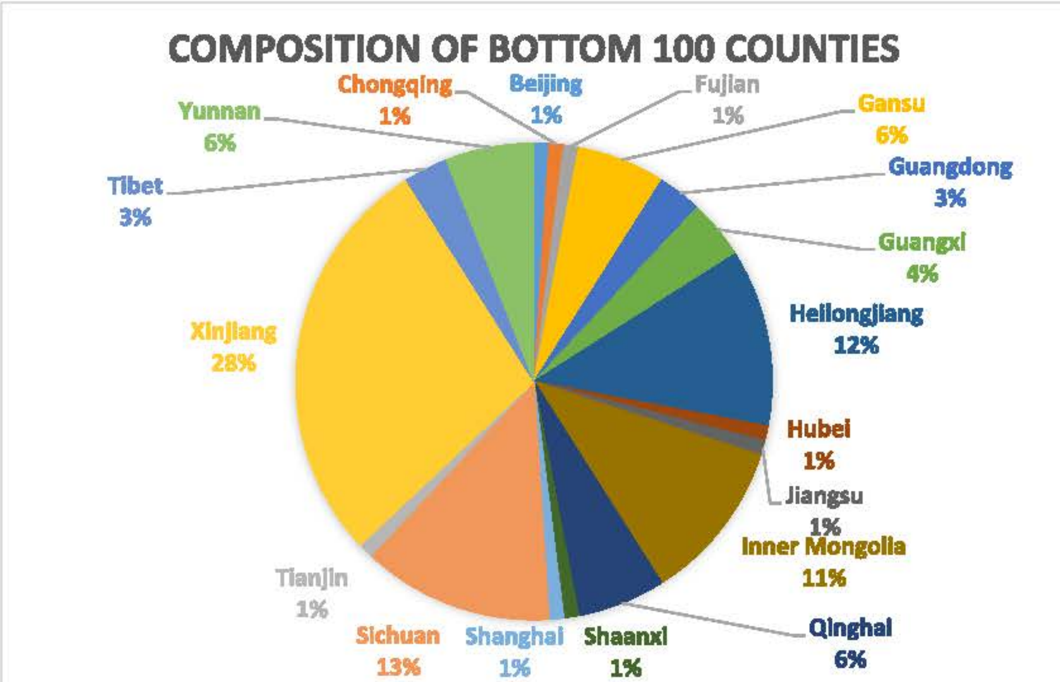

Figure 19 Distribution of the bottom 100 counties ranked by access to roads

When we summarize the bottom 100 counties by provinces, we can clearly see that these bottom ranked counties come from the west of China. Xinjiang and Sichuan are the two provincial level of administration areas with the biggest number of bottom-ranked counties. As we stated above, the performance of big cities– such as Tianjin, Beijing and Shanghai– ranks in the bottom 100 counties under the access to roads indicator. The high population density in these areas is a possible means of explaining their relatively poor ranking.

4.7 Mobile internet coverage

4.7.1 Analysis at the National Level

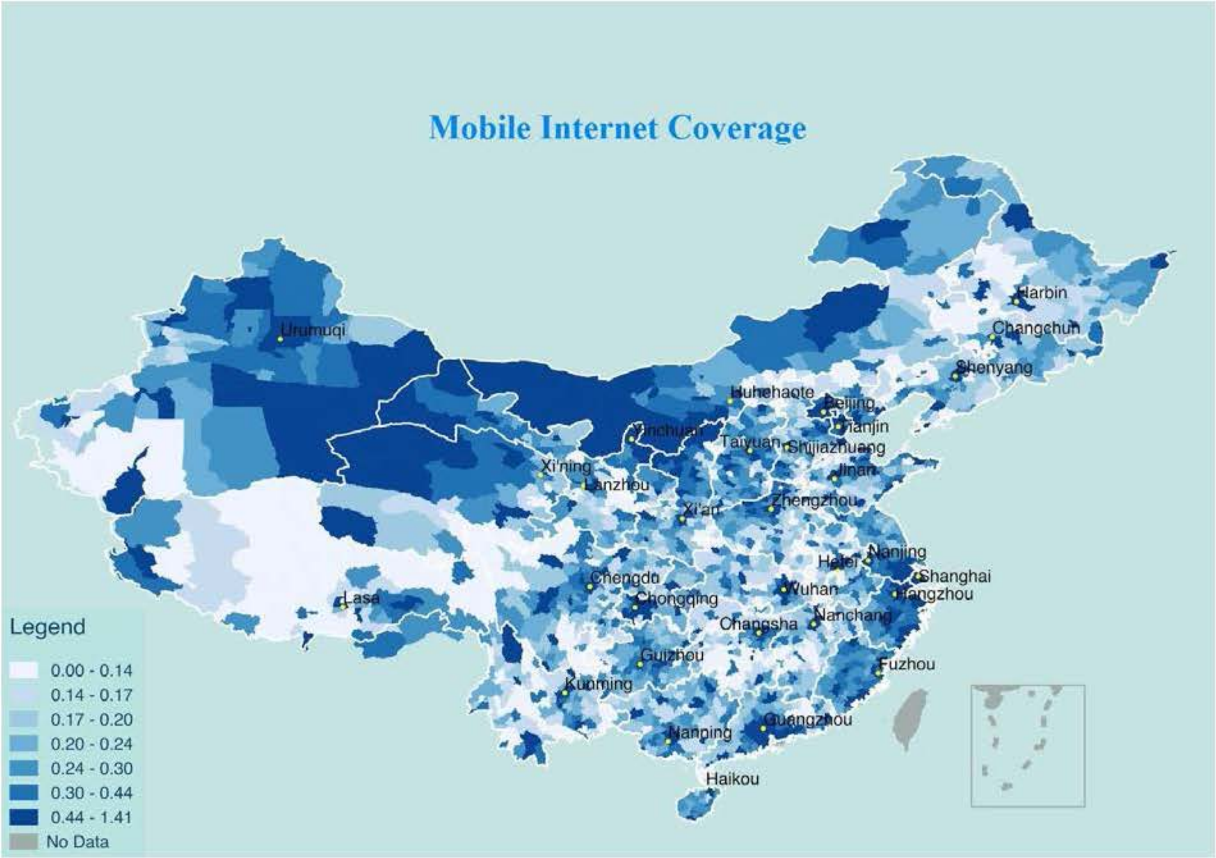

Figure 30 Map based on mobile internet coverage rate

The mobile internet coverage rate is another indicator that has never previously been measured in China. This indicator was constructed by Baidu using individual user location service information. The data can only be obtained from mobile phones that are equipped with location services, in other words, smart phones. Therefore, this indicator can also be understood as being correlated with the smart phone coverage rate. The map shows that the highest rates of mobile coverage are in coastal provinces, eastern Xinjiang Province and western Inner Mongolia. Jiangsu, Zhejiang, Fujian and Guangdong Province all have high mobile internet coverage rates, which indicate a high living standard in terms of communication technology. There are also many dark areas in inland provinces, most of which are urban areas or provincial capitals.

4.7.2 Analysis at the Provincial Level

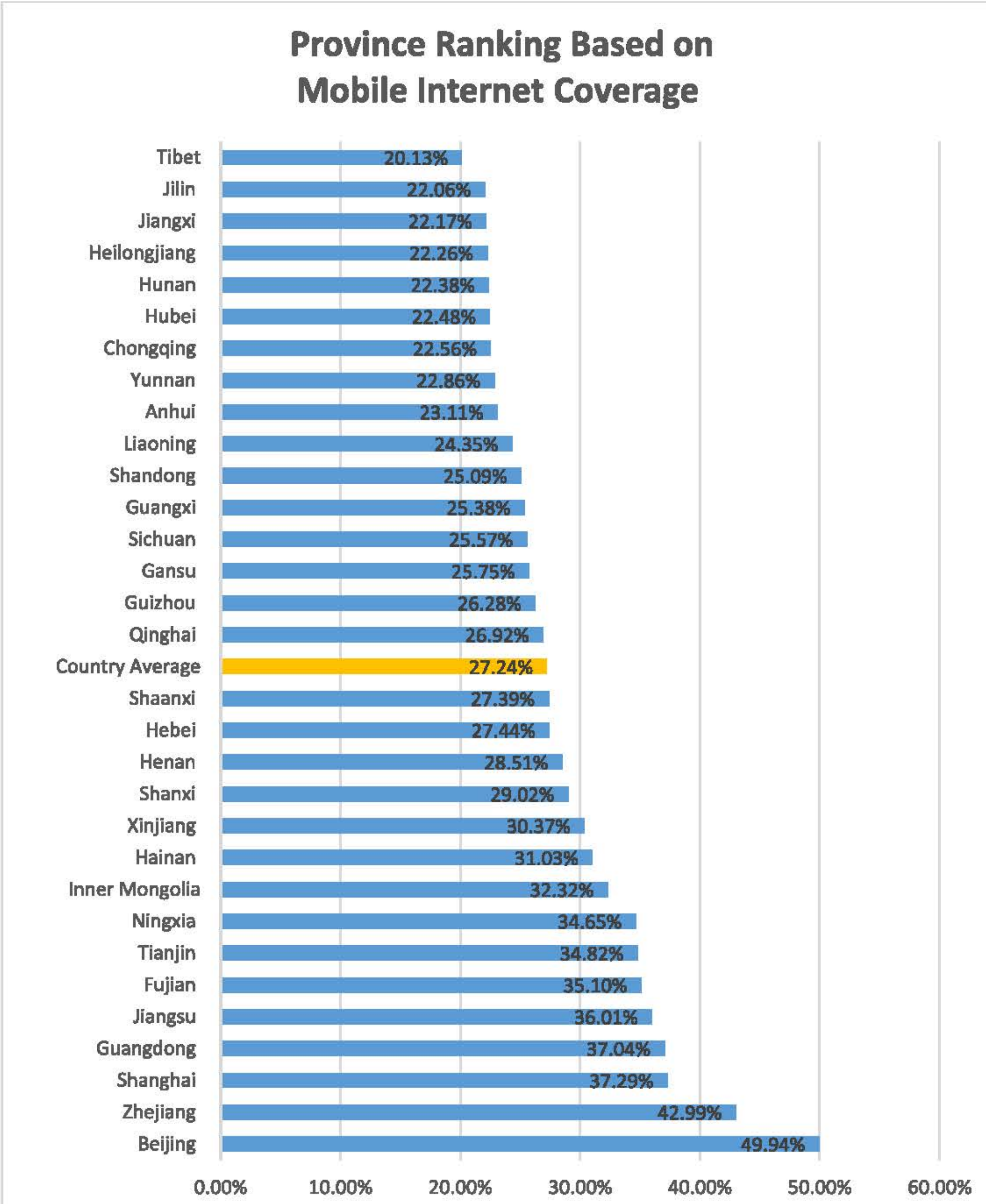

Figure 21 Ranking of provinces by mobile internet coverage

The minimum, average and maximum values of the indicator are 20.1% (Tibet), 27.2% and 50.0% (Beijing) respectively. The five provinces that have the highest rates of mobile internet coverage are Beijing, Zhejiang, Shanghai, Guangdong, and Jiangsu. These five provinces are all recognized as well-developed areas and it is no surprise that these provinces take the lead in terms of access to and usage of mobile internet. The last five provinces in this ranking are Hunan, Heilongjiang, Jiangxi, Jilin and Tibet. This bottom list is quite different from that for previous indicators, since there provinces from western China, such as Xinjiang or Qinghai, are not found. Among the five provinces, Heilongjiang and Jilin come from the northeast of China; Hunan and Jiangxi are from the centre of China.

4.7.3 Analysis of the 100 Lowest-Ranked Counties

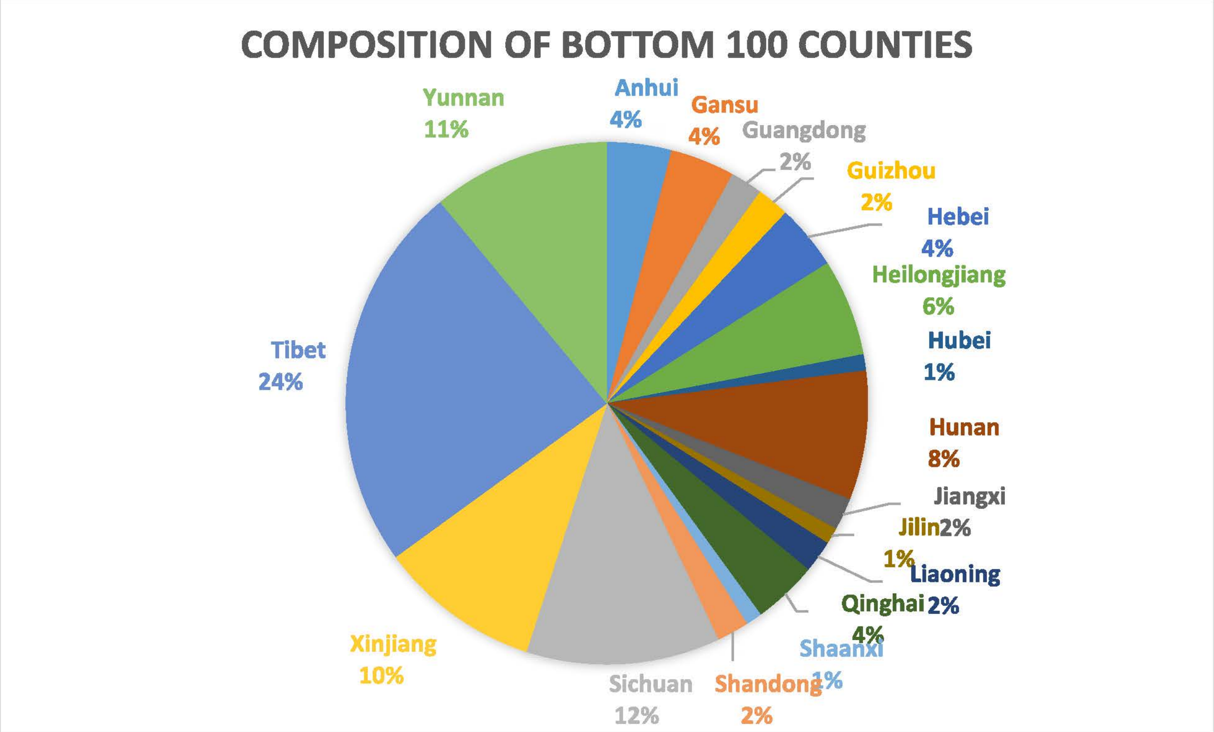

Figure 22 Distribution of the bottom 100 counties ranked by mobile internet coverage

The table above clearly shows that the bottom 100 counties are distributed broadly among 18 provinces. Tibet, Yunnan, Sichuan and Xinjiang provinces together account for more than half of the bottom-ranked counties, which are all in western China.

4.8 Nighttime light density

4.8.1 Analysis at the National Level

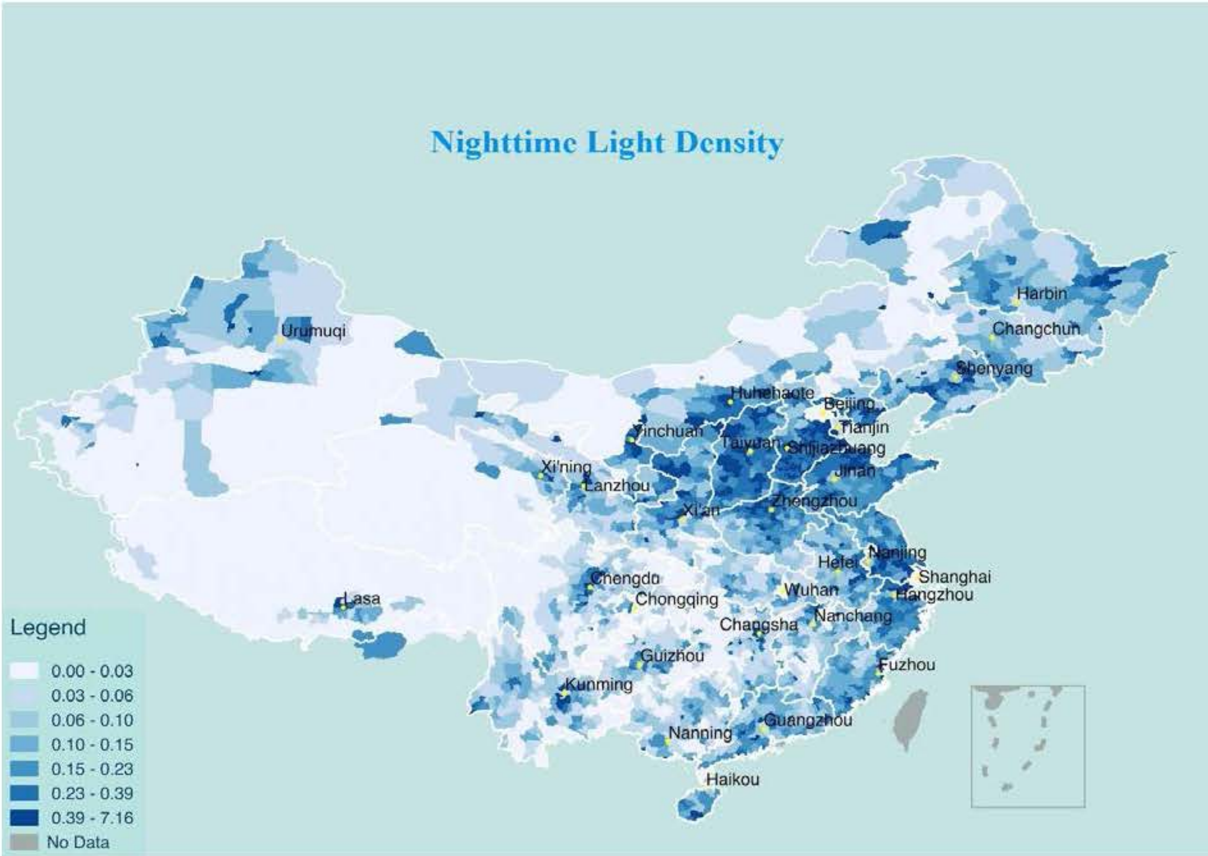

Figure 43 Map based on nighttime light density

On the map, the areas with the most nighttime light are mostly concentrated in coastal provinces. Another major area of high light concentration is along the border of Shandong, Hebei and Henan provinces. Besides these two areas, the remainder of the higher ranked counties are scattered around the country and most of them are provincial capitals.

4.8.2 Analysis at the Provincial Level

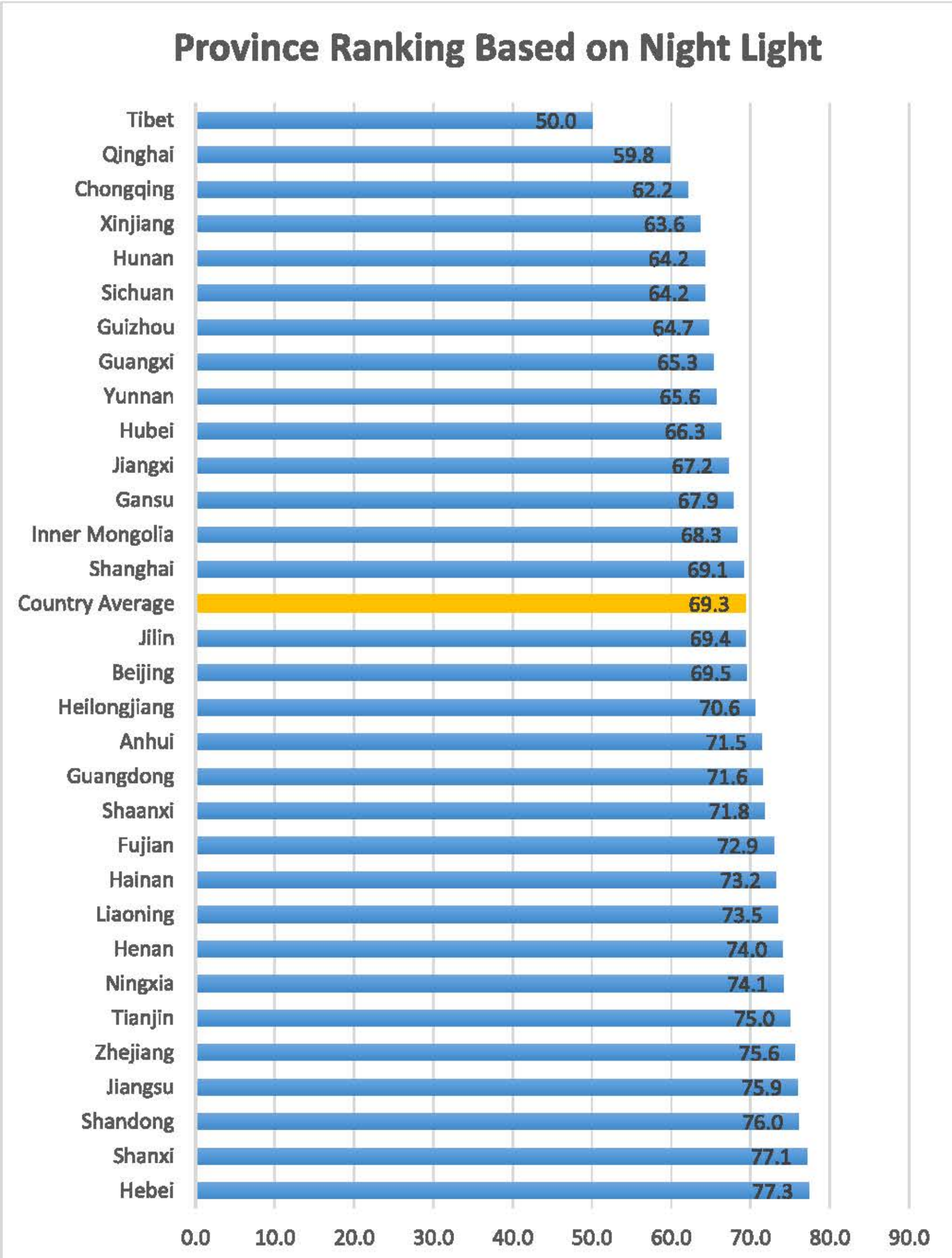

Figure 24 Ranking of provinces by nighttime light intensity

The minimum, country average and maximum values of the indicator are 50.0 (Tibet), 69.3 and 77.3 (Hebei) respectively. Coastal provinces such as Hebei, Shandong, Jiangsu and Zhejiang rank within the top five. Shanxi also has a good ranking, which fits with the dark colour of the top five provinces in the previous map. Provinces that have the lowest nighttime light intensity are Tibet, Qinghai, Chongqing, Xinjiang and Hunan.

4.8.3 Analysis of the 100 Lowest-Ranked Counties

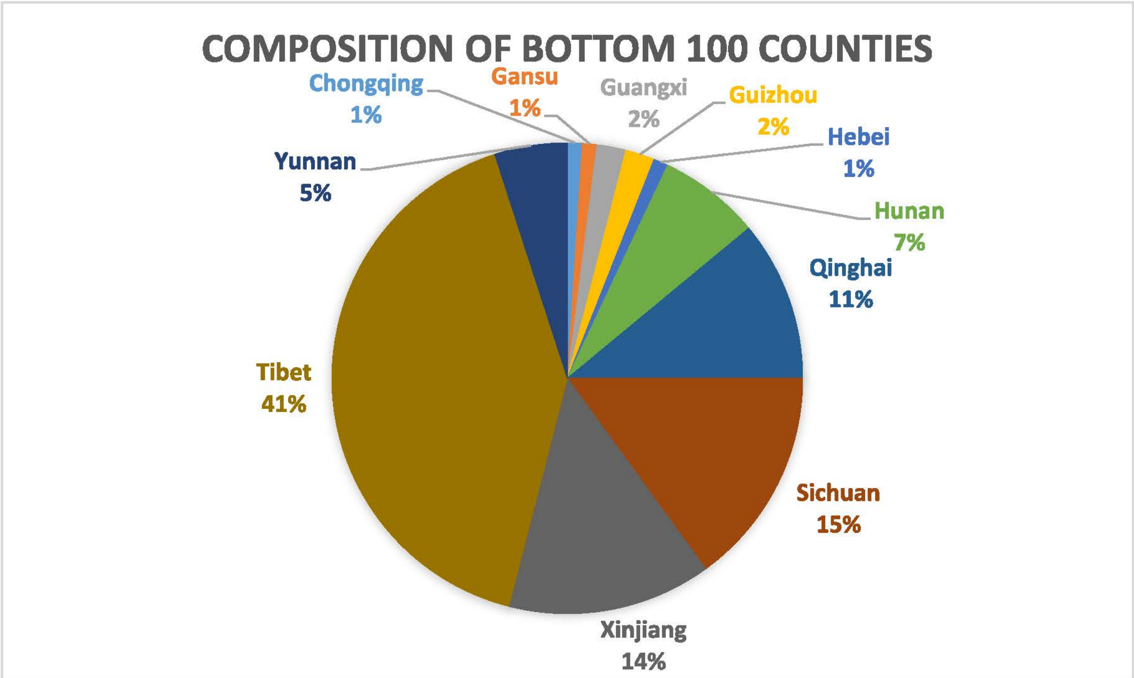

Figure 25 Distribution of the bottom 100 counties by nighttime light intensity

In terms of nighttime light activity, the lowest ranking 100 counties mostly come from Tibet (41%). Xinjiang and Sichuan together account for another 30%. This time, Qinghai only accounts for 11%.

FIVE
FINDINGS BY INDEX

5. Findings by Index

5.1 Map of Living Standards

The Living Standards Index is an aggregate of all eight living standards indicators, giving a measure of the living standards in different counties. The index here takes a value from 0-100 where 0 represents the worst performance and 100 denotes the best. Research findings are presented in the following map, which uses five colours to indicate index values: green is used for the highest values, with yellow, orange, and red representing successively lower values. Grey depicts that no data is available.

Looking at the country map of the Living Standards Index, one may observe a clear trend that the provinces in the eastern part of the country outperform western provinces. Nearly all the eastern coastal provinces have higher index values. Conversely, in the centre, the mixture of green and yellow indicates comparatively lower values in the Living Standards Index. Living standards continue to fall as we move west, where the majority of areas are yellow and orange with only scattered green. The lowest values, represented in red, are mostly concentrated in Tibet and Qinghai provinces.

Within each region of China there are also some more specific patterns. For coastal provinces, the northeast does not perform as well as the south. While a majority of the areas in Heilongjiang, Jilin, Liaoning, Hebei, Guangdong and Hainan provinces are green, there are still some yellow areas within these provinces. In the centre of China, green is mostly concentrated in the plains, namely: the Sichuan Plain, the Yangtze Plain (the intersection of Hubei, Hunan and Jiangxi), the Guanzhong Plain (in the middle of Shaanxi Province), and the Huabei Plain (including Beijing, Tianjin, Hebei, Shandong, Henan, Anhui and Jiangsu). This finding suggests that living standards are closely related to terrain. One explanation for this pattern may be the lower cost of infrastructure development in the flat plain areas compared to mountainous or other terrains. It is to be expected that plain areas have more developed infrastructure, including roads, signal towers, and piped water.

Besides the striking coastal-inland gap and east-west gap in living standards, there may also be a discrepancy in living standards between rural and urban areas. Looking at the map, a majority of dark green areas overlap with provincial capitals, suggesting that big cities may have better living standards than rural areas. As well as the capital Beijing, the Yangtze River Delta, the Pearl River Delta and the Beijing-Tianjin economic zone are also dark green indicating their comparatively high living standards.

Map of Living Standards

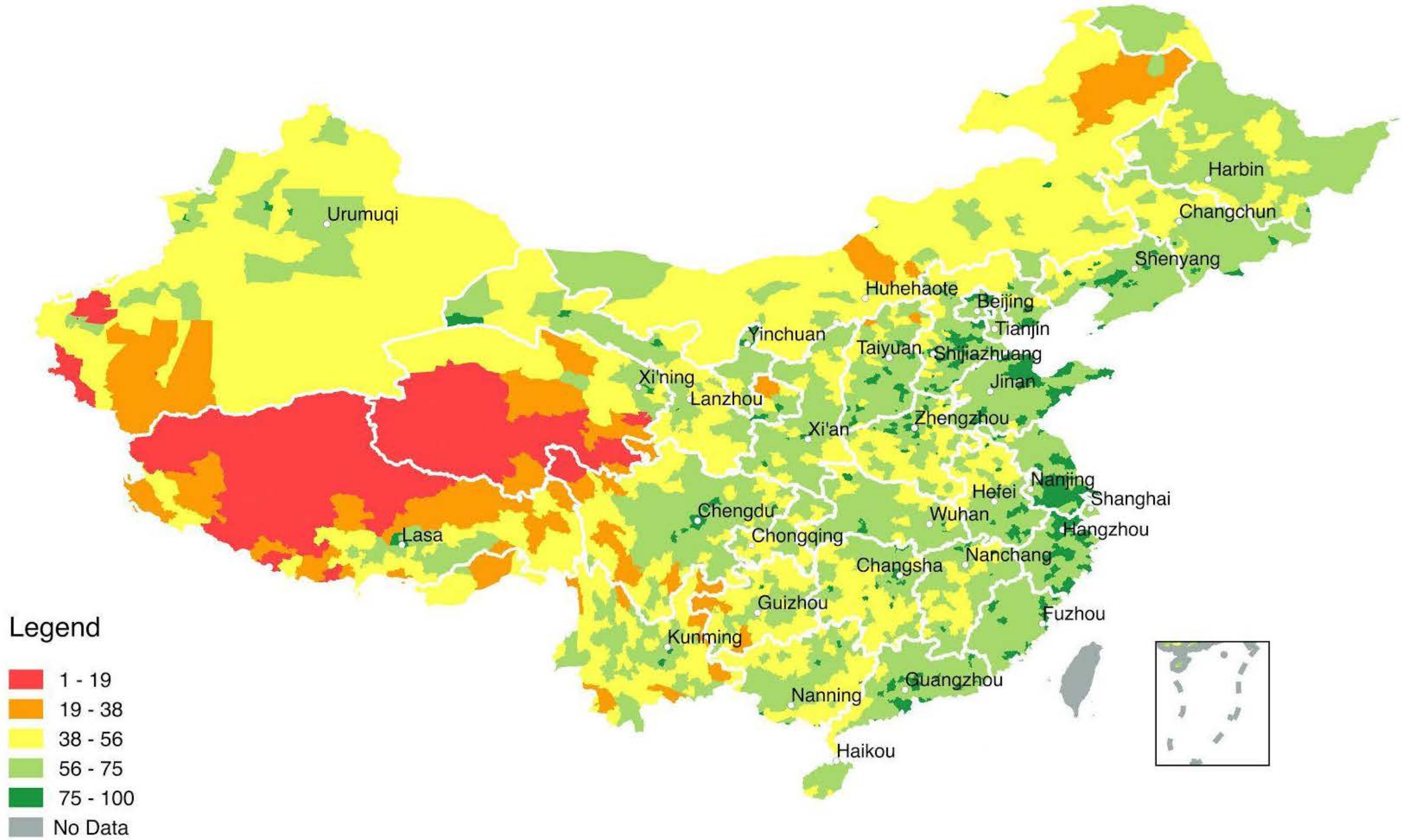

Figure 56 Map based on the Living Standards Index

5.2 Analysis at the Provincial Level

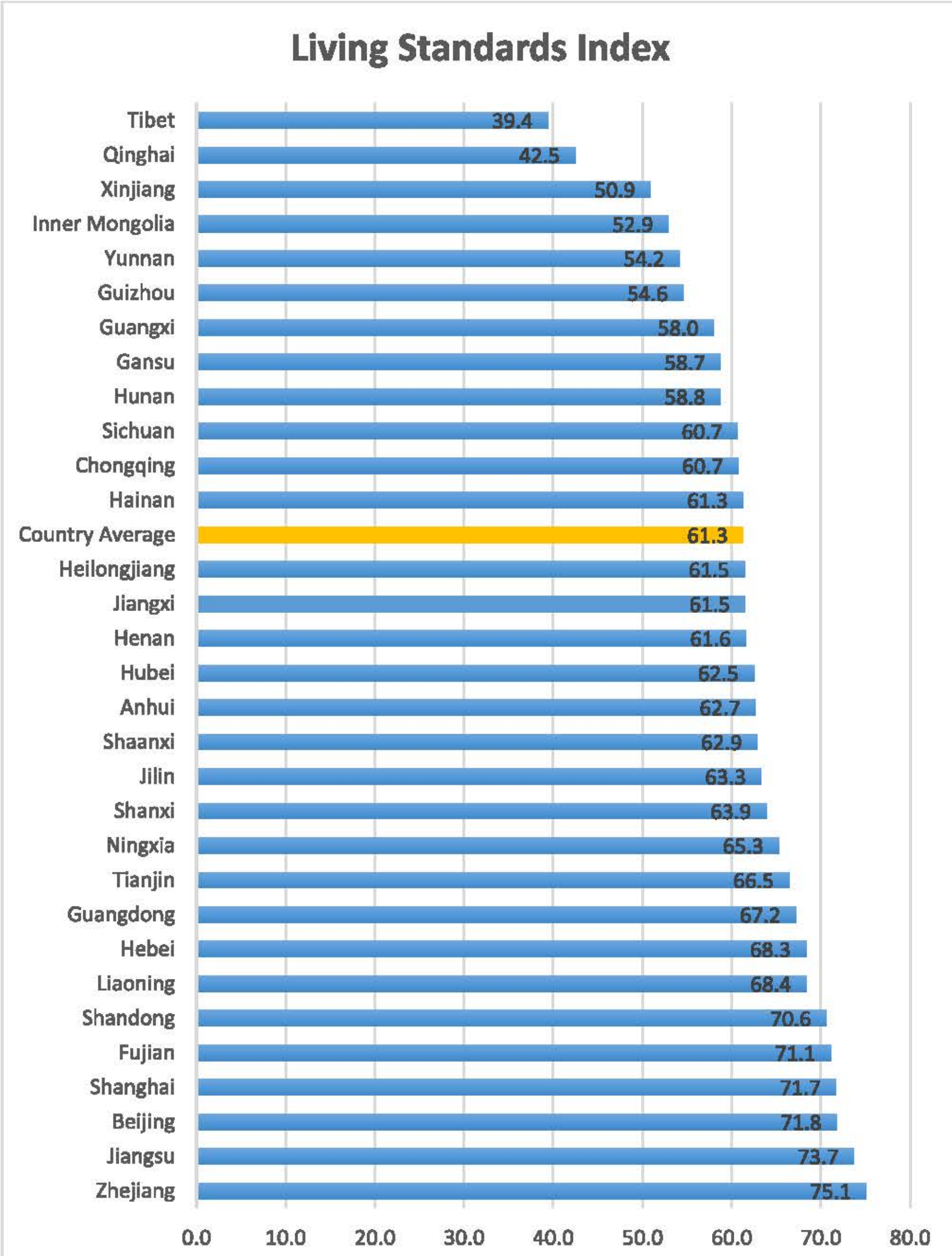

Figure 27 Ranking of provinces based on the Living Standards Index

Table 6.1 above lists all 31 provinces in descending order on the Living Standards Index. The country average score for living standards index is 61. Overall, 19 provinces, municipalities and autonomous regions rank above the average score, which is comprised of 11 provinces and municipalities from eastern coast and 8 provinces and autonomous regions from the centre of China. Provinces and autonomous regions in the west of China all rank below the country average.

The first and second places go to Zhejiang and Jiangsu, respectively, with index values of above 73 followed by Beijing and Shanghai, two municipalities directly under the Chinese central government. As for the other two municipalities, Tianjin ranks 10th and Chongqing ranks 21st. There are some additionally interesting findings. Chongqing is the only municipality among those four with an index value below the country average. Meanwhile, Hainan province just meets the country average score, making it the only province along the coast to not exceed the average. However, Ningxia, which ranks 11th, is the only autonomous region among the five autonomous regions in China to have an index value that exceeds the country average.

5.3 Analysis at the County Level

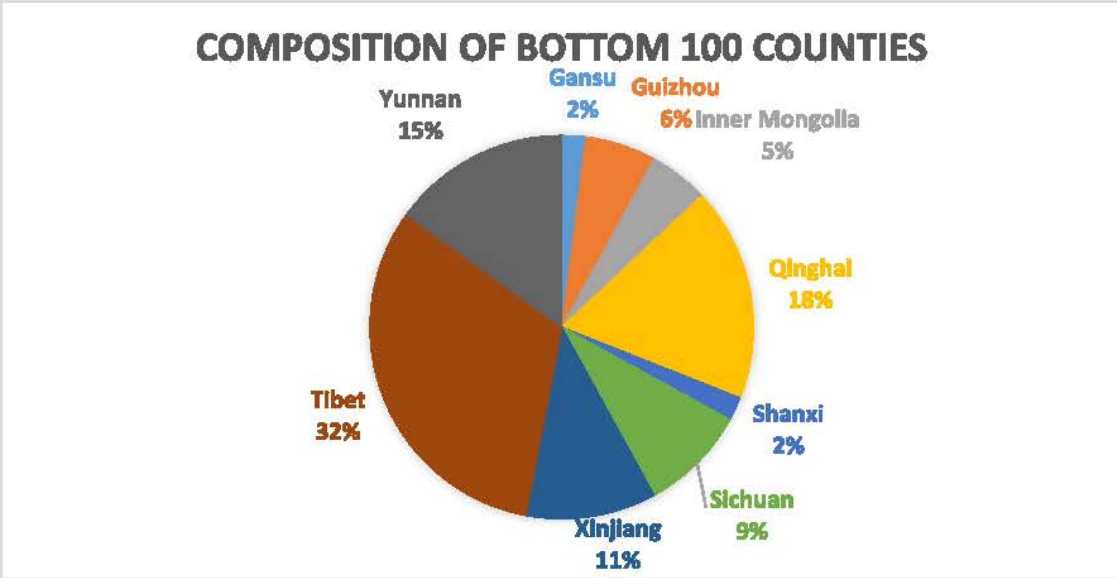

Figure 68 Distribution of the bottom 100 counties ranked by the Living Standards Index

When we summarize the bottom 100 counties by province, we can clearly see that these bottom ranked counties are concentrated in the west of China. Tibet Autonomous Region constitutes 32% of the bottom 100 counties followed by Qinghai, Yunnan and Xinjiang with 18%, 15% and 11% respectively. Sichuan, Guizhou and Inner Mongolia have percentages of 9%, 6% and 5% accordingly. Shanxi and Gansu provinces from the centre of China share 2% of the bottom 100 counties.

5.4 Living Standards Index Dashboard

The Living Standards Index suggests that the most economically developed provinces and municipalities, particularly those provinces along the coast of China, perform best in terms of living standards. Yet this does not mean they all have achieved equitable and sustainable development across the different aspects of living standards.

The Living Standards Index Dashboard ranks 31 provinces, municipalities and autonomous regions based on their Living Standards Index values, which have been classified into three groups. The first group of eight provinces ranks in the top 25% as developed provinces. The second group of 15 provinces ranks in the middle 50% as less developed provinces. The last group of eight provinces ranks in the bottom 25% as the least developed provinces. In the dashboard, each indicator enables us to review and track poverty reduction and development based on each province's performance measurement indicators. Here, good performance, which ranks in the top 25%, scores green; the middle 50% scores yellow, and the bottom 25% scores red.

Looking at the top section of the dashboard with the top eight provinces and municipalities, the top 25% is dominated by green with scattered red and yellow. This indicates that provinces and municipalities along the east coast outperform the rest of those in China. Zhejiang and Jiangsu rank 1st and 2nd with index values of 75 and 73 respectively. Both provinces have seven green indicators, which means they have relatively equitable development and better performance across the indicators of living standards when compared to other provinces. However, Zhejiang has one yellow indicator in the percentage of indoor kitchen users; and Jiangsu has two yellow indicators in the percentage of sanitary toilet users and road infrastructure coverage. Beijing and Shanghai secure 3rd and 4th in the ranking with very close index values of 71.8 and 71.7 respectively. However, both municipalities have red indicators in road infrastructure coverage. Fujian, Shandong, Liaoning and Hebei have three to five green indicators. The development challenges lie in mobile internet coverage, road infrastructure coverage, access to piped water, sanitary toilets and indoor kitchens. All top eight provinces receive green scores on living services coverage. The top section of the dashboard reveals that road coverage is relatively less developed in these provinces, with two provinces scoring red and three provinces scoring yellow on this indicator.

The middle section of the dashboard, from ranking 9 to 23, is dominated by the less developed provinces in the centre of China. Indicators here received a mixture of scores but were dominated by yellow, with each province receiving at least three yellow scores. Heilongjiang has three red indicators on financial services coverage, road infrastructure coverage and mobile internet coverage. Hunan also receives three red scores but on slightly different indicators, namely access to piped water, mobile internet coverage and nightlight density. Jilin, Jiangxi, Hainan and Sichuan have two red scores on different indicators including financial services coverage, mobile internet coverage, access to piped water, toilets and kitchens as well as nightlights. Guangdong, Shanxi and Henan provinces scored one red each for road coverage, access to kitchens and access to piped water respectively. Chongqing is a municipality that receives two red scores on indicators of mobile internet coverage and nightlight; while Tianjin scores one red in road coverage. All provinces and municipalities in this section receive yellow scores on living services coverage. The middle section of the dashboard reveals that the mobile coverage is relatively less developed in these provinces, with six provinces score red and six provinces score yellow on this indicator.

Arriving at the bottom of the dashboard, from ranking 24 to 31, red scores predominate, with only a few yellow and green indicators. The provinces in this section are therefore the least developed provinces and tend mostly to be located in western China. As the dashboard shows, all of these provinces score red on at least two indicators. The lowest ranked are Tibet and Qinghai with index values of 39 and 43 respectively. They score red in seven indicators, followed by Xinjiang with six red indicators. Yunnan, Guizhou and Guangxi have five red indicators followed by Inner Mongolia scoring four red. The dashboard reveals that the least developed indicator at the bottom section is living services coverage. All eight provinces receive red scores on this indicator. Access to sanitary toilets constitutes the second serious development issue, receiving seven red scores followed by access to kitchens and financial services coverage with six scores each. Nightlight density, access to piped water and road coverage receive five, four and three red scores respectively. One interesting finding is that mobile coverage is relatively developed amongst these provinces, with only two provinces receiving red scores on this indicator, fewer red scores than for any of the seven other indicators in this group of provinces. It is also interesting to point out that, of these provinces, only Xinjiang receives a green score, namely, for its access to piped water.

Rank	Province	Living Standards Index	Piped Water	Toilet	Kitchen	Living Services	Financial Services	Roads	Mobile Coverage Rate	Night Light
1	Zhejiang	75.1	Green	Green	Yellow	Green	Green	Green	Green	Green
2	Jiangsu	73.7	Green	Yellow	Green	Green	Green	Yellow	Green	Green
3	Beijing	71.8	Green	Green	Green	Green	Yellow	Red	Green	Yellow
4	Shanghai	71.7	Green	Green	Green	Green	Yellow	Red	Green	Yellow
5	Fujian	71.1	Green	Yellow	Green	Green	Green	Yellow	Green	Yellow
6	Shandong	70.6	Green	Green	Yellow	Green	Green	Green	Yellow	Green
7	Liaoning	68.4	Yellow	Green	Green	Green	Yellow	Yellow	Yellow	Yellow
8	Hebei	68.3	Yellow	Yellow	Yellow	Green	Green	Green	Yellow	Green
9	Guangdong	67.2	Yellow	Green	Green	Yellow	Yellow	Red	Green	Yellow
10	Tianjin	66.5	Green	Yellow	Yellow	Yellow	Green	Red	Green	Green
11	Ningxia	65.3	Yellow	Yellow	Yellow	Yellow	Yellow	Green	Green	Green
12	Shanxi	63.9	Yellow	Yellow	Red	Yellow	Green	Green	Yellow	Green
13	Jilin	63.3	Yellow	Yellow	Green	Yellow	Red	Yellow	Red	Yellow
14	Shaanxi	62.9	Yellow	Green	Yellow	Yellow	Yellow	Green	Yellow	Yellow
15	Anhui	62.7	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow
16	Hubei	62.5	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Red	Yellow
17	Henan	61.6	Red	Yellow	Yellow	Yellow	Green	Green	Yellow	Green
18	Jiangxi	61.5	Red	Yellow	Yellow	Yellow	Yellow	Yellow	Red	Yellow
19	Heilongjiang	61.5	Yellow	Yellow	Green	Yellow	Red	Red	Red	Yellow
20	Hainan	61.3	Yellow	Red	Red	Yellow	Yellow	Green	Yellow	Yellow
21	Chongqing	60.7	Yellow	Yellow	Yellow	Yellow	Yellow	Yellow	Red	Red
22	Sichuan	60.7	Red	Green	Yellow	Yellow	Yellow	Yellow	Yellow	Red
23	Hunan	58.8	Red	Yellow	Yellow	Yellow	Yellow	Yellow	Red	Red
24	Gansu	58.7	Yellow	Yellow	Yellow	Red	Red	Yellow	Yellow	Yellow
25	Guangxi	58.0	Red	Red	Red	Red	Yellow	Yellow	Yellow	Red
26	Guizhou	54.6	Red	Red	Red	Red	Yellow	Yellow	Yellow	Red
27	Yunnan	54.2	Yellow	Red	Red	Red	Red	Yellow	Red	Yellow
28	Inner Mongolia	52.9	Yellow	Red	Yellow	Red	Red	Red	Yellow	Yellow
29	Xinjiang	50.9	Green	Red	Red	Red	Red	Red	Yellow	Red
30	Qinghai	42.5	Red	Red	Red	Red	Red	Red	Yellow	Red
31	Tibet	39.4	Red	Red	Red	Red	Red	Yellow	Red	Red

Living standards index poverty dashboard (red, yellow and green represents bottom 25%, middle 50% and top 25% respectively)

5.5 National Poor Counties ranked by the Living Standards Index

In its own development policy, the Chinese government officially recognises 592 counties as "Key Counties for Poverty Alleviation" based on average per capita income level. In addition, provinces themselves could define particular counties as contiguous poor areas, according to the situations specific to these counties. In the Outline for Development-oriented Poverty Reduction for China's Rural Areas (2011-2020), 630 counties are defined as contiguous poor areas. Since some of them overlap with the 592 "Key Counties for Poverty Alleviation" as described above, in total there are 832 National Poor Counties. Given the limitations on mapping techniques and changes in administrative areas over the years in China, we are only able to locate 825 National Poor Counties in the dataset. The following lists the areas that we are unable to locate.

County Name	City Name	Province	Remarks
Not applicable	Wuzhishan	Hainan	Either Wuzhishan city or four townships and three villages under its jurisdiction cannot be located
Yuanba District Chaotian District	Guangyuan	Sichuan	Aggregate all districts under a city into one unit. In this case, both Yuanba District and Chaotian District will be aggregated under Guangyuan city
Shuanghu Office	Naqu Prefecture	Tibet	Not a county
Yintai District Yaozhou District	Tongchuan	Shaanxi	Not a county
Lenghu Executive Committee Dachaidan Executive Committee Mangya Executive Committee	Not applicable	Qinghai	Not a county

Table 2 List of counties that do not correspond to the "National Poor Counties" list

Subsequently, we ranked the remaining 825 counties by the Living Standards Index to compare the indicator in the Living Standards Index to the ranking by income. To be consistent with the definition by Chinese government, we still use 832 National Poor Counties as the terminology in this report.

Looking at the 832 poor counties ranked by the Living Standards Index, there is a clear trend showing that the eastern provinces outperform the western provinces. Nearly all the eastern coastal provinces are dominated by blue, showing that they are relatively more developed counties, with the exception of Heilongjiang, Jilin and Hebei, which have some poor counties (represented in green). In the central areas, the counties are a mixture of green and yellow with scattered areas of red in Ningxia and Shaanxi, and a larger area of red in Inner Mongolia. Approaching the western part of the country, the dominant colours become red and yellow with only scattered green. The red areas are most densely concentrated in the autonomous regions of Xinjiang, Inner Mongolia and Tibet, and in Qinghai province.

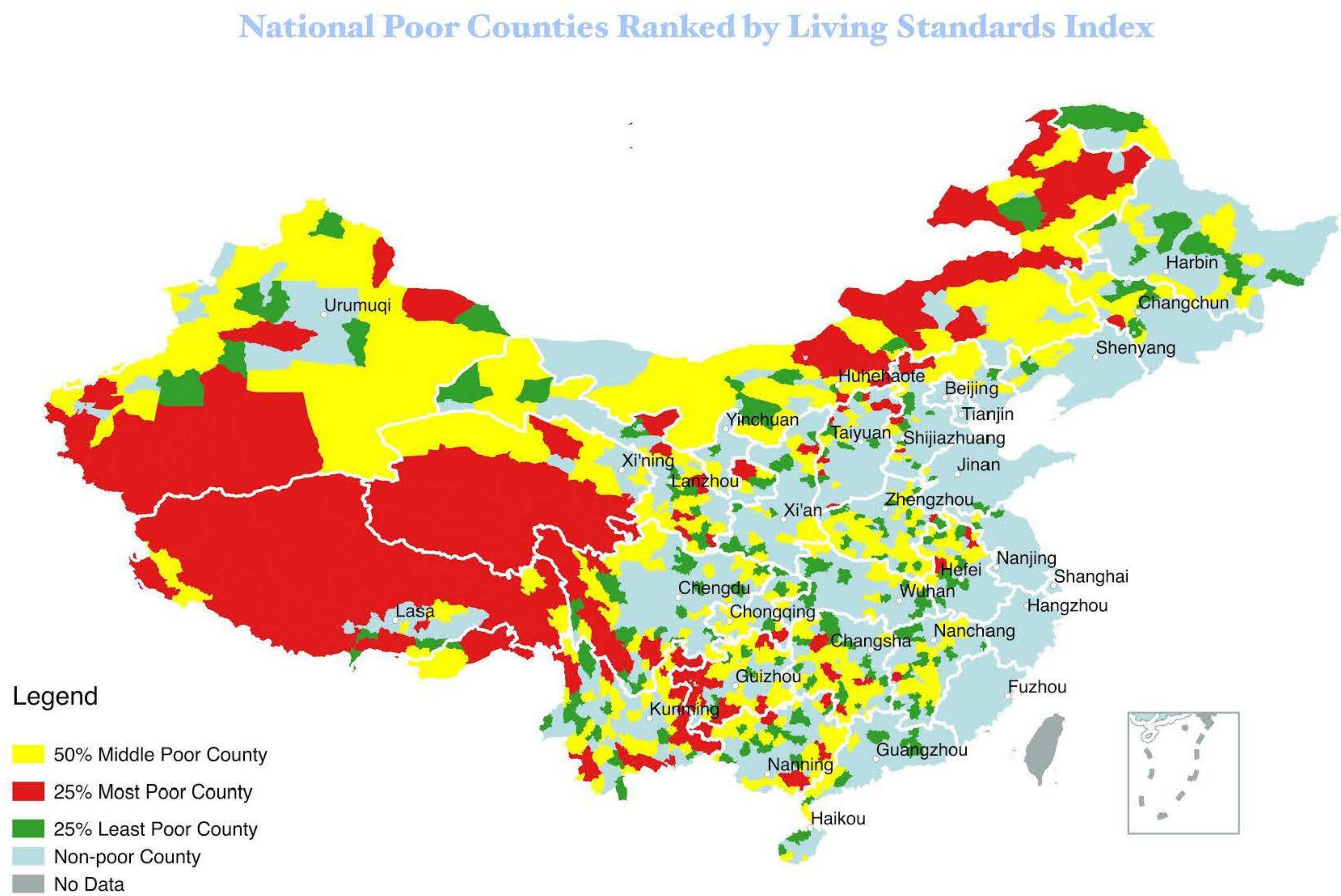

Figure 29 Map based on the Living Standards Index – National Poor County

By using the Living Standards Index to evaluate National Poor Counties, we found these counties vary in their living standards and face different development challenges. Appendix 2 shows the dashboard of 832 National Poor Counties.

The ranking indicates that the lowest 25% of National Poor Counties are mainly distributed in Western China. However, Gansu, Guizhou, Hebei, Heilongjiang, Shaanxi, Shanxi and Sichuan provinces have relatively high living standards as indicated by the concentrated green colour. Tibet has the largest number of counties (48) ranked in the lowest 25% of poor counties, followed by Yunnan and Xinjiang with 32 and 19 counties respectively. The middle 50% of National Poor Counties are spread across the country, but mainly located in Gansu, Guangxi, Guizhou, Sichuan and Yunnan provinces. Yunnan province has 38 poor counties, the largest number of poor counties per province in this second tier. The highest (i.e. least poor) 25% of poor national counties are mainly distributed in Shaanxi, Yunnan, Heilongjiang, Hebei, and Sichuan. Shaanxi stands out again with 28 poor counties, followed by Yunnan with 18 poor counties.

One notable finding is that among all National Poor Counties, there are only three counties which score green on all eight indicators. These are Linxia county in Gansu province, Zuoquan county in Shanxi province and Sansui county in Guizhou province . Compared to the rest of the National Poor Counties, Linxia, Zuoquan and Sansui have the most balanced development in terms of living standards. At the other end of the scale, Weining, Zeku, Zhiduo, Qumalai, Zaduo, Chengduo, Nangqian, Shiqu and Zhaojue score red on all eight indicators, which means those counties are consistently underdeveloped across all eight aspects of living conditions.

Province	National Poor County	Piped Water	Toilet	Kitchen	Living Services	Financial Services	Roads	Mobile Coverage Rate	Night Light
Anhui	20	11	2	0	2	1	5	13	0
Chongqing	14	1	1	1	1	1	5	0	6
Gansu	58	17	12	4	9	10	16	10	2
Guangxi	33	3	3	3	8	1	3	1	6
Guizhou	66	13	26	26	6	9	7	4	13
Hainan	4	0	0	1	0	0	0	0	0
Hebei	45	4	10	10	6	2	3	8	3
Heilongjiang	20	1	3	0	4	5	3	9	0
Henan	38	27	2	9	0	0	0	3	0
Hubei	28	1	3	0	4	1	2	6	4
Hunan	40	6	2	5	18	3	11	17	17
Jiangxi	24	2	1	1	2	1	9	8	7
Jilin	8	0	3	0	3	2	1	1	1
Inner Mongolia	31	2	17	8	14	16	14	2	7
Ningxia	8	4	1	0	2	2	0	2	0
Qinghai	39	18	20	21	11	20	17	6	18
Shaanxi	55	12	1	8	6	0	9	8	1
Shanxi	36	5	10	21	1	1	2	6	0
Sichuan	65	17	10	10	19	22	33	17	31
Xinjiang	32	1	8	15	24	26	20	16	15
Tibet	73	39	30	39	41	54	20	35	51
Yunnan	88	22	41	24	25	29	26	34	24
Total	825	206	206	206	206	206	206	206	206

Table 3 Living Standards Index National Poor Counties total red scores

We will now consider the National Poor Counties in further detail, focusing on their degree of development and highlighting areas with poor living conditions as identified by the eight living standard indicators.

Heilongjiang has the least developed mobile coverage receiving nine red scores. The common areas of underdevelopment between Heilongjiang and Jilin are access to toilets, road infrastructure, living services and financial development, while in Hebei, the most outstanding issues are access to toilets, access to kitchens and mobile internet coverage, as well as access to living services.

In the centre of China, deficiencies in living conditions are more varied. Out of 20 National Poor Counties in Anhui province, 13 poor counties score red on mobile coverage rates followed by 11 on access to piped water. In Hubei and Jiangxi, mobile coverage is a notable issue, with 6 and 8 red scores respectively. Plus, in Jiangxi, access to roads is least developed with nine red scores. However, nearby Henan and Shaanxi provinces face their biggest challenge in access to piped water. Particularly, out of its 38 National Poor Counties, 27 counties in Henan have poor access to piped water, which means 71% of poor counties in Henan lack access to piped water. In Shanxi province, the lowest indicator is access to kitchens, with 58% of its national poor counties having poor access to kitchen facilities. In Hunan province, the lowest indicator is access to living services followed by mobile coverage and night light, with 42% of its poor counties having poor access to living services, mobile coverage and light consumption.

Turning to the western part of China, one can observe that living facilities and night light are the least developed indicators in Guangxi. However, Guangxi also receives low scores on six other indicators. Yunnan has similar issues. In Yunnan province, all eight living standard indicators in a large number of counties receive red scores. Out of 88 National Poor Counties in Yunnan, access to toilets scored the worst with 41 reds and access to kitchens scored the lowest with 22 reds. For 66 National Poor Counties in Guizhou, the poorest indicators are access to toilets and kitchen facilities receiving 26 red scores followed by access to piped water and mobile internet coverage with 13 red scores. When we take a close look at the situation in Sichuan, the most serious problems are roads and night light followed by financial development, living facilities, mobile coverage and access to piped water, which indicates that Sichuan does not have a balanced development across its poor counties.

There are 73 National Poor Counties in the Tibet Autonomous Region The largest development issues for Tibet are financial development and nightlight coverage, with 70% of its National Poor Counties having poor access to financial services and light consumption. A large number of poor counties have red scores for the other six indicators as well.

Xinjiang is one of the most underdeveloped areas evaluated. The analysis indicates that its living services, financial development and road infrastructure are severely underdeveloped, followed by challenges in access to mobile coverage, kitchen facilities and light consumption.

Qinghai exhibits similar patterns, with all eight indicators receiving red scores. The biggest challenge in this province is access to kitchens followed by accesses to toilet and financial development. In Gansu, access to piped water, road infrastructure and access to toilets are the biggest issues, while Ningxia faces difficulties in access to piped water, access to living services, financial development and mobile internet coverage. In Inner Mongolia, all eight indicators receive red scores. Access to toilets has the highest number of red boxes, which means this is the least developed indicator. Indicators for financial development, living facilities and road infrastructure also show need for improvement.

5.6 Comparison of National Poor Counties and Living Standards Index poor counties

This section compares the Living Standards Index to conventional measures of poverty by comparing the National Poor Counties (discussed above) with the poor counties identified by the Index. The National Poor Counties are officially designated based mainly on the income poverty line. We identify a second group of poor counties, which are the 832 poorest counties according to the Living Standards Index, out of a total of 2284 counties studied.

Province	National Poor Counties	Total Counties	Percentage of Poor Counties
Yunnan	88	124	71%
Tibet	73	73	100%
Guizhou	66	81	81%
Sichuan	65	159	41%
Gansu	58	81	72%
Shaanxi	55	93	59%
Hebei	45	147	31%
Hunan	40	101	40%
Qinghai	39	40	98%
Henan	38	126	30%
Shanxi	36	107	34%
Guangxi	33	89	37%
Xinjiang	32	85	38%
Inner Mongolia	31	89	35%
Hubei	28	77	36%
Jiangxi	24	89	27%
Anhui	20	78	26%
Heilongjiang	20	77	26%
Chongqing	14	22	64%
Jilin	8	48	17%
Ningxia	8	19	42%
Hainan	4	18	22%
Beijing	0	3	0%
Fujian	0	66	0%
Guangdong	0	87	0%
Jiangsu	0	64	0%
Liaoning	0	58	0%
Shandong	0	108	0%
Shanghai	0	2	0%
Tianjin	0	4	0%
Zhejiang	0	69	0%

Table 4 Provincial summary of National Poor Counties

The map of officially recognized poor counties indicates that the nine provinces and municipalities along the coast have no National Poor Counties except Hebei and Hainan provinces, with 45 and 4 National Poor Counties respectively.

Out of all the provinces, directly-administered municipalities and autonomous regions, Yunnan has the largest number of National Poor Counties (88), followed by Tibet， Guizhou, Sichuan， Gansu and Shaanxi with 73, 66, 65, 58 and 55 poor counties respectively. The proportion of National Poor Counties to total counties for these four provinces is over 59%, with the exception of Sichuan, where poor counties make up 41% of its counties. The largest proportion of National Poor Counties to total counties is Tibet that stands out with 100% of its counties classed as National Poor Counties followed by Qinghai province with 98%. Chongqing is the only municipality that has 14 counties out of 22 classed as National Poor Counties, or 64% of the total.

Province	Poor Counties Identified by LSI	Total Counties	Percentage of Poor Counties
Yunnan	71	124	57%
Inner Mongolia	65	89	73%
Xinjiang	60	85	71%
Henan	58	126	46%
Tibet	56	73	77%
Sichuan	55	159	35%
Hunan	53	101	52%
Guangxi	49	89	55%
Guizhou	46	81	57%
Gansu	41	81	51%
Jiangxi	34	89	38%
Hebei	30	147	20%
Shaanxi	28	93	30%
Anhui	27	78	35%
Qinghai	26	40	65%
Heilongjiang	24	77	31%
Shanxi	24	107	22%
Hubei	20	77	26%
Guangdong	14	87	16%
Jilin	14	48	29%
Chongqing	7	22	32%
Hainan	6	18	33%
Liaoning	6	58	10%
Ningxia	4	19	21%
Shandong	4	108	4%
Jiangsu	3	64	5%
Beijing	0	3	0%
Fujian	0	66	0%
Shanghai	0	2	0%
Tianjin	0	4	0%
Zhejiang	0	69	0%

Table 5 Provincial summary of poor counties as identified by the Living Standards Index

Comparing with the National Poor County map, the Living Standards Index poverty map shows poor counties over a wider range in China. The index poverty map indicates that only five provinces and municipalities- Beijing, Shanghai, Tianjin, Zhejiang and Fujian- have zero poor counties.

Yunnan, has the greatest number of poor counties at 71 followed by Inner Mongolia, Xinjiang, Henan, Tibet and Sichuan at 65, 60, 58, 56 and 55 poor counties respectively. Chongqing has seven poor counties out of 22 total counties. Looking at the percentage of poor counties, the top five provinces on this measure are Tibet, Inner Mongolia, Xinjiang, Qinghai, Guizhou and Yunnan with percentages of 77%, 73%, 71%, 65%, 57% and 57% respectively. The proportion of Living Standards Index poor counties to total counties for Hunan, Guangxi, Guizhou and Gansu is over 51%.

Province	National Poor Counties	Total Counties	% Poor Counties	Poor Counties Identified by LSI	Total Counties	% of Index Poor Counties	% Difference
Anhui	20	78	26%	27	78	35%	9%
Beijing	0	3	0%	0	3	0%	0%
Chongqing	14	22	64%	7	22	32%	32%
Fujian	0	66	0%	0	66	0%	0%
Gansu	58	81	72%	41	81	51%	21%
Guangdong	0	87	0%	14	87	16%	16%
Guangxi	33	89	37%	49	89	55%	18%
Guizhou	66	81	81%	46	81	57%	25%
Hainan	4	18	22%	6	18	33%	11%
Hebei	45	147	31%	30	147	20%	10%
Heilongjiang	20	77	26%	24	77	31%	5%
Henan	38	126	30%	58	126	46%	16%
Hubei	28	77	36%	20	77	26%	10%
Hunan	40	101	40%	53	101	52%	13%
Inner Mongolia	31	89	35%	65	89	87%	52%
Jiangsu	0	64	0%	3	64	5%	5%
Jiangxi	24	89	27%	34	89	38%	11%
Jilin	8	48	17%	14	48	29%	13%
Liaoning	0	58	0%	6	58	10%	10%
Ningxia	8	19	42%	4	19	21%	21%
Qinghai	39	40	98%	26	40	65%	33%
Shaanxi	55	93	59%	28	93	30%	29%
Shandong	0	108	0%	4	108	4%	4%
Shanghai	0	2	0%	0	2	0%	0%
Shanxi	36	107	34%	24	107	22%	11%
Sichuan	65	159	41%	55	159	35%	6%
Tianjin	0	4	0%	0	4	0%	0%
Tibet	73	73	100%	56	73	77%	23%
Xinjiang	32	85	38%	60	85	71%	33%
Yunnan	88	124	71%	71	124	57%	14%
Zhejiang	0	69	0%	0	69	0%	0%
Total	825	2284	36%	825	2284	36%	0%

Table 6 Provincial summary of differences between the two maps

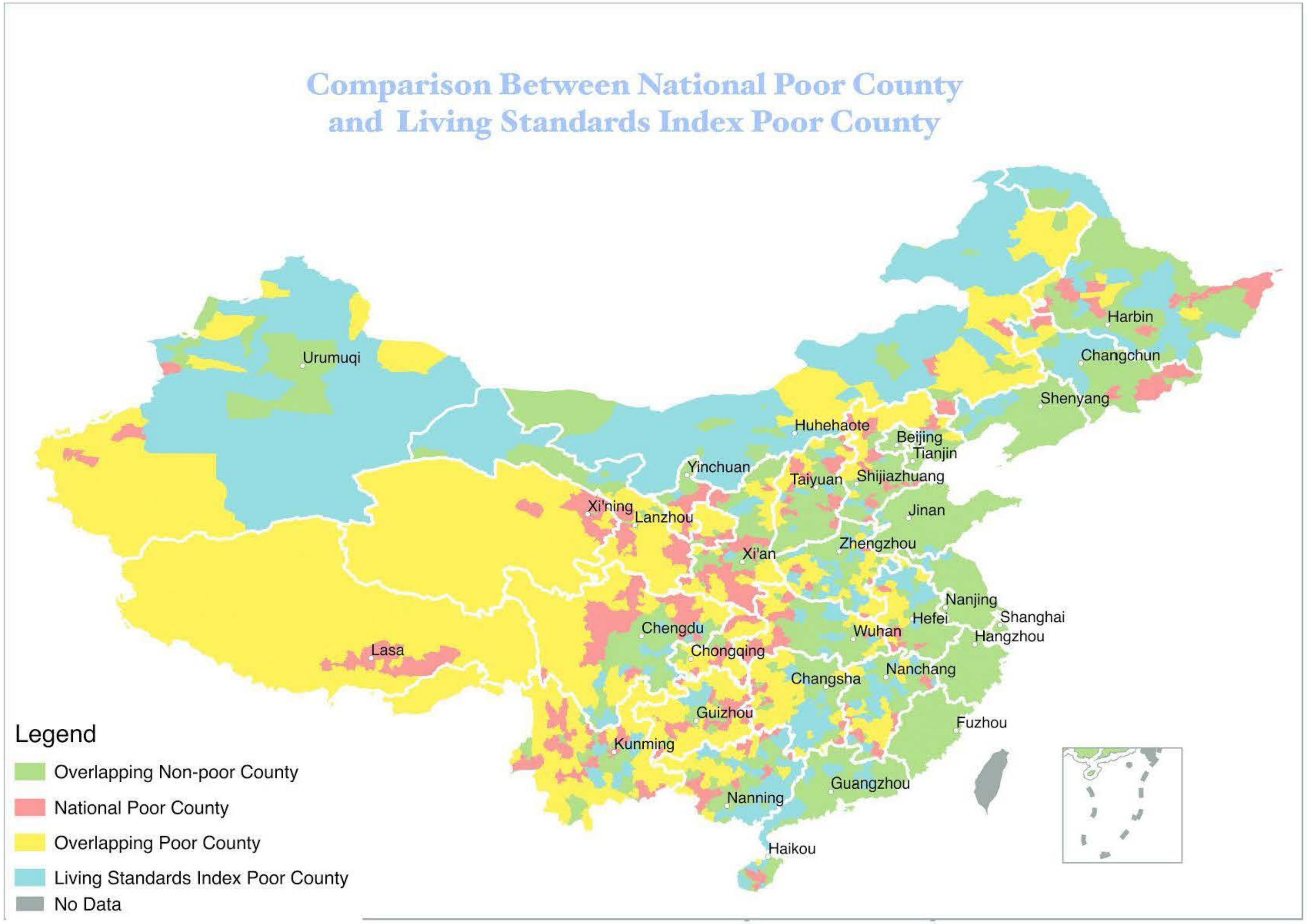

Figure 30 Map of overlapping poor counties

If we compare the two poverty maps, there are 31 provinces, autonomous regions and municipalities which are classified in the same way by both evaluation systems. This represents a 63% overlap in the classification of poor counties. Beijing, Fujian, Shanghai, Tianjin and Zhejiang are mapped in exactly the same way as provinces with no poor counties. Heilongjiang, Jiangsu, Shandong, Sichuan and Anhui provinces are assigned very similar classifications by the two measures, with a difference rate of less than 10%. The biggest difference in the classification of poor counties between the two maps is in Inner Mongolia (52%). Poor counties identified by the Living Standards Index are 34 more than National Poor Counties, which means counties in Inner Mongolia are poorer in terms of the Living Standards Index.

The large between the two poverty maps are in Chongqing, Qinghai and Xinjiang where the maps differ by more than 30%. The difference is Chongqing and Qinghai are poorer according to the official definition. While Xinjiang is poorer when measured by the Living Standards Index with an extra 28 poor counties compared to the National Poor Counties. Gansu, Guizhou, Hebei, Ningxia, Shaanxi, Shanxi, Tibet and Yunnan have more poor counties when measured by income than by the Living Standards Index, but vice versa for Guangxi, Hainan, Hunan, Jiangxi and Jilin. It should be noted that in Guangdong, Jiangsu, Liaoning and Shandong provinces, no counties are classed as National Poor Counties, but there are 14, 5, 6 and 4 Living Standards Index poor counties respectively which contribute to difference rates of 16%, 5%, 10% and 4% between the two measures.

5.7 Correlation between the Living Standards Index and GRP per capita

In order to study the correlation between the Living Standards Index and other economic indicators, we calculate the correlation between the Living Standards Index and the gross regional product (GRP) per capita with a result of 0.359, indicating a positive correlation between them. We generate a scatter plot for the 832 National Poor Counties using the Living Standards Index and GRP per capita. The X-axis represents the Living Standards Index, while the Y-axis stands for GRP per capita. The scatter plot shows that the counties are mainly distributed in the lower right side and quite dispersed along the X-axis. This indicates that despite having similarly low GRP per capita, counties receive very different scores on the Living Standards Index. The Living Standards Index is therefore able to provide more information on the counties that is not captured by GRP per capita. This supports the use of the Living Standards Index as a measure of poverty to complement purely income-based measurements.

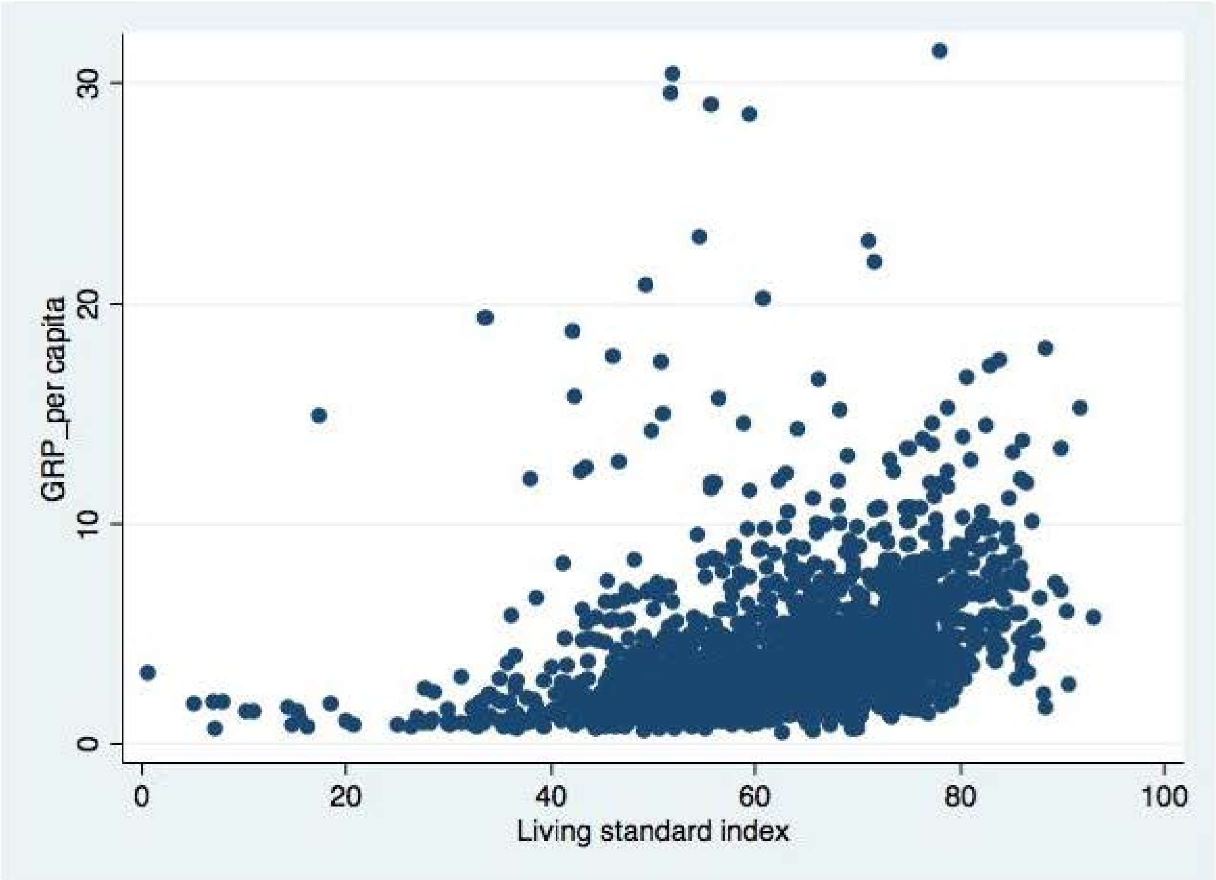

Figure 31 Plot of income versus the Living Standards Index

SIX
CONCLUSIONS AND RECOMMENDATIONS

6. Conclusions and recommendations

KEY POINTS

- Our findings using the Living Standards Index to support the government's current policy of targeting resources to western and mountainous areas for poverty alleviation.
- We also find evidence of variation in poor counties' living standards using the Living Standards Index and its eight indicators. This may help efforts to evaluate the provision of services in the 2,284 counties and improve the allocation of resources for poverty reduction.
- This research demonstrates the potential benefits of harnessing big data for development research, to complement and complete conventional data sources. Further research in this area may consider other dimensions of poverty and real-time poverty tracking.

This report has sought to review and track poverty from the novel perspective provided by big data. Our focus has been on multidimensional poverty, as captured by the Living Standards Index, which brings together eight indicators of prosperity across China. By harnessing new sources of data, we present an analysis of the sources of poverty for each county in China in the form of poverty maps and the poverty dashboard. Together, these findings can support China's "targeted poverty alleviation" strategy to ensure resources are directed to the areas of greatest need and at the root causes of poverty.

The Living Standards Index should be seen as a complementary measurement to income-based measures of poverty.

First, these measures confirm the existing view that western and mountainous counties are the poorest areas. From the comparison between 832 National Poor Counties and the bottom 832 Living Standards Index poor counties, the overlapping rate is 63% which means 63% National Poor Counties are also classed as Living Standards Index poor. This reinforces the prevailing approach to targeted development in China.

Second, the Living Standards Index may supplement this general orthodoxy with more detailed understanding of the variation in living standards in these impoverished areas. The poverty maps and the Living Standards Index dashboard may help policymakers identify the particular county-level obstacles to alleviating income poverty. By uncovering the particular areas of strength and weakness in each county, we hope to enhance the likelihood of sustainable, equitable development.

Finally, this report demonstrates the potential benefits to development research and policy from harnessing big data, both to overcome weaknesses in conventional data sources and to expand our knowledge of local conditions beyond what has been previously possible.

6.1 Confirms need for poverty alleviation in western, inland and rural areas

In line with the existing understanding of poverty in China, the Living Standards Index poverty map indicates clearly that the provinces in the eastern part of the country outperform western provinces China with higher Living Standards Index values, whereas in the centre, the mixture of green and yellow indicates comparatively lower values in the Living Standards Index. Living standards continue to fall as we move to the west, where the majority of areas are mapped in yellow and orange with only scattered green. The lowest values, represented in red, are mostly concentrated in Tibet and Qinghai provinces, the most underdeveloped counties in terms of Living Standards.

As for coastal provinces, the northeast does not perform as well as the south. In the centre of China, provinces in the plain areas are better developed, such as the Sichuan Plain, the Yangtze Plain (at the intersection of Hubei, Hunan and Jiangxi), the Guanzhong Plain (in the centre of Shaanxi Province), and the Huabei Plain (Beijing, Tianjin, Hebei, Shangdong, Henan, Anhui and Jiangsu). The poverty map reveals that living standards are correlated closely to terrain. In particular, the provinces in mountainous regions are relatively less developed since the cost of basic infrastructure and providing local services, including roads, signal towers and piped water, is much higher in these areas.

As well as the striking coastal-inland and east-west gaps in living standards, we also see a disparity in living standards between rural and urban areas. The Living Standards Index poverty map confirms that big cities have better living standards than rural areas. The capital Beijing, the Yangtze River Delta, the Pearl River Delta and the Beijing-Tianjin economic zone all enjoy comparatively high living standards.

Considering the development gaps between east and west, and coastal and inland regions, it is apparent that resources should continue to be directed to provinces in the west of China, as well as the mountainous areas. Our research therefore supports the existing policy of targeting development aid to improve living conditions in those areas.

6.2 Improved data for poverty analysis

In order to ensure balanced and sustainable development in the impoverished areas that we have identified, we recommend that a better understanding of the sources of poverty be developed. This includes tracking poor counties in otherwise developed provinces. The Living Standards Index poverty map suggests that the most developed provinces, particularly those provinces along the coast of China, perform best in terms of living standards. Yet this does not mean they all have achieved balanced development across the different aspects of living standards.

The Living Standards Index dashboard suggests that even amongst the provinces with the highest overall standards of living, each province has areas that need improvement. Income-based measures of poverty might not reveal these development needs in high-performing provinces. Moving down the dashboard brings us to provinces with more serious development needs. Each province in this group has at least three areas with room for improvement. Provinces at the bottom of the dashboard have the most inadequate living standards, each of which having at least two areas that require significant improvement.

For east coast provinces, attention may be given to road infrastructure and night light density. In the centre of China, poverty reduction efforts might focus on improving mobile coverage and access to piped water, which are the two aspects of living standards most in need of development in this region.

In western provinces, which have the greatest concentration of poor counties, we find that the access to living services indicator scores the lowest, followed by access to toilets, access to kitchens, financial development, road infrastructure and night light coverage. Access to piped water also needs improvement. In order to significantly improve people's living conditions in these provinces, it is suggested that resources be targeted at improving the living facilities coverage, electricity supply, financial services coverage, the availability of toilets, kitchens, water and road networks.

One of the most significant contributions of this report is the use of the Living Standards Index to re-evaluate the officially recognized National Poor Counties. Using the Living Standards Index, we identify an overlapping set of counties as the poorest counties nationally. According to this new ranking, the poorest 25% of National Poor Counties are mainly distributed in the autonomous regions of Xinjiang, Inner Mongolia and Tibet, and in Qinghai province. The next 50% of National Poor Counties are spread across the country, but mainly located in Gansu, Guangxi, Guizhou, Sichuan and Yunnan provinces. The final 25% of National Poor Counties are mainly distributed in the centre of China.

The Living Standards Index dashboard may help us evaluate each National Poor County's weaknesses and strengths, in the hope of enhancing our understanding of the sources of poverty in each county. By using the dashboard, we hope that our limited resources can be used to develop an effective and comprehensive poverty alleviation plan, and thereby contribute to real progress in China's "targeted poverty alleviation" strategy.

It is suggested that for poor counties in coastal provinces, such as Heilongjiang and Jilin, the aspects of living standards that are most in need of improvement are mobile coverage and living facilities as well as road infrastructure, while in Guangdong province, road infrastructure is the most outstanding issue. Road infrastructure is also an issue in three of the directly administered municipalities, Beijing, Shanghai, Tianjin, but due to their particular circumstances, i.e. that they are largely densely populated urban areas, this indicator may not be an issue of lack of development. Hainan province faces the biggest challenges in access to toilets and access to kitchen.

In the centre of China, our research suggests that deficiencies in living conditions may be more varied. Improved access to kitchens could be the first priority in Shanxi, while access to piped water is more serious in Henan and Jiangxi. However, nearby Hubei province faces its biggest challenge in access to piped water, mobile internet coverage and night light density. In Hubei province, electricity supply and mobile internet coverage, as well as access to piped water, are in greatest need of development.

Provinces in the west of China appear to require improvement on all of the eight aspects of living standards that we consider. For Guangxi and Sichuan, the priority may be improving access to piped water, and electricity supply and consumption. In Yunnan, poverty-reduction policies and programs may wish to prioritize improved access to toilets and kitchen, as well as access living services and financial development. Development efforts in Qinghai, Ningxia and Gansu may focus on access to piped water. Xinjiang, Inner Mongolia and Tibet are three of most vulnerable areas we consider. Our analysis suggests that their financial development, living services, access to kitchens, access to toilets and electricity supply pose serious developmental challenges and will require greater resources for improvement.

6.3 Big data for development

This research not only serves as a contemporary study of poverty in China using innovative big data tools, but may also form a reference point for the use of big data for development purposes.

The use of big data provides this research with alternative sources of data outside official statistics, greatly extending the scope of the study. In our analysis, we are able to measure the smart phone coverage rate and the convenience of access to facilities and amenities by creating indicators using big data from Baidu. Big data also allows us to analyse and compare poverty at different levels within China, namely, country, province, and county. We believe more innovative approaches to using big data will emerge as more development research harnesses this new resource.

As the UNDP has noted, advances in knowledge and data allow for innovations in measuring multidimensional inequality and poverty, which can be applied globally to enable comparisons and provide new insights (UNDP, 2010). Future research would benefit from comparative analysis on poverty alleviation using big data from other countries.

References

1. Aker, J. C., & Mbiti, I. M. (2010). Mobile phones and economic development in Africa. The Journal of Economic Perspectives, 24(3), 207-232.
2. Asian Development Bank. (2002). 'Impact of Rural Roads on Poverty Reduction: A Case Study-Based Analysis'. Asian Development Bank.
3. Asian Development Bank. (2004) Poverty profiles of the People's Republic of China. Manila: Asian Development Bank.
4. Alkire, S. and Housseini, B. (2014). "Multidimensional Poverty in Sub-Saharan Africa: Levels and Trends." OPHI Working Papers 81, University of Oxford
5. Angulo, R. (2016). "From multidimensional poverty measurement to multisector public policy for poverty reduction: lessons from the Colombian case." OPHI Working Paper 102, University of OxfordBalakrishnan, K., Sambandam, S., Ramaswamy, P., Mehta, S., & Smith, K.R. (2004). 'Exposure Assessment for Respirable Particulates Associated with Household Fuel Use in Rural Districts of Andhra Pradesh, India', Journal of Exposure Analysis and Environmental Epidemiology, 14, S14-S25
6. Ballon, P. and Duclos, J.-Y. (2015) "Multidimensional Poverty in Sudan and South Sudan." OPHI Working Papers 93, University of Oxford.
7. Bhavnani, A., Chiu, R. W., Janakiram, S. & Silarszky, P. (2008). 'The Role of Mobile Phones in Sustainable Rural Poverty Reduction'. ICT Policy Division.
8. Blumenstock, J. & Donaldson, D., (2013). How Do Labor Markets Equilibrate? Using Mobile Phone Records to Estimate the Effect of Local Labor Demand Shocks on Internal Migration and Local Wages. Data Science and Analytics Lab. University of Washington Information School.
9. Boadi, K.O., & Kuitunen, M. (2005). 'Factors Affecting the Choice of Cooking Fuel, Cooking Place and Respiratory Health in the Accra Metropolitan Area, Ghana', Journal of Biosocial Science, 38, 403-412
10. BPP. (2014). The Billion Prices Project @ MIT. Retrieved from http://bpp.mit.edu/usa/
11. Bryceson, D. F., Bradbury, A., & Bradbury T. (2006). 'Roads to Poverty Reduction? Dissecting Rural Roads' Impact on Mobility in Africa and Asia.'
12. Bundervoet, T., Maiyo, L. & Sanghi, A. (2015). 'Bright Lights, Big Cities: Measuring National and Subnational Economic Growth in Africa from Outer Space, with an Application to Kenya and Rwanda'. World Bank Group October 2015.
13. Chen, X., & Nordhaus, W. D. (2011). Using luminosity data as a proxy for economic statistics. Proceedings of the National Academy of Sciences, 108(21), 8589-8594.
14. Cheng. J (2014). "Big data for development in China", UNDP China
15. Chowdry, H. et al. (2010) The role of attitudes and behaviours in explaining socio-economic differences in attainment at age 16. Institute for Fiscal Studies; Jackson et al (2006) Does Home Internet Use Influence the Academic Performance of Low-Income Children? Developmental Psychology Vol. 42, No. 3.

16. Dasgupta, S., Huq, M., Khaliquzzaman, M., Pandey, K. & Wheeler, D. (2004). 'Indoor Air Quality for Poor Families: New Evidence from Bangladesh', World Bank Policy Research Working Paper, 3393.
17. de Barros, R. P., Vega, J. R. M., & Saavedra, J. (2008). Measuring inequality of opportunities for children. Washington, DC: World Bank.
18. Equality of Opportunities (2014), LAC Equity Lab, The World Bank; Retrieved from http://www.worldbank.org/en/topic/poverty/lac-equity-lab1/equality-of-opportunities
19. Esrey, S.A. (1996). 'Water, Waste, and Well-Being: A Multicountry Study', American Journal of Epidemiology, 143(6), 608-623.
20. Fang, Q. (2015). 'Xi: China to lift 70 mln people out of poverty in 5 years'. Retrieved from http://en.chinagate.cn/news/2015-10/16/content_36826840.htm
21. Gadgil, A. (1998). 'Drinking Water in Developing Countries', Annual Review of Energy and the Environment, 23, 23-86.
22. Guerrero, M. (2015). The impact of Internet connectivity on economic development in Sub-Saharan Africa
23. Haughton J. and S. R. Khandker (2009). Handbook on Poverty and Inequality. Washington, DC. World Bank
24. Human Opportunities Index, Equity Lab, World Bank; Retrieved from http://pubdocs.worldbank.org/en/446351421851825357/TN-EoI.pdf
25. Jean, N., Burke, M., Xie, M., Davis, W. M., Lobell, D. B., & Ermon, S. (2016). Combining satellite imagery and machine learning to predict poverty. Science, 353(6301), 790-794.
26. Khandker, S. K., Bakht, Z., Koolwall, G. B. (2006). 'The Poverty Impact of Rural Roads: Evidence from Bangladesh'. World Bank Policy Research Working Paper 3875, April 2006.
27. Letouze. E (2015) Thoughts on big data and the SDGs.
28. Liu X.P. Su, Sh.L, Wang, Yajuan, et al. The index system of spatial poverty of village level to monitor in concentrated contiguous areas with particular difficulties. Sicientia Geogrpahica Sinica, 2014, 24(4): 447-453
29. Liu, Y. H, Xu, Y. (2015) Geographical identification and classification of multi-dimensional poverty in rural China. ACTA Geographica Sinica 2015 Vol. 70, No.6
30. Ma YK and Xiao JC. (2016). "The Basic Thoughts of Targeted Poverty Alleviation during the Period of 13th Five-Year". Economics and Management, 2016 30(4).
31. Mahoozi, H. (2015). "Gender and Spatial Disparity of Multidimensional Poverty in Iran." OPHI Working Papers 95, University of Oxford
32. OECD. 2008 Handbook on Constructing Composite Indicators: Methodology and User Guide; Paris: Organization for Economic Co-operation and Development.
33. Oxford Poverty & Human Development Initiative (OPHI). "Policy - a multidimensional approach". Retrieved from: www.ophi.org.uk
34. Outline for Development-oriented Poverty Reduction for China's Rural Areas (2011-2020)
35. Pande R, Cole S, Sivasankaran A, Bastian G, Durlacher K (2012) Does poor people's access to formal banking services raise their incomes? EPPI-Centre, Social Science Research Unit, Institute of Education, University of London.

36. Prosperity for All: Ending Extreme Poverty (2014). World Bank Group; Retrieved from http://siteresources.worldbank.org/INTPROSPECTS/Resources/334934-1327948020811/8401693-1397074077765/Prosperity_for_All_Final_2014.pdf
37. Pulse, U. G. (2012). Big data for development: Challenges & opportunities. New York: UN Global Pulse.
38. Rehfuess, E. (2006). Fuel for Life: Household Energy and Health. Geneva: World Health Organization; Rehfuess, E., Tzala, L., Best, N., Briggs, D.J., & Joffe, M. (2009). 'Solid Fuel Use and Cooking Practices as a Major Risk Factor for ALRI Mortality among African Children', Journal of Epidemiology and Community Health, 63(111), 887-892.
39. Sen, A. (1976). Poverty: an ordinal approach to measurement. Econometrica: Journal of the Econometric Society, 219-231.
40. Sen, A. (1992) Inequality Re-examined. Oxford: Oxford University Press.
41. Sen. A. (2000) Development as Freedom, Anchor Books: Reprting edition
42. Side, A. S., Kiondo, E., & Lyimo-Macha, J. G. (2010). 'Contribution of Mobile Phones to Rural Livelihoods and Poverty Reduction in Morogoro Region, Tanzania'. The Electronic Journal on Information Systems in Developing Countries (2010) 42, 3, 1-15.
43. Statistics Division (2016). 'Official List of Proposed SDG Indicators'. United Nations Department of Economic and Social Affairs.
44. Stat Counter Global Stats (2016). Top 5 search engine in China on Aug 2016 http://gs.statcounter.com/#all-search_engine-CN-monthly-201608-201608-bar
45. Suppa, N. (2015). "Towards a Multidimensional Poverty Index for Germany." OPHI Working Papers 98, University of Oxford;
46. Thapa A, Anisha(2016) BIG DEAL: How can we use big data to measure poverty in Sudan? Retrieved from: http://www.sd.undp.org/content/sudan/en/home/blog/2016/1/12/A-BIG-DEAL-How-can-we-use-big-data-to-measure-poverty-in-Sudan-.html
47. Thapa, A. (2016). 'A BIG DEAL: How can we use big data to measure poverty in Sudan?' UNDP in Sudan
48. Treinish, Loyd. (2014). Operational Forecasting of Severe Flooding Events in Rio de Janeiro. Retrieved from: http://hepex.irstea.fr/operational-forecasting-of-severe-flooding-events-in-rio-de-janeiro/
49. UN. (1995) The Copenhagen declaration and programme of action. World Summit for Social Development 6-12 March 1995. New York, NY. United Nations Department of Publication.
50. UNDP (2012) Big data for development: Challenges and opportunities. New York: Uniated Nations Development Programme.
51. UNDP. (1997) Human Development Report 1997. New York: United Nations Development Programme.
52. UNDP. (2010) Human Development Report 2010. New York: United Nations Development Programme.
53. UNDP. (2016) Human Development Report 2016. New York: United Nations Development Programme.

54. Wang X.L. and Feng. X (2016). “On the Relationship between Income Poverty and Multidimensional Poverty in China”. OPHI Working Paper No. 101, University of Oxford
55. Wang X.L. and Zhou. L(2015). “Child Poverty in Rural China: Multidimensional Perspective” Asian Social Work and Policy Review 9 (2015) 109-124
56. Wen, W., Hui, C., & Li, Z. (2012). ‘Poverty assessment using DMSP/OLS night-time light satellite imagery at a provincial scale in China’. Advances in Space Research (2012) 49, 8, 1253-1264
57. World Bank (2000). World Development Report 2000/2001: Attacking Poverty. Washington, DC: World Bank
58. World Health Organization and UNICEF, Meeting the MDG drinking water and sanitation target: the urban and rural challenge of the decade. Geneva, WHO, 2006.
59. World Health Organization. (2015). ‘Drinking Water’. World Health Organization Fact Sheet 391.
60. World Health Organization. (2015). ’Sanitation’. World Health Organization Fact Sheet 392.
61. Yearbook of China’s Poverty Alleviation and Development. (2015). Chapter Eight. Poverty Alleviation and Development Leading Group Office of the State Council