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Boosting rural labor off-farm employment through urban expansion in China

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ABSTRACT

Rural development is widely believed to interact with the structural transformation, but little is known about how this happens in developing countries. This paper explores the impact of structural transformation on rural development through the length of analyzing the role of urban growth in creating off-farm employment for rural labor in China. By combining five waves of farm surveys for 1,234 households for the period of 2000–2018 with a newly constructed urban gravity index for 370 cities, we show that rapid urban growth in China has significantly contributed to rural development by increasing off-farm employment for rural labor by 47–71 million since 2000. Moreover, the positive impact started with the emergence of a few large metropolitan cities but ended with the growth of local, relatively small cities, suggesting the interaction between structural transformation and rural development is at a nationwide level.

1. Introduction

The past four decades have witnessed rapid structural transformation (here defined as urbanization and industrialization) in the global economy, altering the development landscape throughout the world that has been dominated by the developed countries. Following the rise of the four dragons in Southeast Asia in the 1990s and the economic growth miracle of China in the 2000s, stronger markets are emerging in some middle-income economies, which are characterized by rapid growth in urban and industrial/service sectors (Nickell, Redding, & Swaffield, 2008; Gollin, Jedwab, & Vollrath, 2016; Felipe, Mehta, & Rhee, 2019). In addition, several low-income developing countries now have the world's fastest economic growth rates (IFAD, 2016). However, economic growth is still uneven across countries, and income inequality within developing countries is much larger than that within developed countries. Rural development is lagging far behind urban and industry growth; yet the rural sector still accounts for a large proportion of the economy in most developing countries (including many of those having achieved economic growth miracles), which may be contributing to uneven economic growth within developing countries and threatening their long-term goal of poverty alleviation (Gollin, Parente, & Rogerson, 2002; Foster & Rosenzweig, 2007; Gollin, Lagakos, & Waugh, 2014; Laborde, Lallemant, McDougal, Smaller, & and Traore, 2018).

Rural development is defined as a continuous and complex process that contains not only agricultural technology progress, structural change of agricultural output, and rural income improvement, but also a gradual transition from a household-based agrarian economy to nonfarm sectors (IFAD, 2016). For decades, many Nobel Laureates, including (Lewis, 1954; Kuznets & Murphy, 1966; Schultz, 1968), have highlighted the importance of rural development, including both agricultural development and rural transformation, to structural transformation; their thoughts influenced scholarship and practice throughout the 1970s and 1980s.[1]. However, recent studies show that structural transformation (in particular its induced urban growth) will also

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[1] See Clark, 1967; Rostow, 1960; Nurkse, 1953; Syrquin, 1988; Syrquin and Chenery, 1989 for the early discussion. In recent years, the studies in the field also include (Gollin, 2010; Timmer, de Vries, & De Vries, 2015)

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benefit rural development (Bustos, Caprettini, & Ponticelli, 2016; IFAD, 2016; Erten & Leight, 2017). In addition to helping agricultural development by improving technology progress (Baumol, 1967), human capital accumulation (Foster & Rosenzweig, 1996) and resource (e.g., land) reallocation efficiency (Restuccia, Yang, & Zhu, 2008; Restuccia & Rogerson, 2017),[2] structural transformation can also facilitate rural development by providing rural households with more opportunities for off-farm employment and income (Foster & Rosenzweig, 2007; Bryan, Chowdhury, & Mobarak, 2014; Bryan & Morten, 2015).

For decades, there have been many studies attempting to explore the channels through which structural transformation affects rural development with a focus on market accessibility, urban proximity and public infrastructure availability. For example, some studies such as Chamberlin and Jayne (2013); Berdegué, Carriazo, Jara, Modrego, and Soloaga (2015); Stifel and Minten (2017); Vandercasteelen, Beyene, Minten, and Swinnen (2018); Vandercasteelen, Beyene, Minten, and Swinnen (2018) examined the impact of market access on agricultural production, farmers' well-being and rural inequality in some African (e.g., Kenya and Ethiopia) and Latin American countries (e.g., Chile, Colombia and Mexico). Other studies including (Deichmann, Shilpi, & Vakis, 2009; Sharma & Chandrasekhar, 2014; Christiaensen & Todo, 2014; Diao, Magalhaes, & Silver, 2019) investigated the impact of urban proximity on spatial distribution of rural commuting workers and/or off-farm employment using the case studies of Bangladesh, India and Ghana. Recently, more studies including (Abate, Dereje, Hirvonen, & Minten, 2020; Wang, Chen, & Araral, 2021) have also explored the role of public service delivery due to urban expansion in facilitating rural transformation. While the positive impact of urban proximity on rural development is well justified, little is known on the global impact of structural transformation on the urban–rural linkage. Because structural transformation is regarded as a nationwide process that may impose complex impacts on rural sectors, using a local measure is unlikely to capture structural transformation and its economic effects on rural development (Redding, 2016; Costinot & Rodríguez-Clare, 2014; Costinot & Donaldson, 2016).

The current paper aims to investigate the impact of structural transformation on rural development through the lens of analyzing the role of urban growth in pulling labor out of agriculture; this will be done by combining macro-level and micro-level data in China. Since the late 1990s, rural development–along with rapid urban growth–has accelerated in China. Between 2000 and 2018, the aggregate urbanization ratio (defined as the proportion of urban citizens in the total population) increased from 36.2% to 59.6% (China National Bureau of Statistics, 2019). In particular, many metropolitan cities, such as Beijing, Shanghai, Guangzhou, and Shenzhen, have emerged as the clusters of newly established industries and rural-to-urban migrants, driven by the export-oriented industrial strategy. Whereas over the same period, agricultural GDP has grown at the rate of 5.3% a year with more than 80 million rural residents moving above the poverty line (Huang & Rozelle, 2018), and there were around 290 million in the rural labor force (around 84% of total rural labor force) working off-farm by 2018 (China National Bureau of Statistics, 2019). Apart from ongoing institutional reforms in rural China, rapid urban growth (partly because of increased exports and the inflow of foreign direct investment) has created a large amount of off-farm employment opportunities and has facilitated rural transformation (Erten & Leight, 2017). This provides a good opportunity to examine the relationship between structural transformation and rural development from an empirical perspective.

The analysis in this study is based on a longitudinal household-level dataset collected through five rounds of nationwide surveys over the period of 2000–2018. These surveys were conducted by the China Centre for Agricultural Policy (CCAP) in 2000, 2009, 2013, 2016, and 2018, collecting information from 58 randomly selected villages in six provinces representing China's major agricultural regions. In addition, we also collected nightlight intensity data from National Aeronautics and Space Administration (NASA) to construct a consistent measure of urban growth for 370 cities (with populations of more than 200,000 in 2000) throughout China for the same time period.

We start by constructing an urban gravity index based on both the nightlight intensities of all the selected cities and the Euclidian distance between the cities and the targeted village to approximate the pulling force because of urban growth. Then, we examine the impact of urban growth on the off-farm employment of rural households, here by considering rural workers' individual and family characteristics, and other factors affecting the off-farm employment of rural households. The fixed-effect panel data regression technique, combined with the instrumental variables for measuring the stability of urban electricity supply, has been used to eliminate the potential endogeneity problem. Finally, we also investigate how the urban growth of different types may affect off-farm employment of rural households across regions and over time.

The results show that urban growth in China has significantly contributed to pulling labor out of agriculture, in turn facilitating rural development. Between 2000 and 2018, urban growth throughout the nation has increased off-farm employment by 26.7% persons for each rural household based on our surveys in six provinces. This implies that urban growth has created off-farm employment by 47–71 million, accounting for more than half of rural migrants. Moreover, the positive employment effects start with the emergence of a few large metropolitan cities but end with the growth of local relatively small cities. This finding suggests that off-farm employment creation driven by urban growth of different types is a nationwide phenomenon and preserves stage-by-stage characteristics.

Our study contributes to the literature in three ways. First, we are the first to analyze the role of urban growth in pulling rural labor out of agriculture economy-wide in China, by constructing the index for "electricity supply crisis" and non-tariff barrier as new identification conditions. This differs the angle from the literature focusing on the impact of urban growth on non-agriculture employment in the proximity areas in other African and Asian developing countries (Otsuka, 2007; Deichmann et al., 2009; Christiaensen, De Weerdt, & Todo, 2013; Sharma & Chandrasekhar, 2014; Diao et al., 2019). Second, we construct a global measure (e.g. the urban gravity index) to approximate structural transformation at the national level, which incorporates the complex spatial spillover effects of economy-wide urban growth into a simple measure. This treatment allows us to investigate the aggregate economic effects of urban growth, and thus complements to the literature using the indirect price response to measure the impact of rural–urban economic integration (Allen & Arkolakis, 2014; Ramondo, Rodríguez-Clare, & Saborío-Rodríguez, 2016; Costinot & Donaldson, 2016; Caliendo, Parro, Rossi-Hansberg, & Sarte, 2018). Third, we use five waves of household-level survey data to trace dynamic changes in the role of urban growth in pulling labor out of agriculture over time in China. In particular, we measured marginal impacts of urban growth on rural development in different development stages for the past two decades, in addition to quantify its long-term average impact as in Sharma and Chandrasekhar (2014) and Diao et al. (2019). The

[2] The agricultural sectors in many developing countries are dominated by small holders, thus suffering from resource allocation efficiency loss because of various long-standing barriers to accessing resources, technology, inputs, finance, knowledge, and markets.

findings provide useful insights for other developing countries to choose among different urbanization strategies to achieve rural transformation (Gollin et al., 2014; McMillan, Rodrik, & Verduzco-Gallo, 2014).

The remainder of the paper is organized as follows: Section 2 reviews the literature on the relationship between structural transformation (e.g., urban growth) and rural development (e.g., off-farm employment) globally and in China. Section 3 presents model specifications and estimation strategies, which is followed by a description of the dataset in Section 4. Section 5 discusses the impact of urban growth on rural off-farm employment in China. Section 6 conducts a series of robustness checks, and Section 7 provides the conclusions.

2. Urban Growth and Off-farm Employment: Experience from the World and China

In many developing countries where small household farms dominate the agricultural sector, off-farm employment and income are essential for rural development. In 2000, on average, off-farm income accounts for around 37% of rural household income in Africa, 47% in Latin America, and 51% in Asia (Haggblade, Hazell, & Reardon, 2007). Apart from other factors such as agricultural technology progress, institutional and marketization reforms, public infrastructure investment, cultural change, and so on, it is believed that structural transformation and its induced urban growth have played an important role in pulling rural labor out of the agricultural sector in developing countries. Because labor productivity (and thus wage) in industries is usually higher than that in agriculture in developing countries, increased off-farm employment because of urban growth will facilitate rural development (Hornbeck & Keskin, 2015; Mellor, 2017).

Conceptually, urban growth affects off-farm employment through two channels. First, urban growth generates more demand for agricultural products and boosts the development of the farm sectors focusing on agricultural production (Satterthwaite & Tacoli, 2003; Tacoli, 2003; Haggblade et al., 2007). In addition, urban growth can also bring new technologies and infrastructure investment to rural areas, providing new opportunities for farming business (Foster & Rosenzweig, 2004; Foster & Rosenzweig, 2007; Galor & Mountford, 2008; Nunn & Qian, 2011; Bustos et al., 2016; Gollin, Hansen, & Wingender, 2018). Second, urban growth can directly create off-farm employment in urban areas and facilitate rural development by increasing off-farm income. Driven by the agglomeration of newly established industries and skilled workers, urban growth can create more employment opportunities outside of agriculture(Lanjouw & Shariff, 2004; Christiaensen et al., 2013; Uy, Yi, & Zhang, 2013; Cravino & Sotelo, 2019).As the two forces from urban growth usually have opposite effects on off-farm employment in theory, it is an empirical question on whether there is the positive impact of urban growth on off-farm employment.

For decades, many studies have devoted to examining the impact of urban growth on non-agriculture employment. For example, Haggblade et al. (1989) find that the linkage between urban growth and nonfarm sector development diminished as the rural–urban distance increased, highlighting that market accessibility matters for rural labor's employment choice. Deichmann et al. (2009), Chamberlin and Jayne (2013) and Berdegué et al. (2015) show that city size could also affect off-farm employment creation. More recently, some studies turns to explore spatial distribution of urban growth and its impact on off-farm employment creation. Sharma and Chandrasekhar (2014) shows that regions with large peripheral urban areas are more likely to host rural commuting workers in India. Alternatively, Christiaensen and Todo (2014) finds that migration out of agriculture into rural nonfarm economy and secondary towns yields more inclusive growth patterns than agglomeration in mega cities. Finally, Diao et al. (2019) shows that market integration in Ghana helps rural households in urban proximity of large cities to more easily participate in non-agriculture employment. Despite what we know from the international experience, little empirical evidence is found for a positive relationship between urban growth and rural off-farm employment in China at the national level. Nor is it known on how the impact of urban growth evolves over time.

China's structural transformation started with rural reforms, but urban sectors caught up with and overtook rural sectors, quickly dominating structural transformation throughout the past two decades. Although there are still debates on the real causes of China's miracle of economic growth, a large literature argues that trade liberalization (Sun & Heshmati, 2010; McMillan et al., 2014; Goldberg & Pavcnik, 2016; Manova & Yu, 2017) and institutional and policy reforms, particularly the state-owned enterprises (SOE) reform and the creation of Special Economic Zones (Song, Storesletten, & Zilibotti, 2011; Autor, Dorn, & Hanson, 2016), are the two most important factors facilitating urban growth in China over the past three decades. Between 1995 and 2018, the total urban built-up land area expanded from 32,318 km^2 to 44,147 km^2, with an annual growth rate of 1.7% a year. Over the same period, the total urban citizen (registered at the end of year) increased by 229%, from 572 million in 1995 to 1,308 million in 2018. In particular, after March 2014, the Central Committee of the Communist Party of China (CPC) and the State Council jointly released a "National New-type Urbanization Plan (2014–2020)", indicating that the urbanization process in China went into a new (e.g. population-oriented) era (Long, 2014).

In terms of geographical distribution, urban growth in China has a dual-mode characteristic. On the one hand, many urban agglomerations have emerged along the coast and expanded quickly with the increasing competitiveness in the modern manufacturing and service industries caused by trade liberalization (Autor et al., 2016; Manova & Yu, 2017; Brandt, Van Biesebroeck, Wang, & Zhang, 2017). In 2012, "total urban built-up land area of 22 urban agglomerates was 32,192 km^2, accounting for 71% of China's total urban built-up land area; however, the share of the total land area of these urban agglomerates, compared with the whole of China, was only about 22%" (Chen, Liu, & Lu, 2016). In 2018, there were more than 14 cities with a GDP of more than 1 trillion yuan, accounting for around 25% of total GDP (China National Bureau of Statistics, 2020). In addition, the three largest urban agglomerates, including Beijing-Tianjin–Hebei, the Yangtze Delta, and the Pearl River Delta, have been forming a -metropolitan-belt type of urbanization model based on the initially created Special Economic Zones. On the other hand, there are plenty of medium and small cities arising inland and diffusing sparsely in rural areas, which also plays a vital role in supporting regional economic growth.

Rapid urban growth in China (as an important component of structural transformation) not only contributes to economic growth, but also benefits rural development through increasing off-farm employment and income. Since the early 2000s, there have been more than 290 million rural migrants moving into urban sectors, among which around 60% (around 170 million) worked in urban areas for at least six months a year (China National Bureau of Statistics, 2020). Within the rural areas, the proportion of employment in the primary industry (mainly, the farming sector) decreased from 73.7% in 2000 to 59.3%, leaving 139 million rural labor workers in rural nonfarm sectors by 2018. Increased off-farm employment brings more off-employment income to rural households and triggers capital investment and technology progress, which has become an important driver of rural development in China (Meng & Zhang, 2010; Combes, Démurger, & Li, 2015). However, there is almost no empirical evidence about the effects of urban growth on off-farm employment and income.

3. Model Specification and Estimation Methodology

3.1. The benchmark model

To quantify the impact of urban growth on off-farm employment of rural households in rural China, we start by using a panel data regression model, which takes the form of

$$\boldsymbol{Y_{irt}} = \beta_0 + \beta_1 \boldsymbol{UG_{rt}} + \beta_3 \boldsymbol{X_{irt}} + \pi_i + \tau_t + \boldsymbol{\epsilon_{irt}} \tag{1}$$

where $\boldsymbol{Y_{irt}} \geqslant 0$ is a continuous variable denoting off-farm employment (i.e. headcount and off-farm employment proportion) of rural household i in village r at time t. $\boldsymbol{UG_{rt}}$ is the log of urban growth capturing the pulling force from the nation-wide urbanisation process faced by rural households in village r for the same period. $\boldsymbol{X_{irt}}$ is a vector of control variables that affect off-farm employment of rural households on the supply side. The control variables include selected household characteristics (such as average age, year of schooling, marriage status of household labor, sex ratio in household, proportion of aged people above 65 years old, and so on), the proportion of labor in household, farmland areas operated, real value of house, and so on. In addition, we have controlled for the proportion of household labor participating in part-time off-farm employment. π_i is unobserved rural household specific effect, τ_t is a time dummy, and $\boldsymbol{\epsilon_{irt}}$ is the residual.

With the control of heteroscedasticity and cluster effects at the village level, we can estimate Eq. (1) by using the generalized least square (GLS) regression technique. However, the estimated β_1 could be biased because of the potential endogeneity problem, caused by time-invariant and time-variant omitted variables and/or the potential reverse causality problem. For example, there are many push factors, such as the rural land and the Hukou reforms (e.g., the Household Responsibility reform), that are likely to affect both off-farm employment and urban expansion (Huang & Ding, 2016; Huang & Rozelle, 2018), but they are not observable. Without properly accounting for these omitted variables, the estimated β_1 would be biased. Meanwhile, an increase in off-farm employment of rural households will also drive urban growth, which causes a reverse causality problem. Thus, Eq. (1) is rewritten as follows:

To deal with the endogeneity problem, we first use a fixed effect (FE) model to eliminate the impact of time-invariant omitted variables at the household level and then combine this with the instrumental variables (FEIV) to eliminate the time-variant endogeneity problem. Thus, Eq. (1) is rewritten as follows:

$$\Delta Y_{irt} = \beta_0 + \beta_1 \Delta \widehat{UG_{rt}} + \beta_3 \Delta X_{irt} + \mu_{irt} \tag{2}$$

where $\Delta Y_{irt} = Y_{irt} - \overline{Y_{ir}}$,$\Delta X_{irt} = X_{irt} - \overline{X_{ir}}$, and $\Delta\mu_{irt} = \mu_{irt} - \overline{\mu_{ir}}$, and $\Delta\widehat{UG_{rt}}$ are predicted changes in the measure of urban growth from (3), and the variable with the bar on the head represents its average of the variable over time.

$$\Delta UG_{rt} = \gamma_0 + \gamma_1 \Delta X_{irt} + \gamma_2 \Delta Z_{irt} + \omega_{irt} \tag{3}$$

where $\Delta UG_{rt} = UG_{rt} - \overline{UG_r}$ and $\Delta Z_{irt} = Z_{irt} - \overline{Z_{ir}}$ are the instrumental variables. Choosing a qualified instrumental variable to identify the relationship between urban growth and off-farm employment is a challenging task. This is because many city-level variables that could affect urban growth are also highly related to rural-to-urban migration. To resolve this problem, we construct the instrument from the perspective of measuring the stability of the electricity supply in urban China.

An extensive literature analyzes the impact of infrastructure investment (such as railroads, highways and electricity network) on industrialization and economic growth, among which many studies find that the stability of electricity supply plays an important role in affecting industrial production and urban growth (Michaels, 2008; Duranton & Turner, 2012; Herrendorf, Schmitz, & Teixeira, 2012; Fajgelbaum & Redding, 2014; Fisher-Vanden, Mansur, & Wang, 2015; Allcott, Collard-Wexler, & O'Connell, 2016). Our identification strategy is closely related to this strand of literature in particular, Allcott et al. (2016) and Fisher-Vanden et al. (2015), using the frequency of electricity-supply crisis occurred (or the "electricity supply crisis" index) as a measure for the stability of electricity supply in urban China. Because the electricity markets are segregated between rural and urban China (Fisher-Vanden et al., 2015), the electricity-supply crisis in urban China is uncorrelated with the electricity-supply crisis in rural areas. Moreover, agricultural production in China does not rely on the electricity supply from the public sector. Thus, the stability of electricity-supply in urban area is unlikely to affect rural households and their decision on off-farm employment, which makes the frequency of electricity-supply crisis and its lags as good instruments.[3]

In this study, we construct the "electricity supply crisis" index following Baker, Bloom, and Davis (2016) and use its five-year lag as an instrument. Specifically, we select at least one most popular (publicly published) daily newspaper from each city in our study and count the frequency of some predetermined keywords related to "electricity supply crisis" appearing in the newspaper for the whole year. These keywords are classified into five categories following Yu and Shi (2020); they include peak-time electricity management, discharge network, electricity generation, the re-use of remaining heat, and electricity demand management measures. Using the procedure proposed by Baker et al. (2016) to measure a macroeconomic crisis, we aggregate those frequency measures for the whole year into one index (using the number of newspapers as weights) for each city to construct an annual average low-frequency index for the electricity supply crisis over the period 1995–2018. Because the "electricity supply crisis" index is designed to capture the stability of urban electricity supply, it is highly related to urban growth but unlikely to affect agricultural production and rural households' off-farm employment decisions.

Eqs. (2) and (3) are estimated using the whole sample of five waves of nationwide rural household surveys, which covers the period 2000–2018. Because urban growth affects off-farm employment mainly through a long time-lag process, we believe that the five periods of data (including 2000, 2008, 2013, 2016, and 2018) can provide a long enough time horizon to capture such an impact. Finally, to ensure the robustness of our results, we also adopt the FE model to estimate the impact of 1–5 periods of lagged urban growth measures on off-employment of rural households.

3.2. Measuring urban growth: The urban gravity index

Measuring urban growth at the national level and linking it to rural households can be challenging. As discussed in Section 2, the urbanization process affects off-farm employment mainly through strengthening the spatial pulling force of urban growth. Yet the existing measures that use either the urban population or output value share only focus on urban growth in local areas while neglecting the nationwide rural–urban linkage. To resolve this problem, we constructed an urban gravity index by combining

[3] Alternatively, we also use the city-level NTR gap, which is widely used as a valid instrument for urban industrial development in China (Pierce & Schott, 2016; Erten & Leight, 2017), as an instrument for the robustness check. The detailed estimated results are reported in the Appendix B.

the urban growth measure and the distance between urban areas and the sample rural villages. Using the nightlight intensity as a proximate for urban growth, we define the urban gravity index as follows:

$$UG_{rt} = \sum_{jt} \boldsymbol{CityNight_{jt}} \times e^{\left(-d_{jr}^{b}/2a^{2}\right)} \quad (4)$$

where $\boldsymbol{CityNight_{jt}}$ denotes the nightlight intensity of city j at time t and $\boldsymbol{d_{jr}^{b}}$ denotes the distance between city j and village r with a, b as two parameters determining the shape and speed of urban growth effects decay along with the distance. Because the distance between the selected cities and our sample villages are fixed over time, changes in the urban gravity index mainly reflect the changes in urban growth.

The nightlight intensity is believed to be a better proxy for urban growth than the urban population and output value shares for three reasons. First, the nightlight intensity is a consistent measure of urban economic activities across regions and over time (Binswanger-Mkhize, Johnson, Samboko, & You, 2016), and is relatively more immune to the measurement errors in statistics caused by the adjustment of administration. Second, it provides a better distinction in economic activities (e.g., production and consumption) between in urban areas and in the neighborhood rural areas, which are usually hard to distinguish in official statistics. Third, official statistics in China can only provide consistent measure of GDP and population for around 268 prefectural-level cities while neglecting majority county-level cities, among which many have grown quickly for the past two decades. Without accounting for those large county-level cities may underestimate the impact of urban growth. Finally, we also used a similar approach to aggregate the "electricity supply crisis" index (and NTR measure) to construct the corresponding instrumental variables.

3.3. Distinguishing the impact of urban growth by city types

Using Eqs. (2)–(4), we can measure the aggregate impact of urban growth on off-farm employment of rural households in China. However, it will not show whether urban growth of different types will play different roles in affecting off-farm employment. To answer this question, we propose two additional scenarios by decomposing the aggregate urban gravity index in two ways and then re-do the exercises.

First, we split all cities into two types by city size (namely, 24 largest metropolitan cities and other relatively small and medium cities) and re-calculated the urban gravity index for each type. The two urban gravity indexes are first used to replace the aggregate urban gravity index in Eq. (4) separately for the regression analysis, and then, we combined them together. The combined equation can be written as follows:

$$\Delta Y_{irt} = \beta_0 + \beta_{11}\Delta \widehat{MUGrt} + \beta_{12}\Delta \widehat{RTO\_BN}_{rt} + \beta_3 \Delta X_{irt} + v_{irt} \quad (5)$$

where $\Delta MUGrt$ denotes the change in urban gravity index for the 24 largest metropolitan cities and $\Delta RTO\_BN_{rt} = OUG_{rt} - MUG_{rt}$ stands for the change in ratio of the urban gravity indexes for the other cities relative to the 24 largest metropolitan cities; this is used to capture the relative importance of urban growth and its impact on other cities. By using the ratio of the urban gravity indexes for other cities relative to the 24 largest metropolitan cities, we eliminate the multicollinearity problem caused by the high correlation between the two urban gravity indexes.[4] The null hypothesis is the following: if β_{12} is significantly positive (negative), urban growth in the 24 largest metropolitan cities will be less (more) likely to affect off-farm employment of rural households than other relatively smaller cities and vice versa.

Second, we split all cities into two types by location (namely, the local cities within 200 km and other far-reaching cities) and re-calculated the urban gravity index for each type. The two urban gravity indexes are then used to replace the aggregate urban gravity index in Eqs. (2) separately for the regression analysis, and then, we combined them to be included in the regression such that:

$$\Delta Y_{irt} = \beta_0 + \beta_{11}\Delta L\widehat{UGrt} + \beta_{12}\Delta \widehat{RTO\_LN}_{rt} + \beta_3 \Delta X_{irt} + \rho \Delta \lambda_{irt} + v_{irt} \quad (6)$$

where ΔLUG_{rt} denotes the change in the urban gravity index for cities within 200 km and $\Delta RTO_L N_{rt} = LUG_{rt} - NUG_{rt}$ stands for the change in the ratio of the urban gravity indexes for local cities within 200 km relative to other cities. The estimation of Eq. (6) can show whether urban growth in rural neighborhoods is more likely to increase off-farm employment than in far-reaching areas.

4. Data Collection and Descriptive Statistics

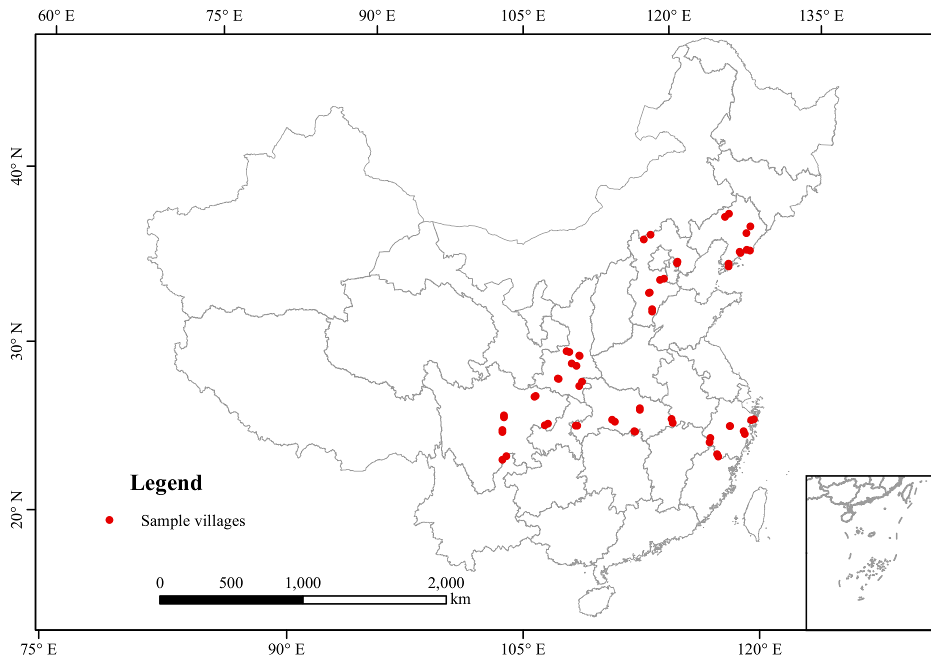
4.1. Rural household survey data

The data used in the current paper mainly come from three nationwide rural household surveys (for five rounds) conducted by the CCAP in 2000, 2009, 2014, 2016, and 2018. The three rural household surveys included China Rural Land and Labor Survey in 2000, 2009 (data for 2008), and 2014 (data for 2013), the China Rural Income Survey in 2016, and the China Rural Revitalization Survey in 2018. All three surveys were questionnaire based and carried out by face-to-face interviews between farm households and the enumerators. When the households were not directly reached during the survey periods, a telephone interview was used as a replacement. Importantly, in addition to collecting data for the surveyed year, we also asked the respondents in each round to recall the information on individual labor's employment history for up to the past 10 years.

The survey for the year 2000 set up the benchmark and collected information from 60 randomly selected villages in six provinces representing China's major agricultural regions. These selected provinces include Hebei, Liaoning, Shaanxi, Zhejiang, Sichuan, and Hubei, and the geographical distribution of the sample villages is shown in Fig. 1. We then randomly selected five counties in each province, two townships in each county, and one village within each township. Twenty households were chosen from each village. Here, 1194 records out of a total of 1,200 households investigated were complete, among which 1,149 households were included because of missing data and incomplete questionnaires problems.

In the 2009 and 2014 surveys, we went back to the same villages that were surveyed in 2000. There are two exceptions. Because of the 2008 earthquake in Sichuan, we were not able to revisit two of the villages. As a consequence, the sample size was reduced from 1200 to 1160. Among the remaining 1160 households surveyed in 2009 and 2014, there are 1,135 households (with 89 interviewed by telephone because they moved out of the village and were residing in an urban area), and 1,130 households were able to be re-investigated in 2009 and 2014, respectively, with the rest of the samples experiencing a situation where either all the members had died or could not be traced. In the 2009 and 2014 waves of the survey, an additional 25 and 35 households were replaced by other households that were randomly chosen from the village roster. After this, we have 1,243 and 1,227 households in 2009 and 2014, respectively.

[4] In our study, the correlation coefficient between the two urban gravity indexes are 0.753 while the correlation coefficient between the MUG_{rt} and RTO_BN_{rt} is only 0.336.



Source: the CCAP rural household surveys

Fig. 1. Geographical distribution of the sample villages in the CCAP farm surveys.

In 2016, we ran a new rural household survey (called the China Rural Income Survey), in which 156 villages were randomly selected from 78 towns in 39 counties located in nine provinces (including Heilongjiang, Jilin, Shandong, Henan, Shaanxi, Sichuan, Hubei, Zhejiang, and Guangdong). Among the nine provinces, four provinces overlapped with the previous three rounds of surveys. In each of the four provinces, we used the same sampling protocol to select 20 villages, among which the 10 villages that had been investigated in 2000, 2009, and 2014 were included. Within each of the re-selected villages, 10 out of the 20 rural households covered by the previous three rounds of surveys were re-interviewed. After removing missing data, there were 373 households included in the sample.

In 2018, we conducted the China Rural Revitalization Survey using the same sampling protocols as in the 2013 survey for two provinces (Liaoning and Hebei) and in the 2016 survey for six provinces (including Shaanxi, Sichuan, Hubei, Zhejiang, and Guangdong). In this survey, all 60 villages investigated in 2000, 2008, and 2013 were included. The 400 rural households that were interviewed in the 2016 survey and the 400 rural households that were interviewed in the 2013 survey were re-investigated as long as they were able to be found.

Finally, the sample with incomplete information on off-farm employment and family characteristics, such as average age, gender, education level, and marriage status of labor, were excluded. Using the three survey data, we created two datasets. One is an unbalanced panel of full datasets, which contain all the rural households that had been investigated for at least in two survey rounds. It includes all 4,411 observations for the five periods (1,149 for 2000, 1,143 for 2008, 1,127 for 2013, 372 for 2016, and 620 for 2018) for the 1,234 households in 58 village. The other is a balanced panel, which contains the rural households that had been consistently followed throughout the five rounds of surveys. It includes 1,280 observations for 256 households in 38 villages each year, and we refer to this dataset as the consistent sample.[5]

Using the household-level data, we define "off-farm employment" as a rural laborer (aged between 15 and 65 and having the full ability to work) who has participated in economic activities not directly related to agricultural production for income within the past 12 months (including both part-time and full-time activities). Two main outcome variables were used. The first variable is the headcount of off-farm employment, and the second variable is the proportion of off-farm employment at the household level. The difference between the two measures is because the second measure accounts for household size. Table 1 shows the change in off-farm employment proportion at the household level between 2000 and 2018, here by using both the full sample and the consistent sample. Based on the full sample, the off-farm employment proportion of rural households in China, on average, increased from 32.9% in 2000 to 46.7% in 2018 with a peak of 55.2% in 2016, which is lower than the consistent sample (which increased from 36.6% in 2000 to 54.4% in 2018).

4.2. Urban nightlight and distance data

The data used to calculate the nightlight intensity come from the National Centers for Environmental Information (NOAA). There are two datasets here: the DMSP/OLS dataset (the Defense Meteorological Satellite Program) for the period of 1992–2013 and the NPP/VIIRS dataset (the Visible Infrared Imaging Radiometer Suite) for the period of 2012–2018.[6] Both datasets are in the form of full-resolution digital images obtained from 0.5–0.9 μm satellite remote-sensor cameras. The resolution of the DMSP/OLS dataset is 30 arc seconds (equal to around 0.83 sq. km), and its light intensity measure ranges between 0 and 63. The resolution of the NPP/VIIRS dataset is 15 arc seconds (equal to around 0.43 sq. km), and its light intensity measure ranges between 0 and 255. Both datasets are coordinated with the WGS-84 system on the ground.

Using the original nightlight intensity data, we first removed the ephemeral lights and background noises associated with fire

[5] For a more detailed discussion on the distribution of our sample across provinces over time, please refers to Table B1 in the Appendix B.

[6] The original data are available at the following website: https://www.noaa.gov/web.html (last accessed: on 17 July 2020).

Table 1
Change in the off-farm employment ratio in Chinese rural households: 2000–2018.

	2000	2008	2013	2016	2018	2000–2018[a]	Num. of HH	Datasets
Two periods	0.291	0.415	-	-	-	0.353	81	**Unbalanced sample**
	(0.297)	(0.358)	-	-	-	(0.334)		
	0.111	-	0.667	-	-	0.389	3	
	(0.192)	-	(0.577)	-	-	(0.491)		
	-	-	0.167	0.417	-	0.292	2	
	-	-	(0.236)	(0.118)	-	(0.210)		
	-	-	0.274	-	0.387	0.330	14	
	-	-	(0.350)	-	(0.332)	(0.339)		
Three periods	0.339	0.450	0.508	-	-	0.432	489	
	(0.296)	(0.322)	(0.349)	-	-	(0.330)		
	0.306	0.350	-	-	0.467	0.374	21	
	(0.263)	(0.302)	-	-	(0.374)	(0.318)		
	0.000	-	0.125	-	0.375	0.167	2	
	(0.000)	-	(0.177)	-	(0.530)	(0.303)		
	-	-	0.480	0.560	0.532	0.524	69	
	-	-	(0.288)	(0.303)	(0.314)	(0.302)		
Four periods	0.344	0.481	0.479	0.614	-	0.479	39	
	(0.281)	(0.296)	(0.354)	(0.361)	-	(0.336)		
	0.287	0.343	0.335	-	0.370	0.334	252	
	(0.287)	(0.314)	(0.329)	-	(0.371)	(0.328)		
	0.667	0.427	-	0.483	0.583	0.540	6	
	(0.358)	(0.393)	-	(0.291)	(0.373)	(0.340)		
Five periods	0.360	0.442	0.482	0.541	0.544	0.474	256	**Consistent sample**
	(0.301)	(0.298)	(0.325)	(0.336)	(0.321)	(0.324)		
All Sample	0.329	0.421	0.457	0.551	0.466	0.424		
	(0.296)	(0.319)	(0.343)	(0.331)	(0.353)	(0.332)		
Num. of observations	1,149	1,143	1,127	372	620	4411		

Notes: The full sample include both the unbalanced sample and the balanced sample. The unbalanced sample includes households surveyed in different years and the consistent sample includes households surveyed over five years. a: 2000–2018 is the five-year means. Standard deviations are shown in parentheses.
Source: Authors' estimation by using the data from the CCAP rural household surveys.

light, lunar halos, and so on to achieve "stable lights" (Small, Elvidge, Balk, & Montgomery, 2011). Then, we aggregated "stable lights" for 370 selected cities using a spatial model. These cities include 276 administrative cities (containing 24 metropolitan cities) and 94 county-level cities (as shown in Fig. 2), which are defined as an aggregate from 449 geographical regions with a population of more than 200,000 in the year 2000. ArcGIS 10.2 was used to match the pixel-level nightlight map with the boundary of urban areas for each city, and a spatial model was employed to add up the density of the nightlight (DN) value for each pixel within the urban boundaries of each city (Elvidge, Zhizhin, Hsu, & Baugh, 2013; Zhao, Zhou, & Samson, 2014). Moreover, to resolve the consistency between the DMSP/OLS dataset and the NPP/VIIRS dataset, we further used the overlapping years of 2012 and 2013 to coordinate the two datasets to minimize the measurement errors in predictive performance between the two systems (Gibson, Rosen, Stucker, & Khorasani, 2021). Finally, a consistent measure of the nightlight intensity for the selected 370 cities was obtained by using the multinominal equation extension approach proposed by Zhao et al. (2014) for the period of 1992–2018.

In the paper, we used the Euclidean distance between the geometric centers of 370 cities to the centers of the target rural villages to calculate the urban gravity index while leaving other distance measures as the robustness check.[7] We made this estimate by using the latitude and longitude information of both the selected cities and villages based on Eq. (4). In the literature, there is little information on the choice of decay parameters that can determine the shape and speed of the distance decay function. Thus, we have taken the approach of computing urban gravities by using different parameter values and chose the parameters by using the system of equations for the best fit following Binswanger et al. (2019). Based on the R-squared value, the decay parameter that gives the best fit is determined as follows: $a = 2$ and $b = 100$.[8] Finally, because the Euclidean distance is fixed over time, the urban gravity index mainly captures the impact of urban growth.

4.3. Descriptive statistics

Table 2 provides the summary statistics for the main variables. Between 2000 and 2018, the average age and year of schooling of household labor, as well as land areas operated and real value of house, continued to increase as off-farm employment increased. However, because the proportion of aged family members (above 65 years old) also increased, the proportion of labor in households fluctuated. In addition, the distance from a rural village to the local main road also decreased over time with improved rural infrastructure investment.

Fig. 3 further shows the apparent relationship between off-farm employment of rural households and the urban gravity index and its changes for the five periods at the village level (i.e., 2000, 2008, 2013, 2016, and 2018). Between 2000 and 2018, off-farm employment (in terms of both headcount and proportion) tends to increase with urban growth (measured by using the urban gravity index) although there are some cross-period differences.

5. Urban Growth and Off-farm Employment of Rural Households in China

Based on Eqs. (1) and (6), we first examine the impact of urban growth on off-farm employment of rural households in China at the aggregate level and then decompose the aggregate impact by types of urban growth, examining its change over time. The estimation results are shown in Tables 3–6.

[7] We also estimated the road distance between 370 cities and 58 rural villages by using the 2018 transportation network, and the estimation results are similar as those obtained from using the Euclidian distance.

[8] A detailed discussion on how to choose parameters a and b are provided in Appendix A.

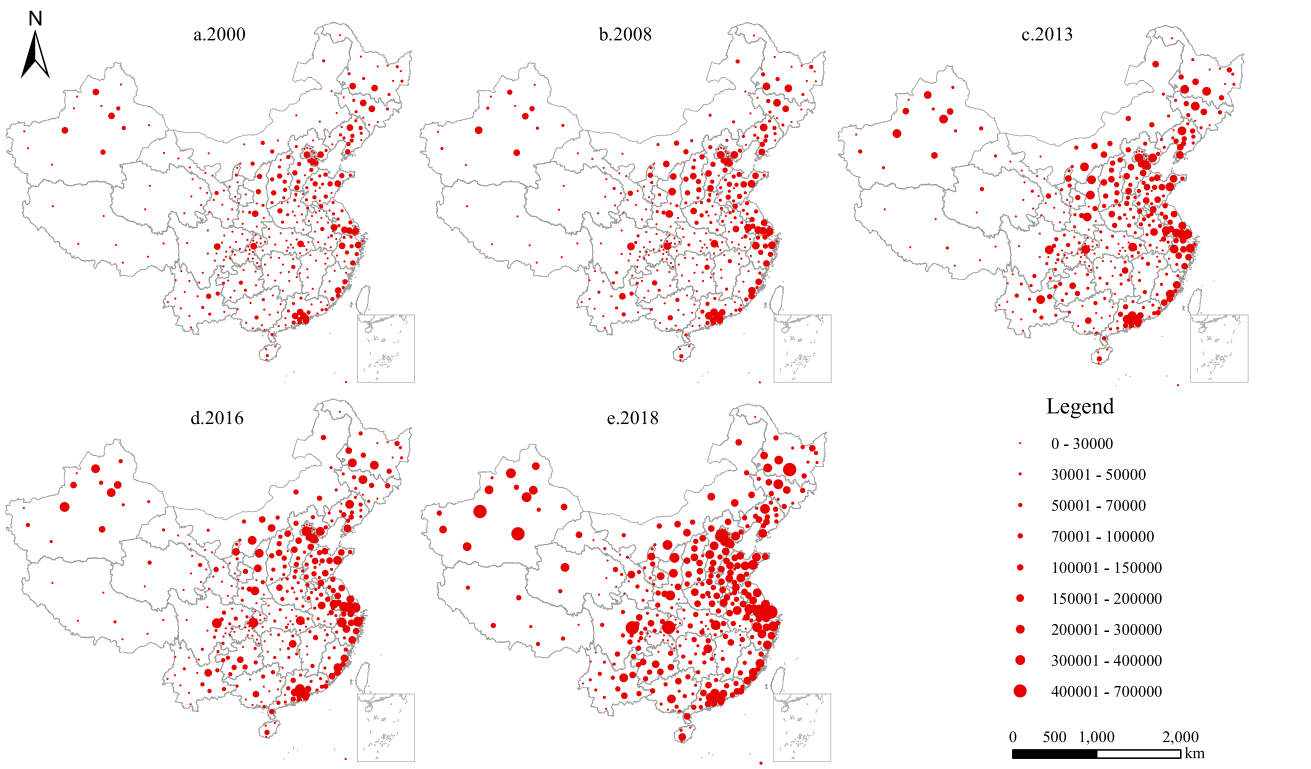


Fig. 2. The nightlight intensities for the 370 cities in China: 2000, 2008, 2013, 2016 and 2018 *Note*: a,b,c,d and e represent 2000, 2008, 2013, 2016 and 2018. *Source*: Authors' own estimation by using the night light intensity data.

5.1. Impact of urban growth on off-farm employment: Aggregate level

Using the GLS estimation technique, we first regress the off-farm employment of rural households on the aggregate urban gravity index at the village level. In addition to the headcount of off-farm employment, we also use the off-farm employment proportion of household labor as the dependent variable to account for household size and its impact. By controlling for some household characteristics (such as average age, education level, marriage ratio of labor, land area in operation, real value of house, etc.), the time dummies for each time period that could affect the labor supply, and the village cluster effects, we find that urban growth tends to significantly increase off-farm employment at the household level. As shown in Columns (1) and (2) of Table 3, the estimated coefficients in front of the log of the urban gravity index are 0.389 for the headcount regression and 0.104 for the off-farm employment proportion regression, respectively, and both coefficients are significant at the 1% level. These results are generally consistent with those obtained from the household FE model (Columns (3) and (4) of Table 3).

Moreover, we apply the instrumental variable (IV) regression technique to the FE model, here in an attempt to eliminate the potential time-variant endogeneity problem (and/or the reverse causality problem). Such problems could arise from our inability to incorporate the unobserved variables representing rural institutional reforms and macroeconomic business cycles into our regressions because they may affect both the urban growth and off-farm employment of rural households at the same time. Compared with the results obtained from the FE model, we show that the estimated impact of urban growth on off-farm employment from the FEIV model has significantly increased. This finding implies that the omitted variables (such as institutional reforms and macroeconomic growth) are positively related to urban growth but negatively related to off-farm employment, causing an under-estimation of the off-farm employment effects of urban growth. A possible explanation is that the rigid institutional arrangements in the labor market, which are associated with rural-to-urban migration in China, have lagged behind the expansion of the urban economy and have restricted rural labor from participating in off-farm employment over the past two decades (Cai, Du, & Wang, 2001; Du, Gregory, & and Meng, 2006; Meng & Zhang, 2010).

After dealing with the endogeneity problem, we find that urban growth in China has significantly increased off-farm employment of rural households. The estimated coefficients in front of the log of the urban gravity index are 1.12 from the headcount regression and 0.27 from the off-farm proportion regression, and both coefficients are significant at the 1% level. This implies that a 1% increase in the urbanization level at the national level on average created 1.1 off-farm employment opportunities for each rural household or around 27% of household rural labor.[9] Because the urbanization level (measured by the urban gravity index) increased by 9% between 2000 and 2018 (or around 0.5% a year), this suggests that urban growth throughout the nation has generated off-farm employment by 47–71 million accounting for 59% of the total newly created off-farm employment over the past two decades (given that there were around 150 million off-farm employment in rural China in 2000).

As for the control variables, the labor proportion in household and average years of schooling positively contribute to off-farm employment, while the distance to a concrete road is negatively related to off-farm employment. This implies that rural households with more well-educated labor and low transportation costs are more likely to participate in off-farm activities, reflecting the importance of supply-side factors in affecting off-farm employment of rural households. In contrast, the land area in operation

[9] The difference between headcount and off-farm proportion might reflect the impact of part-time off-farm employment on the statistics in our sample.

Table 2
Descriptive statistics on the main variables: 2000–2018.

	2000	2008	2013	2016	2018	2000–2018[a]
Dummy for off-farm emp.	0.640	0.743	0.736	0.833	0.724	0.719
	(0.480)	(0.437)	(0.441)	(0.373)	(0.447)	(0.449)
Head count of off-farm emp. (num.)	1.003	1.334	1.461	1.855	1.456	1.341
	(0.973)	(1.095)	(1.183)	(1.242)	(1.216)	(1.144)
Proportion of off-farm emp. (%)	0.329	0.421	0.457	0.551	0.466	0.424
	(0.296)	(0.319)	(0.343)	(0.331)	(0.353)	(0.332)
Proportion of part-time off-farm (%)	16.899	13.618	10.432	15.666	18.042	14.453
	(24.064)	(22.967)	(20.815)	(26.849)	(27.939)	(23.999)
Urban gravity index (log)	13.253	13.675	13.981	13.906	14.438	13.770
	(0.469)	(0.429)	(0.367)	(0.389)	(0.360)	(0.564)
Ave. age of household labor	38.535	43.289	44.132	45.019	48.409	43.132
	(9.421)	(11.328)	(13.553)	(13.614)	(15.551)	(12.757)
Proportion of labor in household (%)	62.822	64.301	59.927	69.111	76.014	64.850
	(20.996)	(22.805)	(24.380)	(25.852)	(25.903)	(24.041)
Percentage of male in household (%)	51.069	50.406	49.754	53.499	53.372	51.090
	(16.480)	(16.953)	(17.371)	(17.224)	(17.297)	(17.056)
Labor marriage proportion (%)	79.806	77.034	77.287	78.507	79.982	78.359
	(25.063)	(27.477)	(30.708)	(29.755)	(32.273)	(28.673)
Ave. years of schooling for labor (year)	6.258	6.713	6.876	7.102	6.629	6.657
	(2.719)	(2.877)	(3.097)	(3.125)	(3.208)	(2.976)
Percentage of aged (above 65 years) (%)	4.125	5.264	7.671	15.469	24.124	9.094
	(8.894)	(10.859)	(13.667)	(26.990)	(35.132)	(19.475)
Land areas in operation (mu)[b]	6.564	6.079	6.164	6.956	6.372	6.342
	(7.955)	(9.028)	(10.641)	(11.191)	(11.743)	(9.821)
Distance to local concrete road (km)[c]	1.378	0.652	0.623	0.628	0.6449	3.052
	(1.915)	(1.223)	(1.310)	(0.903)	(19.117)	(9.089)
Real value of house (1000 yuan)	41.413	79.111	143.548	290.710	146.155	113.023
	(52.230)	(94.469)	(133.605)	(176.826)	(149.537)	(134.305)
Dummy for telephone survey	0.000	0.157	0.151	0.051	0.000	0.083
	(0.000)	(0.364)	(0.358)	(0.220)	(0.000)	(0.277)
length of off-farm employment history	6.958	13.924	17.355	18.973	20.887	14.391
	(7.055)	(8.403)	(9.536)	(10.289)	(10.570)	(10.171)
Year of schooling for household head	6.531	6.529	6.565	7.013	6.631	6.594
	(3.475)	(3.424)	(3.373)	(2.757)	(3.329)	(3.361)
Proportion of not working (%)	7.721	12.279	15.723	4.301	16.570	11.902
	(17.938)	(22.125)	(28.131)	(20.315)	(29.428)	(24.189)

Notes: Standard deviations are reported in parentheses, and total number of observations is 4,411. a: 2000–2018 refers to the five-year average. b:15 mu equals 1 hector. c: the distance to the local concrete road is from the center of the village.
Source: the CCAP rural household surveys.

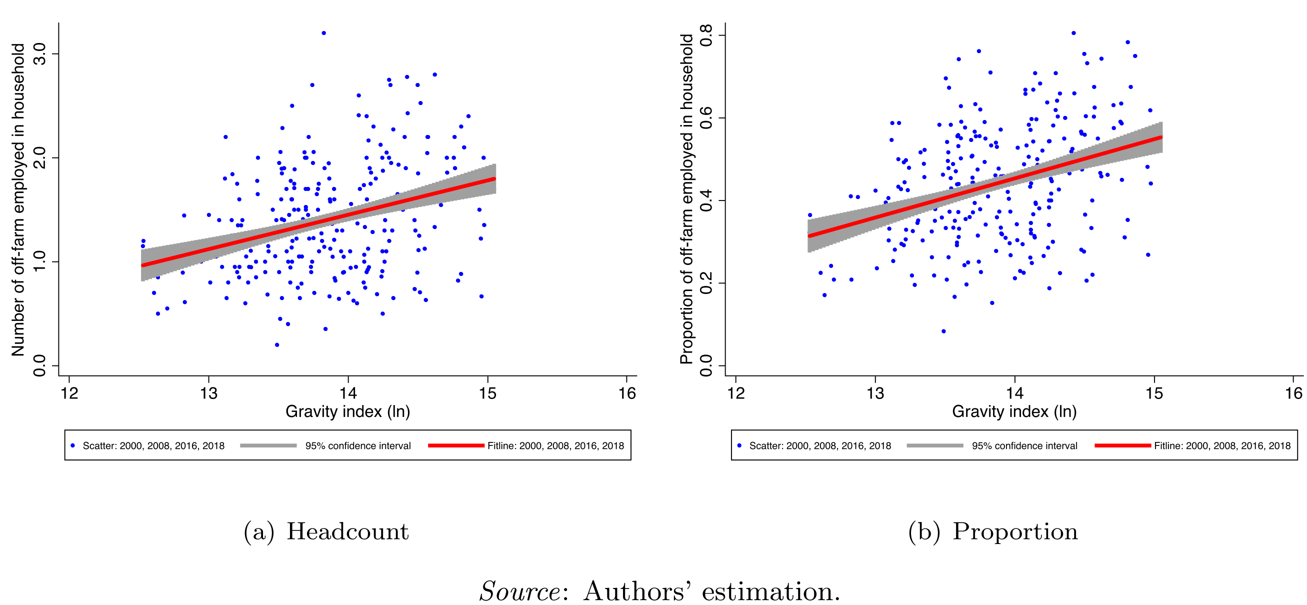


Fig. 3. The apparent relationship between the urban gravity index and off-farm employment of rural households in China.

negatively affects off-farm employment, suggesting that rural households specializing in agricultural production (by expending their land operating scale) are likely to reduce their off-farm employment. Finally, we also find that off-farm employment will first increase with the average age of household labor and then decrease after the average age of household members have reached

Table 3
Impact of urban growth on off-farm employment of rural households: The baseline model.

	GLS		FE	
	Person	Proportion	Person	Proportion
Dependent variable: off-farm employment				
Urban gravity index (log)	0.389***	0.104***	0.419***	0.122***
	(0.086)	(0.026)	(0.123)	(0.034)
Ave. age of household labor	0.069***	0.014***	0.033***	0.011***
	(0.009)	(0.003)	(0.010)	(0.003)
Ave. age of household labor (sqr.)	−0.001***	−0.000***	−0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Proportion of labor in household	0.015***	0.002***	0.017***	0.003***
	(0.001)	(0.000)	(0.001)	(0.000)
Percentage of male in household (%)	−0.002	0.000	−0.006***	0.000
	(0.001)	(0.000)	(0.002)	(0.000)
Marriage ratio in household	0.000	−0.001***	−0.002*	−0.001***
	(0.001)	(0.000)	(0.001)	(0.000)
Ave. years of schooling for labor	0.032***	0.011***	0.032***	0.009**
	(0.008)	(0.002)	(0.010)	(0.004)
Proportion of aged (above 65 years)	0.013***	0.002***	0.009***	0.002**
	(0.001)	(0.000)	(0.002)	(0.000)
Land areas in operation	−0.013***	-0.005***	−0.012***	−0.005***
	(0.003)	(0.001)	(0.004)	(0.001)
Distance to local concrete road	-0.004**	−0.001**	−0.000	−0.000
	(0.002)	(0.000)	(0.002)	(0.001)
Real value of house (log)	0.025**	0.004	0.012	0.002
	(0.011)	(0.003)	(0.010)	(0.003)
Dummy for telephone survey	0.333***	0.130***	0.266***	0.094***
	(0.066)	(0.019)	(0.069)	(0.021)
Proportion of part-time off-farm	0.013***	0.006***	0.015***	0.007***
	(0.001)	(0.000)	(0.001)	(0.000)
Time dummies	Yes	Yes	No	No
Cluster effect (at village level)	Yes	Yes	Yes	Yes
Constant	−6.596***	−1.535***	-5.955***	−1.691***
	(1.179)	(0.341)	(1.661)	(0.452)
Num. of observations	4,411	4,411	4,411	4,411
R-squared	0.467	0.469	0.452	0.450
Num. of households	1,234	1,234	1,234	1,234
Num. of villages	58	58	58	58

Note: Robust standard errors in parentheses, and "***","**" and "*" represent $p < 0.01$, $p < 0.05$ and $p < 0.1$ respectively. We have also controlled the off-farm employment in location in the regressions.
Source: Authors' estimation using the full dataset.

38. Because the average age of rural labor in our sample is more than 38 in 2000, this inversed U-shaped relationship between average age of rural laborers and off-farm employment indicates that the aging problem is threatening rural labor when it comes to participating in off-farm activities.

5.2. Impact of urban growth on off-farm employment: Disaggregate level

Although urban growth at the aggregate level will increase off-farm employment of rural households in China, it is not known whether urban growth of different types (i.e., large vs. small cities or local vs. far-reach cities) may affect off-farm employment in different ways. To address this issue, we split the 370 cities in our sample by two criteria. One is to split the cities by size into the 24 largest metropolitan cities and the other 346 cities, while the other is to split the cities by distance into the cities within 200 km and the other cities. In both scenarios, we measured the urban gravity index for different types of urban growth and compare their relative impacts on off-farm employment. see Table 4.

In the first scenario, we ran the regressions of headcount and off-farm proportion with the log of the urban gravity index for the top 24 largest cities and for other cities separately. Then, based on Eqs. (5), we regressed the headcount and off-farm proportion on the log of the urban gravity index for the top 24 largest metropolitan cities and the ratio of the urban gravity index for large cities relative to other cities. As discussed in Section 3, the two exercises provide a cross-check for each other on the relative impact between the extreme large cities and others. For simplicity, only the results obtained from the FEIV model with an adjustment for sample selection bias are reported in Table 5.

As shown in Table 5, the estimated coefficients in front of the log of the urban gravity index for the 24 largest metropolitan cities is 1.06 and 1.05 for the other cities from the headcount regression, and both coefficients are significant at the 1% level (Columns (2) and (3) in Table 5). A similar pattern regarding the impact of urban growth on off-farm employment proportion is also found (i.e., 0.29 and 0.24) between the 24 largest metropolitan cities and the other cities. This implies that urban growth of both mega-large metropolitan cities and of other relatively smaller ones positively contribute to rural off-farm employment, and their impacts are similar.

Moreover, comparing the growth of the two groups of cities, we show that the impact of the top 24 largest cities is a bit smaller than for other cities, but there are no significant differences in the estimated coefficients in the log of the urban gravity index. This is consistent with the statistical test results. When we incorporate both the urban gravity index for the top 24 largest metropolitan cities and the ratio of the urban gravity index for other cities relative to the large cities into the regression, the estimated coefficient in front of the ratio variable is insignificant at the 10% level.

This suggests that the growth of other relatively smaller cities is as important as the largest cities in creating off-farm employment in China. Our finding is generally consistent with the dynamic monitoring statistics from the National Bureau of Statistics of China (CNBS) on the geographical allocation of rural-to-urban migrants in recent years. In 2018, there were 288.4 million rural-

Table 4
Impact of urban growth on off-farm employment of rural households: FEIV model.

	Person	Proportion
Dependent variable: non-farm employment of rural households		
Urban gravity index (log)	1.119***	0.267***
	(0.129)	(0.036)
Ave. age of household labor	0.026**	0.010***
	(0.011)	(0.003)
Ave. age of household labor (sqr.)	−0.001***	−0.000***
	(0.000)	(0.000)
Proportion of labor in household	0.017***	0.003***
	(0.001)	(0.000)
Percentage of male in household (%)	−0.006***	−0.000
	(0.002)	(0.000)
Marriage ratio in household	−0.002	-0.001***
	(0.001)	(0.000)
Ave. years of schooling for labor	0.026**	0.009**
	(0.011)	(0.004)
Proportion of aged (above 65 years)	0.009***	0.002***
	(0.002)	(0.000)
Land areas in operation	−0.008**	−0.004***
	(0.004)	(0.001)
Distance to local concrete road	−0.009***	−0.002***
	(0.002)	(0.001)
Real value of house (log)	0.017	0.004
	(0.011)	(0.003)
Dummy for telephone survey	0.142	0.075***
	(0.088)	(0.027)
Proportion of part-time off-farm	0.015***	0.007***
	(0.001)	(0.000)
Time dummies	No	No
Cluster effect (at village level)	Yes	Yes
Constant	No	No
Num. of observations	4,411	4,411
R-squared	0.431	0.439
Num. of households	1,234	1,234
Num. of villages	58	58

Note: Robust standard errors in parentheses, and "***", "**" and "*" represent $p < 0.01$, $p < 0.05$ and $p < 0.1$ respectively. We have also controlled the off-farm employment in location in the regressions. The F-statistics for FEIV regression is 61.83. The first-stage results are reported in Appendix B.
Source: Authors' estimation using the full dataset.

to-urban migrants, among which 73.6% were working within the same province and more than 40% were working in the local region (China National Bureau of Statistics, 2019).

In the second scenario, we broke the urban gravity index into the measures representing two groups of cities with different distances to our sample villages (namely, local vs. far-reaching cities). Both headcount and off-farm employment proportion were regressed on the measure for local cities (defined as cities within a radius of 200 km in terms of Euclidian distance) and that for the far-reaching cities separately and together based on Eq. (6). For consistency, only the results obtained from the FEIV model are reported in Table 6.

As shown in Table 5, the estimated coefficients in front of the log of the urban gravity index for the cities within 200 km in the headcount regression is 1.67, which is significantly larger than that of other cities (0.97). However, the significant level of the coefficient for off-farm employment proportion is only at the 5% level. The relative impact between the two groups of cities for the headcount regression is similar to that obtained from the off-farm employment proportion regression. The results are consistent with the findings in previous studies such as Sharma and Chandrasekhar (2014) and Diao et al. (2019), suggesting that urban growth in neighborhoods is likely to generate a relatively larger impact on off-farm employment of rural households, but it is not as stable as that from the far-reaching cities.

The above finding is supported by the statistical test as well. When we include the log of urban gravity index for cities within 200 km and the ratio of urban gravity index for the other cities relative to the urban gravity index for neighborhood cities into the same regression, the difference between the impact of far-reaching cities and that of the neighborhood cities are not substantial. As shown in Table 6, the estimated coefficients in front of the ratio variable are positive but not significant at the 5% level. Yet our finding still provides some interesting evidence that urban growth in neighborhood and far-reaching areas may have some different merits in increasing off-farm employment in China. Specifically, urban growth in neighborhood is likely to generate a larger but unstable impact on off-employment creation, compared to that in far-reaching areas.

As additional evidence, although the off-farm employment ratio has continued to increase over the past two decades, most rural labor chooses to participate in off-farm employment (around 80–90%) within the province. In particular, in Zhejiang and Liaoning, the within-province proportion of off-farm employment on average has been more than 90% throughout the sample period of 2000–2018. Meanwhile, the out-of-province proportion of off-farm employment tends to decline after 2013 in all provinces except for Zhejiang, reflecting a different role of urban growth in

Table 5
Impact of urban growth on off-farm employment of rural households: Large vs. other cities.

	Person			Proportion		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: non-farm employment						
Urban gravity index of LC (log)	1.275***	1.055***	-	0.306***	0.293***	-
	(0.400)	(0.161)	-	(0.095)	(0.054)	-
Urban gravity index of OC (log)	-	-	1.044***	-	-	0.243***
	-	-	(0.124)	-	-	(0.033)
Ratio of OC/LC UGs	−0.917	-	-	−0.053	-	-
	(1.330)	-	-	(0.255)	-	-
Other controlled variables	Yes	Yes	Yes	Yes	Yes	Yes
Cluster effect (at village level)	Yes	Yes	Yes	Yes	Yes	Yes
Num. of observations	4,411	4,411	4,411	4,411	4,411	4,411
R-squared	0.437	0.442	0.427	0.443	0.443	0.436
Num. of households	1,234	1,234	1,234	1,234	1,234	1,234
Num. of villages	58	58	58	58	58	58

Notes: Robust standard errors in parentheses, and "***", "**" and "*" represent $p < 0.01$, $p < 0.05$ and $p < 0.1$ respectively. Model (2), (3) and (5), (6) regressed on the urban gravity index of large cities (LC) and that for the other cities (OC) separately, while Model (1) and (4) include both LC and OC based on Eq. (5). The F-statistics from the first-stage FEIV regressions for model (1), (2) and (3) are 12.61, 12.85 and 79.15, while for model (4), (5) and (6) are 16.64, 12.41 and 102.54. The first-stage results are reported in Appendix B.
Source: Authors' estimation using the full dataset.

Table 6
Impact of urban growth on off-farm employment of rural households: Local vs. other cities.

	Person			Proportion		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: non-farm employment						
Urban gravity index of NC^a (log)	1.419***	1.665***	-	0.222***	0.350**	-
	(0.419)	(0.430)	-	(0.033)	(0.154)	-
Urban gravity index of OT^a (log)	-	-	0.965***	-	-	0.246***
	-	-	(0.127)	-	-	(0.034)
Ratio of OT/NC UGs	4.709	-	-	0.069	-	-
	(2.871)	-	-	(0.234)	-	-
Other controlled variables	Yes	Yes	Yes	Yes	Yes	Yes
Cluster effect (at village level)	Yes	Yes	Yes	Yes	Yes	Yes
Num. of observations	4,411	4,411	4,411	4,411	4,411	4,411
R-squared	0.340	0.314	0.440	0.438	0.396	0.443
Num. of households	1,234	1,234	1,234	1,234	1,234	1,234
Num. of villages	58	58	58	58	58	58

Notes: Robust standard errors in parentheses, and "***", "**" and "*" represent $p < 0.01$, $p < 0.05$ and $p < 0.1$ respectively. Model (2), (3) and (5), (6) regressed on the urban gravity index of local cities within 200 km (NC), and that for the far-reaching cities (OT) separately, while Model (1) and (4) include both NC and OT based on Eq. (6). The F-statistics from the first-stage FEIV regressions for model (1), (2) and (3) are 13.36, 18.92 and 61.48, while for model (4), (5) and (6) are 15.08, 12.92 and 107.69. The first-stage results are reported in Appendix B.
Source: Authors' estimation using the full dataset.

local regions when it comes to affecting off-farm employment patterns in China relative to that in far-reaching areas.

5.3. Impact of urban growth on off-farm employment: Trans-temporal change

How does the impact of urban growth on off-farm employment of rural households change over time in China? Is the impact of urban growth growing consistently throughout the whole period of 2000–2018? To answer these questions, we re-categorized the whole period into four subperiods: 2000–2008, 2000–2013, 2000–2016, and 2000–2018 and estimated the accumulated impacts of urban growth on off-farm employment for each period. To allow the estimated results to be comparable over time, we used the balanced panel data, which only cover 256 rural households in 38 villages traced throughout the five waves of farm surveys.

Fig. 4 compares the accumulated impact of urban growth on off-farm employment for the four subperiods. As shown in Fig. 4, urban growth at the aggregate level does not generate a positive impact on off-farm employment consistently over time. For all the traced rural households, urban growth initially generated no impact on off-farm employment of rural households between 2000 and 2008. However, after 2008, the positive impact of urban growth on off-farm employment (in terms of headcount) started to accumulate, and the estimated elasticity increased from 1.74 for the period of 2000–2013 to 2.47 for the period of 2000–2016. However, this trend has reversed in recent years and dropped to 1.75 for the period of 2000–2018. A similar pattern is also found for off-farm employment proportion. This suggests that urban growth contributing to off-farm employment in China mainly occurred after 2008, when both the rural and urban reforms promoted the development of tertiary industry and built a strong rural–urban linkage through rural-to-urban migration, supporting the finding of Diao et al. (2019) which shows that market integration strengthens the urban–rural linkage in Ghana. The period of these changing impacts also coincides with the release of "National New-type urbanization Plan (2014–2020)" with a target of population-oriented urbanization (Zhu, 2014; Chen et al., 2016), reflecting the important role of urban reforms in affecting rural transformation through the creation of off-farm employment.

Moreover, when we split the sample cities by city size and its distance to the sample villages, we find that urban growth of different types tends to generate different impacts on off-farm employment of rural households in different time periods. Specifically, the off-farm employment creation starts with the emergence of the largest 24 metropolitan areas over the period of 2000–2008, and they are more stable throughout the whole period of 2000–2018. This corroborates the findings of Erten and Leight (2017), who showed that China's access to the World Trade Organization (WTO) created a positive impact on rural transformation through off-farm employment creation. In contrast, the growth of local relatively small cities contributes more to off-farm employment creation between 2013 and 2016 when "rural revitalization" and new-style urbanization policies were implemented (Zhu, 2014; Chen et al., 2016).

However, these positive accumulated effects obtained from the growth of the small cities (or in the neighborhood rural areas) dropped more quickly in recent years than the large cities when the labor market became more integrated. Reflected in the change in migration pattern over time, the out-province proportions of off-farm employment in all provinces (except for Zhejiang) declined between 2013 and 2016. However, after 2016, the out-province proportions of off-farm employment in the inland provinces, such as Sichuan and Shaanxi, have increased again (from 16.0% and 9.5% in 2016 to 16.7% and 9.7% in 2018). This suggests that urban growth pulling labor out of agriculture follows different patterns in different stages of economic structural transformation (IFAD, 2016; Mellor, 2017).

6. Robustness Check

In this section, we conduct four groups of sensitivity analyses to examine the robustness of our results; the findings are reported in Appendix C.

First, there could be concerns that our results are related to the choice of a particular identification strategy. To deal with these concerns, we also conducted the estimation by using two alternative identification strategies. First, we construct an alternative instrumental variable, namely the lagged city-level nominal tariff rate (NTR) gap, following (Pierce & Schott, 2016; Erten & Leight, 2017). We construct the NTR gap by using the industry-level employment share for 370 cities (based on the 1990 population census) as weights to aggregate the difference between the Non-NTR rate and the NTR rate for the manufacturing industries. The mechanism, as argued by Erten and Leight (2017), is that the reduction in tariff uncertainty positively affects urban growth through promoting secondary exports, but is unlikely to directly

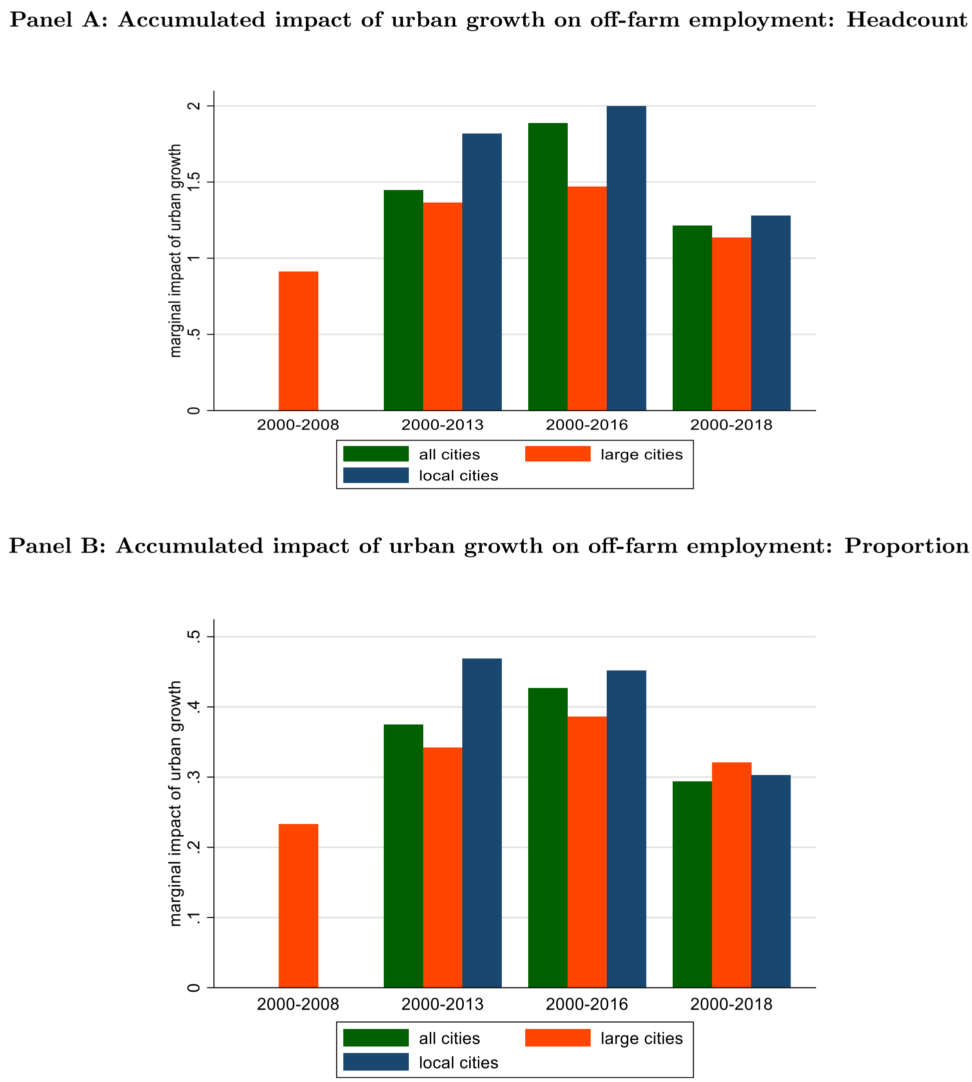


Fig. 4. Comparing accumulated impact of urban growth on off-farm employment of rural households in China between 2000 and 2018. *Note*: the estimated coefficients are obtained from the balance panel with the 256 farm households existing through all 5 periods. (*Source*: Authors' estimation by using the balanced panel data.).

affect the agricultural sector [10]. Second, instead of using the FEIV approach, we also use the FE model with a one-to-five-year lag in the urban gravity index to cope with the endogeneity problem. The results (shown in Appendix C) are generally consistent with what was obtained, suggesting that the findings are robust to the choice of instrumental variables.

Second, our results could be highly influenced by how we measured nightlight intensity and the distance between cities and targeted villages. To avoid measurement errors, we first adopted three different approaches to re-measure the nightlight intensities for a cross-check. In particular, we compared the estimates by using only the DMSP/OLS dataset before 2013 and only the NPP/VIIRS dataset after 2013. The results show that there are some differences in the measurement of the nightlight intensities, but our estimation results are generally consistent with each other when different measures for the nightlight intensities are used. Next, we also used the transportation distance in 2018 to replace the Euclidian distance in calculating the gravity index. The comparison of urban gravity indexes calculated by using the two distance measures shows that they are highly correlated, and the correlation coefficient is around 95% (Figure C1 and Columns (1)-(2) in Table C3).

Third, our results could be flawed by how we measured off-farm employment based on the number of people because many off-farm activities in rural China are seasonal in nature and could change following a seasonal pattern.[11] Although we have controlled for the proportion of part-time job in the regressions, there still could be a possibility that these measurement errors may contaminate our findings. To deal with this issue, we convert the number of months that each household labor participates in off-farm activities into full-time headcounts and off-farm employment proportion. Using this alternative measure on off-farm employment, we re-estimate the impact of urban growth on rural off-farm employment. As shown in Columns (3)-(4) of Table C3, the estimated coefficients in front of the log of urban growth index are generally consistent with those obtained in the main results.

Fourth, the willingness of rural labor to participate in off-farm employment is also highly related to the income obtained from

[10] A more detailed discussion on the construction of the alternative instrumental variable is in Appendix B.

[11] According to the definition of NBSC, a person who worked on non-farm activities for more than or equal six months a year could be treated as a full-time non-farm labor. Yet aggregating the off-farm labor working for six months a year with that working for 12 months will cause a large measurement problem.

off-farm activities. In the literature, an increase in off-farm income could reduce farmers' willingness to participate in off-farm activities because of income effects. Not accounting for off-farm income will incur measurement errors in the initial regressions. To resolve this concern, we conducted a sensitivity test by incorporating the log of off-farm income at the household level at 2000 constant price into the regression analysis. Meanwhile, we have also examined the impact of potential sample selection bias that could be caused by those farm households with no off-farm employment and its impact on our regression results. The regression results are reported in Columns (5)-(8) of Table C3. Generally, the estimated impacts of urban growth on off-farm employment of rural households are consistent with those we obtained before.

7. Conclusions

A better understanding of the interaction between structural transformation and rural development is essential for development economists and policy makers to initiate good development strategies. While there are many studies having examined the impact of urban proximity on off-farm employment, little is known on whether and how urban growth at the national level would pull labor out of agriculture. By constructing an urban gravity index to link rural households to the nationwide urbanization process, we investigate the impact of urban growth, an important aspect of structural transformation, on rural development through its creation of off-farm employment in China.

We show that rapid urban growth significantly increased off-farm employment of rural households in China over the past two decades. Between 2000 and 2018, urban growth throughout the nation on average has generated off-farm employment opportunities by 15–18 million annually by using a nationwide farm household survey for six provinces, accounting for a significant proportion of rural migrants. This helps to strengthen the ties between the rural and urban areas and facilitate rural development by enabling farmers to obtain more off-farm income. Moreover, the positive impact started with the emergence of a few large metropolitan cities but ended with the growth of local, relatively smaller ones. This implies that off-farm employment creation is a nationwide phenomenon and could be driven by different types of urban growth in different stages of structural transformation. Finally, it is forecasted that the role of urban growth in pulling labor out of agriculture is diminishing, as urban and rural labor markets are more integrated due to wide-spread of ICT technology. While large cities used to impose a large impact on pulling labor out of agriculture for the past two decades, the pattern is gradually shifting towards to small cities. Our findings provide useful insights for policy makers who want to facilitate rural transformation through speeding up urbanization in China and should consider its sequential strategy, as well as in other developing countries.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.worlddev.2021.105727.

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