Income Inequality and Subjective Wellbeing: Panel Data Evidence from China

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11 December 2019

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This version accepted for publication in *China Economic Review*

Abstract

Using four waves of longitudinal data from the China Family Panel Studies (CFPS), we examine the effects of income inequality on subjective wellbeing (SWB). We take a dual approach in measuring income inequality, and thus, we examine the effects of inequality using province-level Gini coefficient as well as between-group inequality or identity-related inequality defined as the income gap between migrants without urban household registration identity (*hukou*) and urban residents. We find negative effects of both province-level income inequality and between-group income inequality on SWB, measured by life satisfaction. Our results also show that the effects of income inequality on SWB is stronger for rural *hukou* residents compared to urban *hukou* residents. These findings are robust to alternative ways of measuring SWB and income inequality. In addition, we find evidence suggesting that neighbourhood trust is an important channel through which income inequality operates to reduce SWB. We suggest policies that promote trust in communities with high inequality with a view of addressing the negative effects of inequality on SWB.

Keywords: Subjective wellbeing, Identity, Inequality, *hukou*, Life satisfaction, China

JEL Codes: D63, I31

1. Introduction

A widening of the income gap reported across the globe (see, e.g., Caminada & Goudswaard, 2001; McCall & Percheski, 2010; Xie & Zhou, 2014) has led to a growing interest in understanding the implications of income inequality. Further, with the recent popularity of subjective wellbeing (SWB), and its proposition as an important metric in devising policy (Fujiwara & Campbell, 2011; Sachs, Becchetti, & Annett, 2016), the consequence of income inequality on subjective welfare or wellbeing has become of general concern and importance (Schneider, 2016). However, findings on the relationship between income inequality and wellbeing remain mixed. Some studies suggest a negative association (see, e.g., Hagerty, 2000; Oishi, Kesebir, & Diener, 2011; Oshio & Kobayashi, 2011), while others find a positive association (see, e.g., Jiang, Lu, & Sato, 2012; Knight & Gunatilaka, 2010b) or even ambiguous patterns between inequality and wellbeing (see, e.g., Blanchflower & Oswald, 2004; Helliwell, 2003).

A recent systematic review on the inequality-wellbeing relationship (Ngamaba, Panagioti, & Armitage, 2018) argues that the inconsistent or inconclusive findings in the literature can be explained by the fact that the strength and direction of the inequality-wellbeing relationship is mediated by several other factors. Thus, Ngamaba, et al. (2018) emphasise the importance of examining the factors through which inequality influences wellbeing. For instance, social capital and trust is a channel of influence that has received much attention in the literature. Here, it is argued that income inequality works through social dimensions where it is likely to erode social capital (Graham & Felton, 2006; Kawachi & Kennedy, 1999), which is important for promoting wellbeing (Awaworyi Churchill & Mishra, 2017). Specifically, if individuals perceive inequality as unfair, it is likely to erode trust, reduce generosity and reciprocity, thus undermining SWB (Kawachi & Kennedy, 1999; Wilkinson & Pickett, 2009; Wilkinson, 1997). Further, the dislike for inequality which erodes trust tends to engender conflicts, high level of violence and crime, which in turn negatively influence wellbeing (Diener et al., 1995; Haller & Hadler, 2006).

Larger income inequalities have therefore been assumed to engender steeper social disparities. However, as noted by Schneider (2016), existing research has remained speculative on the validity of this assumption, rarely testing the proposed mechanisms with empirical data. To our knowledge, only two studies (Delhey & Dragolov, 2013; Oishi, et al., 2011) attempt to examine the validity of this assumption. Oishi, et al. (2011) examine how trust and the perceptions of fairness mediate the relationship between income inequality and SWB in the United States, while Delhey and Dragolov (2013) examine whether social conflict, anxiety and social trust function as mediators in the inequality-wellbeing relationship in Europe.

We build on the existing literature by focusing on China. A growing body of literature presents empirical evidence on the effects of income inequality on wellbeing in China (Huang, 2019; Jiang, et al., 2012; Knight & Gunatilaka, 2010b; Wang, Pan, & Luo, 2015; Wu & Li, 2017). Among other things, these studies are distinguished by the data used with the majority using either cross-section data from a single year (see, e.g., Jiang, et al., 2012; Knight & Gunatilaka, 2010b; Wang, Pan, & Luo, 2015) or repeated cross-section data from multiple years (see, e.g., Wu & Li, 2017).

On the use of cross-section data, Knight and Gunatilaka (2010b) use data from the Chinese Household Income Project 2002 (CHIP 2002) to examine differences in SWB between rural and urban households in China. Their results show higher average wellbeing for rural households compared to urban households. The authors argue that wellbeing is sensitive to respondent's perception of their household position in the neighbourhood income distribution, and that for most people in rural areas, their relative position is confined to a narrow reference group of others in the same village. Similarly, Jiang, et al. (2012) use the CHIP 2002 data to examine the impact of income inequality measured by city-level Gini coefficients and between-group inequality on SWB. Between-group inequality is measured as the income gap between migrants without urban household registration identity (*hukou*) and urban residents. Their results show that higher levels of between-group inequality is associated with lower levels of SWB, however, the opposite is observed for the effects of city-level inequality.

Diverging slightly in terms of the choice of survey, Wang, et al. (2015) use cross-sectional data from the 2006 Chinese General Social Survey (CGSS) to examine the relationship between income inequality and SWB. They find evidence of an inverted-U shaped relationship between income inequality and SWB such that an increase in income inequality is associated with lower levels of SWB until a threshold beyond which further increases in inequality is associated with an increase in SWB levels. More recently, Yan and Wen (2019) add to the income inequality-wellbeing literature by incorporating corruption into the discourse. Using data from 2013 CGSS, Yan and Wen (2019) examine the role of corruption in the inequality-wellbeing relationship, and conclude that corruption is an important channel through which income inequality influences wellbeing. Other studies that have used the CGSS to examine the inequality-wellbeing relationship include Zhao (2012) and Wu and Li (2017), although Wu and Li (2017) add on to the literature by providing a perspective that draws on repeated cross-sections from the 2003 to 2010 surveys, rather than inferences from a single year.

Other data sources that have featured in the literature that examines the relationship between income inequality and SWB in China include the China Labor-force Dynamics Survey (CLDS) (Huang, 2019), single wave from the China Family Panel Studies (CFPS) (Lei et al., 2018), and other surveys (Smyth & Qian, 2008). Huang (2019) examines the role of distributive justice beliefs in shaping the inequality-wellbeing relationship. Using multi-level modelling, they find that lower inequality is associated with higher SWB. Lei et al. (2018) use the 2012 wave of the CFPS but focus on the role of expenditure inequality on SWB. Smyth and Qian (2008) use cross-section data from 31 cities across China. Their study emphasises on the relationship between inequality and SWB in urban China. They report heterogeneous effects of inequality across high and low income individuals.

Our study contributes to this growing but inconclusive literature on the relationship between inequality and wellbeing in China. We use four waves of data from the China Family Panel Studies (CFPS) survey to examine the relationship between income inequality and SWB, and examine trust and social network as important channels through which income inequality influences wellbeing. Following Jiang, et al. (2012), we take a dual approach to measure income inequality. We use a general measure of income inequality measured by province-level Gini coefficient as well as a between-group measure of income inequality or identity-related inequality defined as the income gap between migrants without urban household registration identity (*hukou*) and urban residents. Findings from Knight and Gunatilaka (2010b), which suggest that the effects of inequality on wellbeing are influenced by respondent's reference group or perception of their household position in their neighbourhood, lends support to the importance of understanding the role of between-group inequality in promoting or hindering SWB. Thus, similar to Jiang, et al. (2012) we distinguish between general inequality and between-group inequality, and examine the effects of these distinct types of inequalities on SWB. We also examine the role of social network and trust as potential channels through which income inequality influences wellbeing.

Our study differs from the above studies that have focussed on China in several ways. First, unlike these studies, we use panel data which allows us to control for unobservable factors. Unless one includes time-invariant personality traits as regressors, it is difficult to control for unobservable factors using cross-sectional data. Controlling for unobserved factors requires the use of panel data, and this makes it possible to eliminate the influence of unobserved time-invariant individual fixed effects. Further, the tunnel effect hypothesis lends support to the importance of using panel data to examine the effects of income inequality on wellbeing. Using panel data makes it possible to account for the effects of inequality across different time periods and thus more likely to capture the potential positive effects associated with the tunnel effect as well as the potential negative effects which emerge over time after the tunnel effect dies out. Further, the effects of inequality on SWB is determined by two competing effects. When the tunnel effect is stronger, positive effects are observed. However, when inequality persists overtime and the relative deprivation effect becomes stronger, negative effects are observed. This time-varying relationship can only be appropriately studied using panel data.

Second, our study refines earlier work on China by testing if social capital, particularly trust and social networks, are channels through which income inequality influence SWB. As noted earlier, existing research has remained speculative on the validity of the assumption that income inequality tends to engender lower social capital, rarely testing the proposed mechanisms with empirical data (Schneider, 2016). We build on the existing literature by examining the validity of this assumption using longitudinal data from China.

Third, while previous studies ignore the endogeneity of income inequality given the inability to find valid instruments that meet the exclusion restriction, we adopt different econometric techniques that take into account the endogeneity issue. Specifically, we adopt the Lewbel (2012) two-stage least square (2SLS) approach, which has been effectively used to address endogeneity in the absence of external instruments (see, e.g., Awaworyi Churchill & Farrell, 2017; Awaworyi Churchill and Mishra, 2017).

The remainder of the study is structured as follows. The next section provides an overview why income inequality might affect SWB while Section 3 describes the data and methodology. Section 4 presents and discusses the empirical results. Section 5 concludes with policy suggestions.

2. Why might income inequality affect SWB differently?

Two different hypotheses – the relative deprivation hypothesis and the tunnel effect hypothesis – have been used to explain the conflicting findings in the literature on the relationship between income inequality and SWB. The relative deprivation hypothesis posits that the negative effect of inequality on wellbeing is explained by the feeling of being deprived when others are better-off (Walker & Smith, 2002; Yitzhaki, 1979). Thus, when those in lower income quintiles compare their income to others in higher quintiles, it creates a sense of unhappiness and dissatisfaction. This argument has received support from the empirical literature (see, e.g., Alesina, Di Tella, & MacCulloch, 2004; Oshio & Kobayashi, 2011; Schwarze & Härpfer, 2007).

The tunnel effect hypothesis, on the other hand, suggests that the poor may not build up a sense of dissatisfaction when they compare their income to the rich. However, seeing the disproportionate higher income of others in society can inspire optimism and serve as an indication of better prospects for those with poor income, thus increasing the level of SWB. Hirschman and Rothschild's (1973) analogy using a traffic jam scenario provides a more vivid exposition into the hypothesis. According to Hirschman and Rothschild (1973), when stuck in a traffic jam in a two-lane tunnel with both lanes headed in the same direction, the sudden movement of cars in the lane next to yours inspires optimism and happiness. Thus, even though you may still be stuck in your lane, you feel better knowing that the traffic jam has been broken and it will soon be your turn to move. The tunnel effect, therefore, suggests that high inequality associated with rapid economic development may be tolerated by society in the onset, and even poor people may exhibit positive attitude towards inequality, which is likely to enhance their wellbeing. However, overtime, when these income disparities persist the tunnel effect fails and inequality reverses to having a negative effect on wellbeing.

In the case of China, despite its rapid economic growth in recent years, inequality has been on the rise. Xie and Zhou (2014) estimate that China's Gini coefficient increased from 0.30 in 1980 to 0.55 in 2002. Moreover, amidst the enormous success in economic performance, evidence suggests that happiness has decreased in China (Brockmann et al., 2009). Given China's institutional framework, we ex ante lean more towards the relative deprivation effect, and thus expect a negative effect of income inequality on SWB. Particularly, considering how China's economy has been growing over the past few years, one would expect inequality effects consistent with the tunnel effect hypothesis. However, as evidence suggests, an overview of inequality over the past few decades suggests higher trends of income inequality in China. Accordingly, as predicted by the tunnel effect hypothesis when income disparities persist, inequality reverses to having a negative effect on wellbeing. Further, existing research has emphasised the strong influence of income comparison on SWB (Senik, 2009). Consistent with the relative deprivation hypothesis, Senik (2009) shows that income comparisons across different benchmarks and even one's own past are very powerful in shaping welfare.

Overall, the preceding discussion advances two main arguments. First, existing evidence which attests to the significance of income comparisons lends strong support to the relative deprivation hypothesis which suggests a negative effect of income inequality on SWB. Second, the persistence of inequality in China despite high economic growth is likely to confirm predictions from the tunnel effect hypothesis, which suggest a negative effect on wellbeing if inequality persists. On the basis of these arguments, we expect that:

H1: *Income inequality will have a negative influence on subjective wellbeing.*

3. Data and methodology

Our analysis draws on data from the China Family Panel Studies (CFPS), a nationally representative longitudinal survey of Chinese communities, families and individuals (Xie, 2012; Xie & Hu, 2014). The CFPS focuses on both economic and non-economic well-being of the Chinese population, covering various economic outcomes, family dynamics and relationships, migration, and health, among others. The CFPS, which was launched in 2010, commenced with a total of 14,960 households from 635 communities, including 33,600 adults and 8,990 youths, located in 25 provinces/municipalities/autonomouFs regions (Xie, 2012). The CFPS employs a novel rural-urban, integrated, multi-stage probability-proportion-to-size (PPS) sampling scheme with implicit stratification to ensure the validity and representativeness of its sample.[1] Currently, the CFPS has four waves with the second, third and fourth waves conducted in 2012, 2014 and 2016, respectively. We use all available waves in this study.

To examine the association between income inequality and SWB, we specify the following empirical model:

$$SW_{it} = \beta_0 + \beta_1 * Hukou_{it} + \beta_2 * BI_{jt} + \beta_3 * H_{it}BI_{jt} + \beta_4 * GINI_{it} + \beta_5 * X_{it} + \beta_6 * Z_{jt} + \varepsilon_{it} \qquad (1)$$

where i, j and t denotes individual, province and time, respectively and ε_{it} is the error term. The dependent variable SW_{it} is the SWB score of respondent i at time t. In each sampled household, individuals were asked the same question: "are you satisfied with your life ?" with a five-point scale (very unsatisfied=1, very satisfied=5).[2] This question or its variants are often used in the literature to measure SWB (see, e.g., Appau et al., 2019; Lei et al., 2018).

$Hukou_{it}$ is a measure of identity. We measure an individual's *hukou* identity using a dummy variable which equals one if the respondent has urban status and zero otherwise. BI_{jt} is a measure of between-group inequality (BI), which we calculate as the ratio between the mean income of urban *hukou* residents and the rural *hukou* residents within the same province. Following Jiang, et al. (2012), we use this variable as a measure of the socioeconomic gap generated by the *hukou* status and other rural-urban segmentation policies. We examine the effects of income inequality on each *hukou* identity group by including an interaction term ($H_{it}BI_{jt}$) between the *hukou* identity dummy and BI. Lastly, we include the Gini coefficient for each province ($GINI$) as a measure of overall inequality, which is distinct from the *hukou* identity-related inequality.

X_{it} and Z_{jt} represent a set of individual-level and province-level control variables, respectively, that are consistent with the literature (see, e.g., Awaworyi Churchill & Smyth, 2019; Cheng et al., 2016; Hu, 2013). For individual-level covariates we include a rural-urban dummy, gender, age, health status (an interviewer rated health status score of the respondent), political identity (whether or not a member of the China Communist Party), education, marital status, employment status (employed or unemployed) and household income per capita.[3] Consistent with the literature (see, e.g., Cheng et al., 2016; Hu,

[1] Refer to Xie and Hu (2014) for a detailed description about CFPS.
[2] The CFPS collects information on respondent's happiness in selected waves. However, we did not use it as the measure of subjective wellbeing given the scant nature of the available data. In robustness check, we examine the robustness of our results to an alternative measure of subjective wellbeing which focuses on respondents' level of confidence about the future.
[3] Rural-urban dummy variable is not to be confused with hukou dummy variable. Rural-urban dummy variable equals one if a respondent lives in an urban area and zero if in a rural area, whereas the *hukou* dummy variable equals one if a

2013), we also include a dummy variable that captures each respondents' homeownership status. Our province-level control variables include GDP per capita and population growth, drawn from the National Bureau of Statistics of China. We also control for province fixed effects and province-specific time trends to account for the effect of exogenous factors on (changes in) SWB. Table 1 provides a summary and descriptive statistics of variables included in the analysis.

For our baseline, we estimate equation (1) using panel fixed effect estimators (Panel FE).[4] However, endogeneity is likely to be a problem. In order to correct for endogeneity, we employ the heteroscedasticity-based identification strategy developed by Lewbel (2012).

4. Results

4.1. Benchmark panel fixed effect results

Table 2 presents fixed effect results with different combinations of explanatory variables. Columns (1) and (2) report results for a model which adds on BI and province-level inequality to the standard set of covariates previously discussed. To examine the sensitivity of our results, Column (1) excludes province-level characteristics while Column (2) adds on province-level population growth and GDP per capita to account for province-level characteristics. Turning to Column (1), we find that the coefficient on BI is negative and statistically significant at one per cent level with an effect size of 0.09. This implies that a unit increase in between-group inequality is associated with a 0.09 unit decline in SWB on a 1-5 point scale. Findings from Column (2) which control for province-level characteristics including population and economic performance also confirm this finding. Specifically, the coefficient on BI here is also negative and statistically significant at one per cent level with an effect size of 0.12, implying a 0.12 decline in SWB on a 1-5 point scale for a unit increase in between-group inequality. These results suggest that higher levels of identity-related inequality is associated with lower levels of SWB measured by life satisfaction. This finding is also true for overall province-level inequality which is negative and statistically significant at one per cent level in both columns. The effect seems to be relatively large with effect size in Column (1) being 3.10 which reduces to 2.93 once we control for province-level characteristics.

Given that *hukou* status is argued to generate discrimination and cause various rural-urban divisions, the effects of inequality on SWB might be heterogeneous across rural and urban *hukou* residents. In order to investigate this heterogeneity, we include a dummy variable that captures respondents' *hukou* status and its interaction term with BI in Columns (3) and (4). Here, Column (3) excludes province-level characteristics while Column (4) includes them. We find that, across both columns, the effect of BI and province-level inequality remain robust with relatively higher effect sizes, compared to effect sizes in Columns (1) and (2). Specifically, in Columns (3) and (4), the coefficient on BI is negative and statistically significant at one percent level with effect size of 0.12 and 0.15, respectively. While

respondent has an urban *hukou* and zero if a rural *hukou*. A respondent who has a rural *hukou* status may not necessarily live in a rural area, and could move to an urban area because there are more opportunities and better infrastructure.

[4] In robustness checks, we examine the robustness of our results to the treatment of life satisfaction as an ordinal variable by using ordered probit regressions (Panel A in Table 6). Our results remain consistent.

for province-level inequality, the coefficient is -3.14 and -2.98 in Columns (3) and (4) with the same significance level.

We also find that the coefficient on the interaction term in both columns is statistically significant at one per cent level, suggesting that the effects of inequality on SWB is heterogeneous across rural and urban *hukou* residents. For example, the coefficient in Column (4) is 0.13, indicating that for urban *hukou* residents (*hukou*=1), a unit increase in BI is associated with 0.02 (-0.15+0.13) unit decrease in SWB, whereas for rural *hukou* residents (*hukou*=0), a unit increase in BI is associated with 0.15 unit decrease in SWB. This finding indicates that the effects of inequality on SWB is stronger for rural *hukou* residents than urban *hukou* residents.

The direction of effects concerning the coefficient of other covariates are consistent with previous literature (see, e.g., Jiang, et al., 2012; Knight & Gunatilaka, 2010a; Knight, Lina, & Gunatilaka, 2009). Specifically, better health status is associated with higher level of SWB. House ownership also influences SWB: compared with individuals who do not own houses, individuals who own houses, on average, report higher levels of SWB. Educational attainment and household income per capita have a significant and positive effect on SWB.

4.2. Endogeneity corrected results using heteroskedasticity-based identification

As noted earlier, endogeneity is likely to be a problem. For instance, BI is likely to be endogenous because individuals who exhibit low levels of SWB may be less motivated to work thus giving rise to inequality. We resort to the Lewbel (2012) approach to address endogeneity given the inability to find appropriate external instruments. The Lewbel (2012) approach exploits heteroscedasticity for identification. Identification can be achieved without imposing any exclusion restrictions if there is a vector of exogenous variables Z and the errors are heteroskedastic. The Z vector can be a subset of the exogenous X vector included in the regression or even Z=X. In the first stage, each endogenous variable is regressed on the Z vector, and the vector of residuals $\hat{\varepsilon}$ is retrieved. These estimated residuals are then used to construct instruments (Z - $\bar{Z}$) $\hat{\varepsilon}$, where $\bar{Z}$ is the mean of Z. This approach has been used in the SWB literature to address endogeneity (see, e.g., Appau & Awaworyi Churchill, 2018).

In our case, in the first stage we run regressions of BI on individual and province characteristics and then retrieve residuals $\hat{\varepsilon}$. In the second stage, Eq. (1) is estimated by IV with (Z - $\bar{Z}$) $\hat{\varepsilon}$ as the instruments. The results are presented in Column (5) of Table 2.[5] The coefficient on BI is -0.26 and is statistically significant at one per cent level. The magnitude of this coefficient compared to that from the fixed effect model in Column 4 (which uses the same set of controls) suggests that endogeneity generates a downward bias in the fixed effect estimate. However, we find that the coefficient on *hukou* status and the interaction term are statistically insignificant.

4.3. Potential channel analysis

As previously discussed, social capital is argued as an important channel through which inequality operates to influence wellbeing. Income inequality is likely to hinder social capital. Particularly, social

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[5] Although the Hansen J statistic is significant, the p-value of the heteroskedastic-robust Kleibergen-Paap (2006) rk statistic and the robust Kleibergen-Paap Wald rk F statistic look good.

capital mobility is infrequent and people mostly remain segregated in societies with high inequality. This eventually reflects inequalities in other forms of beyond income. Yet, the role of social capital in promoting SWB is largely discussed in the literature, and thus, with the expected effects of inequality on social capital, we expect that social capital is a channel through which inequality operates to influence SWB.

Our data allows us to examine the potential role of neighbourhood trust, which is an important measure of social capital.[6] In waves 2 to 4 of the CFPS, survey respondents are asked to rate how much they trust their neighbours on a scale of 0-10, where 0 is distrustful and 10 is very trustworthy. For neighbourhood trust to qualify as a channel of influence in the inequality-wellbeing relationship, in addition to being correlated with income inequality, it should also be correlated with SWB, and the inclusion of neighbourhood trust as an additional covariate in the regression linking SWB to income inequality should decrease the magnitude of the coefficient on income inequality or render it statistically insignificant.

In Table 3, we estimate alternative models where we examine the effects of between-group inequality and province-level inequality on neighbourhood trust. Results from Column (1) of Table 3 show a statistically insignificant effect of between-group inequality on neighbourhood trust. However, from Column (2), we find that an increase in province-level inequality is associated with a decline in neighbourhood trust. Given that only province-level inequality has a significant effect on trust, we proceed to include trust as an additional covariate in a model that links SWB to province-level inequality.

We first re-estimate the SWB model with a restricted sample based on waves 2 to 4 given that neighbourhood trust is only available in these waves. This will ensure that the same sample size is used when we compare the coefficient on province-level inequality. Column (1) of Table 4 reports results for the effects of province-level inequality on SWB. Here, we find that the effects of inequality is consistent with those reported in our baseline estimates. In Column (2) of Table 4, we add on trust as an additional covariate. Consistent with existing literature that has examined the impact of trust on SWB in China (see, e.g., Awaworyi Churchill & Mishra, 2017), we find that trust is positively associated with SWB. Thus, higher levels of neighbourhood trust is associated with higher levels of SWB. Further, we observe that with the inclusion of trust as an additional covariate, the coefficient on province-level inequality drops in magnitude, confirming that trust is a channel through which province-level inequality influences SWB.

Our findings here are consistent with conclusions from Oishi, et al. (2011) which focuses on the US and Delhey and Dragolov (2013) which focuses on Europe. Oishi, et al. (2011) find that the negative relationship between income inequality and SWB in the US can be explained by perceived fairness and trust. They further report that with higher levels of income inequality, Americans perceive other people to be less fair and trust other people less. Similarly, Delhey and Dragolov (2013) find that income inequality decreases social trust and this in turn lowers SWB.

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[6] We also examine the potential role of social networks, measured by membership in trade union, religious group or communist party. However, we do not find evidence to support social networks as a channel through which inequality operates.

4.4. Robustness checks and extensions

We undertake various analyses to test the robustness of our results. First, we examine the robustness of our results to an alternative measure of SWB, which captures respondents' level of confidence about the future. The results reported in Column (1) of Table 5 are consistent with our baseline results.

Second, we examine the robustness of our results to alternative measures of income inequality. We construct an alternative measure of between-group inequality (denoted as BI*). We define this measure of between-group inequality as the ratio between mean income of urban residents and rural residents. Compared with the original BI, this alternative measure captures inequality arising from rural and urban divide. The Chinese economy is characterised by a significant rural-urban divide (Knight & Song, 1999) that takes the form of disparities in income and in the provision of services such as education and health. Accordingly, where an individual lives – rural or urban area – matters in forming his/her identity. Our main set of results are based on inequality measures that are constructed using information on the provinces in which respondents live. In further checks, we also use an alternative measure of inequality that are based on the county in which respondents live, although this construct of inequality has significantly lower number of observations due to missing observations. Thus, the measure of between-group inequality here (BI^{+}) is calculated as the ratio between the mean income of urban *hukou* residents and the rural *hukou* residents within the same county. Gini included in BI^{+} models are GINI coefficient for each county. We report the effects of BI* and BI^{+} on life satisfaction and future confidence in alternating models. Results reported in Columns (2) to (5) of Table 5 are largely consistent with the baseline results.

Third, we examine the robustness of our results to alternative estimation methods. We examine the sensitivity of our results to the treatment of SWB as an ordinal variable. Given the ordinal nature of how SWB is measured, we estimate the SWB regressions using panel ordered probit. The main findings, as shown in Panel A of Table 6, are consistent with our baseline estimates which treat SWB as cardinal. This finding is consistent with conclusions from Ferrer-i-Carbonell and Frijters (2004), which suggest that in the context of SWB research, SWB regressions are not sensitive to whether the outcome variable is treated as cardinal or ordinal. As an alternative to addressing endogeneity, we adopt the Coarsened Exact Matching (CEM) approach (Iacus et al., 2012). CEM is a matching method that allows us to draw causal inferences about the effect of income inequality on SWB. The matching method allows us to ex ante choose the balance between the treated and control groups, and is widely used in the literature as a method for improving causal inferences (see, e.g., Pierskalla and Hollenbach, 2013; Singh and Agrawal, 2011). The CEM results reported in Panel B of Table 6 suggest that higher BI and Gini are associated with lower SWB. Hence, the CEM results are consistent with our baseline findings.

Lastly, we extend our results to examine if the effect of income inequality is different across different groups. Following Smyth and Qian (2008), we interact income inequality with dummy variables for the bottom 20 per cent and top 20 per cent of income earners. We also interact income inequality with dummy variables for different educational attainment and age groups. Results for this exercise are reported in Table 7. From Column 1, we find the interaction with income is statistically insignificant for the top 20 per cent of income earners but significant for the bottom 20 per cent of income earners.

Taking into account the coefficient on other variables in the model, the coefficient on the interaction term suggests that the effects of income inequality on SWB for low income earners (20 per cent of income earners) is more pronounced compared to other income groups. This finding is consistent with the jealousy effect of income inequality. From Column 2, we find that the effect of income inequality is not heterogenous across those with different education status. From Column 3, the results suggest that the interaction with age dummy for those 60 years and above is statistically insignificant but significant for the interaction with age dummy for those up to 24 years. Taking into account other effect sizes, the coefficient on the interaction term suggests that the effects of income inequality for younger people is more pronounced compared to other age groups. This finding could be because younger people are more likely to have stronger social capital, which when disrupted by inequality, causes more dissatisfaction.

5. Conclusions

We examined the relationship between income inequality and SWB using a nationally representative panel dataset from China. We measure inequality with two indicators that capture province-level inequality and between-group inequality or identity-related inequality. We define between-group inequality as the income gap between migrants without urban household registration identity (*hukou*) and urban residents. In our baseline results, we find that high levels of province-level inequality and identity-related inequality are associated with low level of SWB measured by life satisfaction. This general conclusion is robust to a number of sensitivity checks including alternative ways of measuring SWB and inequality. When we account for endogeneity using CEM and heteroskedasticity-based identification, we consistently find a causal negative relationship between inequality and wellbeing.

The observed negative effects of inequality across various levels on SWB lends support to the idea that redistributing income from the rich to the poor in society will raise average levels of SWB. Economic theory demonstrates that as income increases, an individual's marginal utility diminishes. Given that SWB is an important measure of utility, marginal increases in wellbeing will be smaller at higher levels of income. Practically, an extra dollar of income has less value, in terms of wellbeing, to a rich person than to a poor person (Helliwell, Layard, & Sachs, 2012; Reyes-García et al., 2019). Given that majority of populations tend to find themselves within the lower income quintiles, it follows from the concept of diminishing marginal return to income that a more equal distribution of income will result in higher average wellbeing.

In the Chinese context, an important policy recommendation stemming from our results is to adopt strategies that ensure a more inclusive society devoid of discrimination. The negative effects of between-group or identity-related inequality suggests that policies aimed at reducing income inequality engendered by rural-urban segmentation are crucial. As a result of the rural-urban segmentation induced by the *hukou* system, rural *hukou* residents face discrimination in various aspects of their lives. This discrimination extends to important areas such as health, education and the use of public goods in general.[7] Accordingly, policies aimed at promoting a more inclusive access to infrastructure are crucial to narrow the inequality gap.

Our findings also point to the importance of building trust and strong social capital. We demonstrate that trust is a channel through which inequality operates to hinder wellbeing. Thus, in addition to policies aimed at reducing discrimination, it is important that social policies aimed at fostering trust between rural and urban *hukou* residents are implemented.

[7] Scholars have conducted many studies that investigate the impact of the discriminatory social and economic policies induced by the *hukou* system (Afridi, Li, & Ren, 2015; Liu, 2005; Song, 2014).

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Table 1 Descriptive statistics

Variable	Definitions	Mean	SD	Min	Max
Life	Life satisfaction, cardinal scores	3.59	1.06	1.00	5.00
BI	Between-group inequality	1.61	0.34	0.61	2.91
Gini	Gini coefficient	0.46	0.05	0.29	0.65
Hukou	Household register, urban hukou=1	0.28	0.45	0.00	1.00
Urban	Urban area=1	0.44	0.50	0.00	1.00
Age	Age (years)	49.73	14.13	16.00	110.00
Party	Communist Party member=1	0.08	0.28	0.00	1.00
Health	Health status, cardinal scores	5.36	1.24	1.00	7.00
Education	Highest education attained, cardinal scores	2.26	1.26	1.00	8.00
Marry	Married=1	0.88	0.32	0.00	1.00
Employed	Employed=1	0.71	0.45	0.00	1.00
House	Owns house(s)=1	0.91	0.29	0.00	1.00
Income	Household income per capita (log)	8.80	1.20	3.00	14.21
GDP per capita	GDP per capita	10.59	0.46	9.48	11.68
Population growth	Population growth (‰)	4.79	2.42	-0.49	10.84

Data sources: GDP per capita and population growth are obtained from the National Bureau of Statistics of China (http://data.stats.gov.cn). Other variables are author's calculation based on the data set from CFPS 2010, 2012, 2014 and 2016 (http://www.isss.pku.edu.cn/cfps).
Notes: 1. *Life* is the subjective life satisfaction score of the respondent. Each respondent was asked the same question: "are you satisfied with your life?" with a five-point scale (very unsatisfied=1, very satisfied=5). 2. We follow the rural-urban classification from the National Bureau of Statistics China to construct the dummy variable *Urban* (http://www.stats.gov.cn/tjsj/tjbz/tjyqhdmhcxhfdm/2018/index.html). 3. Respondents' education is measured in an eight-point scale (illiterate=1, primary school=2, junior high=3,…, doctorate=8). 4. *Health* is the interviewer rated health status score of the respondent. It is a seven-point scale (very poor=1, very good=7).

Table 2 Results from panel FE and IV estimation

	Dependent variable: Life satisfaction				
	Panel FE				IV
	(1)	(2)	(3)	(4)	(5)
BI	-0.090***	-0.116***	-0.124***	-0.149***	-0.257***
	(0.022)	(0.025)	(0.025)	(0.027)	(0.066)
Hukou			-0.177***	-0.171***	-0.221
			(0.066)	(0.066)	(0.159)
Hukou x BI			0.130***	0.126***	0.159+
			(0.037)	(0.037)	(0.100)
Gini	-3.096***	-2.933***	-3.140***	-2.978***	-2.405***
	(0.133)	(0.138)	(0.133)	(0.139)	(0.119)
Age	0.010	0.012	0.010	0.012	0.081***
	(0.020)	(0.021)	(0.020)	(0.021)	(0.007)
Health	0.050***	0.052***	0.050***	0.052***	0.051***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
Party	0.040	0.040	0.039	0.039	0.044
	(0.041)	(0.041)	(0.041)	(0.041)	(0.040)
Education	0.169***	0.188***	0.167***	0.187***	0.173***
	(0.012)	(0.013)	(0.012)	(0.013)	(0.013)
Marry	0.051	0.053*	0.052	0.053*	0.050
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
Employed	0.002	0.008	0.003	0.008	-0.004
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Urban	-0.096***	-0.091***	-0.094***	-0.090**	-0.080**
	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)
House	0.048**	0.050**	0.049**	0.050**	0.045**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Income	0.031***	0.031***	0.031***	0.030***	0.030***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Province characteristics	No	Yes	No	Yes	Yes
Under-id. test					0.000
F-stat.					63.831
Over-id. test					0.000
Observations	56,662	56,662	56,662	56,662	56,662

Notes: ***, **, * represent significance at 1%, 5%, 10% level, respectively. The numbers in brackets are heteroskedasticity-robust standard errors. 'IV' refers to the Lewbel (2012) approach. Under-id. test reports the p-value of the Kleibergen and Paap (2006) rk statistic; F-stat. reports the Kleibergen-Paap Wald rk F statistic; Over-id. test reports the p-value of Hansen J statistic. +: p-value is 0.112.

Table 3 Effects of inequality on trust

	Dependent variable: Neighbourhood trust	
	Panel FE	
	(1)	(2)
BI	0.140	
	(0.090)	
Gini		-1.736***
		(0.462)
Other control	Yes	Yes
Province characteristics	Yes	Yes
Observations	41,670	41,670

Notes: *** represent significance at 1% level. The numbers in brackets are heteroskedasticity-robust standard errors.

Table 4 Potential channel analysis

	Dependent variable: Life satisfaction	
	Panel FE	
	(1)	(2)
Gini	-2.080***	-1.992***
	(0.226)	(0.225)
Trust		0.051***
		(0.003)
Other control	Yes	Yes
Province characteristics	Yes	Yes
Observations	41,765	41,765

Notes: *** represent significance at 1% level. The numbers in brackets are heteroskedasticity-robust standard errors.

Table 5 Robustness test (alternative measure of inequality and SWB)

	(1)	(2)	(3)	(4)	(5)
BI	-0.137***				
	(0.029)				
BI*		-0.150***	-0.177***		
		(0.027)	(0.028)		
BI^+				0.012	-0.045***
				(0.013)	(0.014)
Gini	-2.155***	-2.857***	-2.024***	-0.163	-0.095
	(0.144)	(0.141)	(0.146)	(0.124)	(0.131)
Other controls	Yes	Yes	Yes	Yes	Yes
Observations	56,662	56,325	56,325	31,160	31,160

Notes: ***, **, * represent significance at 1%, 5%, 10% level, respectively. Dependent variable in Columns (2) and (4) is life satisfaction while in Columns (1), (3) and (5) is confidence in future. BI* and BI^+ are alternative measures of BI, see text for more details. The numbers in brackets are heteroskedasticity-robust standard errors.

Table 6 Robustness test (alternative estimation methods)

	Dependent variable	
	life satisfaction	future confidence
Panel A: Alternative estimation method using panel ordered probit		
	(1)	(2)
BI	-0.128***	-0.127***
	(0.030)	(0.031)
Gini	-3.773***	-2.747***
	(0.167)	(0.168)
Other controls	Yes	Yes
Observations	56,662	56,662
Panel B: Coarsened Exact Matching		
	(1)	(2)
BI	-0.121***	-0.140***
	(0.036)	(0.037)
Gini	-3.253***	-2.198***
	(0.212)	(0.217)
Other controls	Yes	Yes
Observations	42,025	42,025

Notes: ***, **, * represent significance at 1%, 5%, 10% level, respectively. The numbers in brackets are heteroskedasticity-robust standard errors.

Table 7 Income, education and age interactions

	Dependent variable: Life satisfaction		
	(1)	(2)	(3)
BI	-0.121***	-0.129***	-0.122***
	(0.025)	(0.033)	(0.025)
BI x Income in Top 20%	0.006		
	(0.009)		
BI x Income in Bottom 20%	0.024**		
	(0.011)		
BI x Primary School and Below		0.007	
		(0.026)	
BI x Middle School		0.024	
		(0.021)	
BI x Young (24 and below)			0.098***
			(0.023)
BI x Senior (60 and above)			0.008
			(0.013)
Gini	-2.927***	-2.929***	-2.933***
	(0.139)	(0.139)	(0.138)
Other controls	Yes	Yes	Yes
Observations	56,662	56,662	56,662

Notes: ***, **, * represent significance at 1%, 5%, 10% level, respectively. The numbers in brackets are heteroskedasticity-robust standard errors.