Clustering, Growth, and Inequality in China

Abstract

This study examines the effects of China's industrial clusters on regional economic growth and urban-rural income inequality within a region. A density-based index (DBI) is developed to capture the unique features of cluster development in China. From a county-level DBI panel data constructed based on firm-level and county-level datasets, we find that clusters enhance local economic growth substantially. Moreover, the existence of entrepreneurial clusters (clusters mainly consist of non-state-owned firms) helps to reduce local urban-rural income inequality by increasing the income of local rural residents. We also find that the clustering effects on growth and reduction of inequality are less significant in more urbanized regions or megacities. Identification issues are carefully addressed by deploying two-stage estimations with instrumental variables and Granger test.

Keywords: China, clustering, geography, growth and inequality, institutions
JEL Classification: D2, H7, O1, R1, R3

1. Introduction

This study investigates the co-existence of industrial clustering, economic growth, and income inequality and their interactions in China. The post-Mao economic reforms have transformed the world's largest developing country from one of the poorest nations into a major power (World Bank, 2013). The emergence of industrial clusters in numerous towns, mostly along China's coastal areas, is among the most striking developments throughout the said reforms. Various Chinese townships became national or international production centers for certain products because of the clustering of a large number of small entrepreneurial firms.[1] Considering the rise of industrial clusters as one of the primary engines of China's growth is a warranted assertion (Sonobe and Otsuka, 2006; Fleisher et al., 2010; Long and Zhang, 2011).[2]

However, along with China's record-breaking growth was the rapid increase in inequality. China now has become one of the least equal economies in the world (Sicular, 2013), a status that may threaten the country's social stability and economic sustainability. The national Gini coefficient of household per capita income increased from 0.38 in 1988 to 0.49 in 2007 (Li et al., 2013), and to 0.53–0.55 (Xie and Zhou, 2014) or even 0.61 in 2010 (Gan, 2013).[3] The urban-rural income gap has been a dominant component of the overall inequality (Li et al., 2013). Meanwhile, regional disparity, particularly inland–coastal disparity, remains an important dimension of the increased inequality during the reform era (Chen and Fleisher, 1996; Kanbur and Zhang, 1999).

This study links the phenomena mentioned above by examining how industrial clusters affect economic growth and inequality in China simultaneously. First, we determine whether clustering associated with different strengths and ownership structures affects local economic growth and its implications for regional disparity. Second, we investigate whether such clustering influences urban-rural income inequality within a region, and if so, through which channel. Third, we examine the heterogeneous effects of industrial clusters focusing on the urbanization level of the regions. In our paper, we are particularly interested in the impacts of clustered entrepreneurial firms, which we call entrepreneurial clusters. Based on available data, the best statistical proxy for entrepreneurial firms in China are non-state-owned firms (non-state firms in short) as discussed in the literature (Che and Qian, 1998; Xu, 2011; Long and Zhang, 2011).[4]

To address the above research questions, we first define the measurements of clustering in the context of China. In a market economy, the industrial agglomeration is an outcome of the co-location decisions of firms in the spatial equilibrium model (Ellison and Glaeser, 1997; Glaeser and Gottlieb, 2009) or the new economic geography model (Krugman, 1991b). Industrialization and urbanization often co-occur in market economies. However, production factors such as land, labor, and capital are not freely mobile or accessible in China, because of the state control over ownership of land and major financial institutions, as well as labor mobility through

[1] For instance, one-third of the world's socks, 40% of the world's neckties, and 60% of China's cashmere sweaters were produced in the towns of Datang, Shengzhou, and Puyuan, respectively (Xu and Zhang, 2009).

[2] According to Long and Zhang (2011), 62% of the growth of the number of firms in China from 1995 to 2004 was caused by the rise of these clusters; 14% of China's total industrial GDP growth during the same period was attributed to the firms within clusters.

[3] Although Gini coefficient estimations vary depending on the different data sources used, almost all studies show the same rising inequality trend in China over the past three decades.

[4] In the rest of the paper, our discussions designate clusters composed mainly of non-state firms as entrepreneurial clusters. However, when merely presenting statistics, we simply use the term non-state firms or non-state clusters when referring to the data.

the residence registration (*Hukou*) system. Consequent to these restrictions, a substantial proportion of entrepreneurial firms in China are clustered in officially-defined rural towns, highly specialized and small in size. In contrast to the clusters of entrepreneurial firms are the industrial cities or agglomerations of highly specialized gigantic state-owned enterprises (SOEs), which were planned by the government, with very minimum, if not zero, consideration of markets.

To capture the distinctive features of the industrial clusters created and developed under the institutional restrictions in China and reduce the noise in the data created by state-owned industrial agglomerations, we create a density-based index (DBI) of clusters based on the density of firms of each industry within a geographical location. The indices are constructed based on the firm-level panel dataset from the Above-Scale Industrial Firm Panel (ASIFP)[5] between 1998 and 2007. Applying the DBI measurements, we further construct a panel of county-level cluster indices that measure the existence, strength, and ownership structure of industrial clusters.

Based on our county-level DBI cluster indices, which is a panel of 2,815 Chinese counties from 1998 to 2007, we find that counties with clusters, particularly strong clusters (measured by clusters' outputs and establishment) or with entrepreneurial clusters (clusters composed of mainly non-state firms), grow significantly faster than other counties. On average a 1% increase in the clusters' contribution to national industrial output within a country will result in a 1% increase of per capita GDP growth in that county; and a 1% increase in the non-state firms' contribution to the clusters' outputs or establishment number will result in approximately 1.6% increase in the per capita GDP growth. More interestingly, we discover that entrepreneurial clusters not only promote economic growth but also substantially reduce local urban-rural income inequality, and this outcome is driven by the increased income of rural residents in the counties where these clusters are located. An increase of 1% in the outputs or establishment number of non-state firms within the clusters is associated with a 3% reduction in the urban-rural inequality in the county. Moreover, from subsample analysis, we find that the clustering effects are less significant in mega-city regions (e.g., Beijing, Shanghai, Shenzhen) or more urbanized regions according to *Hukou* registration.

Two-stage estimations and Granger tests are deployed to address identification concerns. Regarding clustering effects on local economic growth, we use per capita mining outputs in a region as an instrumental variable (IV). Mine-rich regions are typically dominated by large companies and entrepreneurship is often weakened (Chinitz, 1961; Rosenthal and Strange, 2003; and Glaeser et al., 2010, 2015). Therefore, provinces with higher per capita mining outputs have weaker industrial clusters and fewer private firms in the clusters. Furthermore, the mine richness of a region is determined geologically. So, the per capita mining output of a province is exogenous to the county level growth. Two-stages estimations using this IV confirm the causality of the effect of clusters on regional economic growth.

For identifying clustering effects on within-county urban-rural income inequality, we use two IVs: the per capita length of classified highways in a city, and the number of Christian churches in a county in a given year. The access to transportation network is expected to be related to the development of clusters because transportation infrastructure helps to reduce the trade and shipping costs, increase the market size, and facilitate knowledge diffusion of firms within a region that are ultimately

[5] ASIFP is composed of virtually all manufacturing firms in China with annual sales of RMB 5 million (US$ 750,000) or more between 1998 and 2007. The database provides detailed financial information and other firm-specific information, including location, industry, age, and ownership structure.

important for clustering of firms. Additionally, Christianity culture plays an important role in fostering entrepreneurship and trade and facilitating coordination of local society that are major roots for the development of clusters. These two IVs are relevant to the clustering while are exogenous to the error terms of the estimations for local urban-rural income inequality. The two-stage estimations confirm the validity of the IVs and the causal relationships between clustering, urban-rural inequality and per capita household income of rural residents.

Finally, Granger causality tests further confirm our findings on the clustering effects on regional growth and local urban-rural income inequality. Additional robustness checks further rule out alternative explanations.

Our discoveries contribute to the literature on economic geography and urban economics by providing new evidence for the clustering effects on economic growth. There is no empirical consensus in prior studies on the effects of clusters on growth. Glaeser et al. (1992) find that employment and wage growth are positively correlated to the clusters of diverse industries in the United States. Conversely, based on manufacturing data, Cingano and Schivardi (2004) and Dekle (2002) find no evidence for agglomeration externalities on regional growth in Italy or Japan, respectively. Our study complements the existing discussions by suggesting that the effects of clustering on growth is conditional on institutions. In our context, it depends on the ownership type of firms within the clusters and the nature of urbanization of the regions. Moreover, using county-level data, this study complements the new micro-geography literature, which suggests that it is important to 'zoom in' to a smaller scale of the geographical territories to gain the insights of the local advantages (e.g. Feldman, 2014; Catalini, 2018; Mudambi et al., 2018). This is a new dimension in studying the effects of clusters on economic growth.

More importantly, perhaps, this study is the first one which examines the effects of clustering on income inequality. We hope this contribution may shed some light on discussions of the tradeoffs of agglomeration (e.g., Fujita and Ogawa, 1982; Fujita and Thisse, 2013; Combes et al., 2018). Additionally, the present study enriches the literature on economic development and inequality by suggesting an alternative trend between growth and inequality under different institutions. The relationship between economic growth and inequality raises challenging questions since the beginning of industrialization (Kuznets, 1963). Some studies report a negative relationship between growth and inequality (e.g., Alesina and Rodrik, 1994; Persson and Tabellini, 1994; Knowles, 2001) while others find such relationship to be positive (e.g., Forbes, 2000; Barro, 2000; Banerjee and Duflo, 2003). The present study discovers that entrepreneurial clusters distinctively differ from clusters dominated by state-owned firms that they stimulate economic development and reduce local inequality simultaneously. These findings indicate that the underlying institutions deeply influence the relationship between development and inequality. Our results are consistent with the arguments that good institution simultaneously promotes development and reduces inequality (Acemoglu et al., 2002, 2005; Benjamine et al., 2005, 2011; Engermann and Sokoloff, 1997, 2000; Easterly, 2007).

Furthermore, this study contributes to the literature on income inequality in China. From 1984 to 2005, urban-rural income disparity almost doubled (Sicular et al. 2007), and inequality in rural China is related to impeding institutions, such as the *Hukou* system (Whyte, 2010). Moreover, inter-regional income difference increases over time (Fujita and Hu, 2001; Kanbur and Zhang, 1999, 2005). The primary sources of persistent regional inequality include structural and long-term factors (Candelaria et al., 2013) and policy, such as fiscal decentralization (Li et al., 2013). The findings in this paper complement those of previous studies by providing mechanisms of different types of inequalities. On the one hand, we find clustering increases regional disparity by widening the gap of the growth rates between counties with and without clusters. On the other hand, we find there is a reduction in urban-rural income inequality within a county if there are entrepreneurial clusters in the county.

Finally, our study provides a methodological contribution to the research on economic geography and urban economics. Given the strong institutional constraints to factor mobility in China, directly applying the agglomeration indices used in the existing literature (e.g., Ellison and Glaeser, 1997; Krugman, 1991a; Porter, 1990) may not be the most suitable approach because entrepreneurial industrial clusters would be mixed with or even overwhelmed by the SOE-dominated agglomerations.[6] The indices of clustering we constructed, however, can capture the institutionally constrained entrepreneurial clusters in China.

The rest of the paper is organized as follows. Section 2 introduces the institutional background of industrial clusters in China. Section 3 discusses the related literature. Section 4 constructs the density-based indices and presents the data. Section 5 reports our empirical findings on clustering, economic growth, and urban-rural inequality with the identification issues addressed. Section 6 concludes this study.

2. Industrial Clusters in China

The definition for the term "cluster" or "geographical agglomeration" can vary depending on the purpose of a study. In general, it refers to the co-location choices of groups of firms, which are either in the same or related industries or, in diverse industries. The central condition for the "clustering" to happen in a market economy is factor mobility: labor and capital are perfectly mobile, and the land is freely tradable, whereas market prices of the factors affect the co-location decisions of firms.

However, the market economy in China has been anything but well-functioned that almost all major production factors were not sufficiently mobile, particularly at the beginning of the economic reform when entrepreneurial industrial clusters first emerged. The rapid growth of entrepreneurial industrial clusters since the 1980s is an essential element in transforming China from an administratively planned and state-ownership dominated economy into a partial market economy. These clusters emerged from the struggles and maneuvers of entrepreneurs and local governments under institutional restrictions. Such restrictions determine that the emergence and the characteristics of Chinese clusters are different from those examined in the literature in many aspects.

Above all, entrepreneurs in China face serious institutional constraints that prevent them from choosing locations freely for setting up their businesses. The number one issue is land ownership. According to the constitution, urban land is state-owned, whereas rural land is collectively owned by villages and is not tradable for non-agricultural usage. Peasants, individually or collectively, remain prohibited from trading "their" land for non-agricultural purposes. Before the mid-1990s, the only way for peasants to use their collectively-owned land beyond agriculture activities was to establish industrial firms within their villages or towns, i.e., township–village enterprises (TVEs, see Weitzman and Xu, 1994).[7] Since the late

[6] When the purpose is to measure agglomeration itself without considering the type and formation of clusters (through markets or through bureaucracies' planning), applying the Ellison–Glaeser index to China can still produce informative results, as Lu and Tao (2009).

[7] Land ownership restriction was somewhat relaxed in the recent 15 years, such that non-local entrepreneurs could lease a piece of "collectively owned" land to develop rural industrial firms by recruiting local peasants who

1990s, when political and legal resistance to private ownership was gradually relaxed, many TVEs have become privatized (Xu, 2011). Such firms are becoming increasingly specialized and clustered together. With the concentration of a vast number of small and specialized firms, many townships have become national or international production centers of specific products. For instance, in Zhejiang Province, the Songxia Township produces 350 million umbrellas annually, the Qiaotou Township supplies 70% of the buttons for clothing made in China (Hessler, 2007), and the Puyuan Township produces over 500 million cashmere sweaters per year (Ruan and Zhang, 2009). Many of these clusters consist of privatized TVEs or their spin-offs.

The second issue is the restriction of labor mobility by the *Hukou* system, particularly the movement of peasants from rural to urban areas. *Hukou* is a household registration system that officially identifies a person as a resident of a specific region, as well as the duties and the social welfare that the person may be obligated and entitled to. Under the *Hukou* system, individuals are classified as "rural" or "urban" residents and "local" or "non-local" residents. Converting one's registration status from a "rural" to an "urban" resident is required to get government approval which is very tough. A peasant who seeks to move from a rural to an urban area and takes up a non-agricultural job used to require approval, which involved complicated bureaucratic processes. Meanwhile, people working outside the geographical area of their *Hukou* identities (i.e., "non-local" citizen) are rendered unqualified for local social welfare, including housing, health care, and education benefits, etc. (Cai, 2000; Au and Henderson, 2006). Whyte (2010) characterizes the *Hukou* system as "socialist serfdom". Moving businesses to urban areas remains extremely difficult because of various discriminatory policies imposed on rural residents, although the *Hukou* system has been relaxed over time such that peasant migrants were allowed to work in cities as lower-level residents.

The third restriction is the underdeveloped capital market in China (Allen et al., 2005). China's banking system is particularly biased against lending to private enterprises. Although the share of the private sector in the national GDP soared to 50% in 2009, the short-term bank loans issued to the private sector was only 4.9% of the national total (Guo et al., 2014). Consequently, the size and scope of entrepreneurial firms in China are, in general, constrained by difficulties in external financing.

To summarize, the aforementioned institutional restrictions make China's industrial clusters differ from the concept of "clustering" or "geographical agglomeration" studied in the existing literature. First, industrial clusters in China tend to be defined by administrative boundaries. As discussed, clustered TVEs before the mid-1990s and the subsequently privatized firms were the stepping stones for various entrepreneurial industrial clusters today. They are concentrated within the administrative boundaries of certain local governments, which facilitate and protect the interests of private firms. Second, in association with the *Hukou* system, "rural" and "urban" are official terms standing for official recognition and describing social status rather than economic reality. Therefore, a large percentage of employees of the firms within clusters are officially defined as peasants, although they are manufacturing or service workers (in officially defined urban areas they are called peasant-workers). Third, many clusters in China consist of numerous small private firms working closely with each other. Highly specialized clustering can effectively decompose the production process of a product into many small steps, which lowers

collectively "own" the land. Nevertheless, developing real estate for urban residences before nationalization is strictly forbidden by the constitution.

both technical and capital barriers to entry (Huang et al. 2008; Ruan and Zhang, 2009; Xu and Zhang, 2009; Long and Zhang, 2011).[8]

3. Related Literature: Industrial Clusters, Growth, and Inequality

The central idea of the economics of agglomeration is that firms can benefit from co-locating with each other. Both anecdotal and systematic evidence shows that in general clustering areas are more productive than other areas (Ciccone and Hall, 1996). There are different explanations for the sources of advantages of industrial clusters, focusing on regional specialization and urbanization. The well-known Marshall-Arrow-Romer (MAR) model which is formalized by Glaeser et al. (1992) based on the studies of Marshall (1890), Arrow (1962), and Romer (1986), emphasizes on regional specialization. This model claims that firms of similar industries clustered in a region can enjoy the advantages of knowledge spillovers from each other, lower transportation costs of customer-supplier interactions and a sizeable common labor pool.

On the other hand, Jacobs (1969) highlights the benefits of urban diversity. The theory of Jacobs externalities claims that the primary source of knowledge spillovers comes from exchanges and competition among firms in diverse industries co-located in metropolitan cities. Supporting regional specialization, Porter (1990), however, emphasizes the benefits from intensified competitions of firms specialized geographically, sharing with the spirit of Jacobs externalities.

While individual firms benefit from being clustered, the manner in which clustering or geographical agglomeration affects regional economic growth remains a contested issue. A perfectly competitive market for production resources results in diminishing returns to scale, and there will be economic convergence (Solow, 1956; Baumol, 1986; Barro and Sala-i-Martin, 1992). When firms cluster together, the diminishing returns of clustering is expected with the intense competition and increasing prices of production inputs. By contrast, endogenous growth theory explains growth through the Schumpeterian processes of creative destruction with a focus on entrepreneurship and innovation (Aghion and Howitt, 1992). Thus, the convergence or divergence across regions depends on how various regions adapt to new technologies or innovation. Aghion et al. (1999) emphasize that the role of organizational change in the production process (which specifies the way in which workers or organizations interact and learn from each other) may be crucial in determining productivity, and thus economic growth. A significant advantage of clustering is the strong cross-firm spillovers that include the externalities generated by sharing knowledge, innovation, and entrepreneurial culture. Indeed, some empirical studies find a strong positive relationship between clustering and regional innovation (Saxenian, 1994; Audretsch and Feldman, 1996; Delgado et al., 2010; Kerr, 2010) and entrepreneurial activities (Arthur, 1990; Baptista, 1996; Baptista and Swann, 1998; Delgado et al., 2010; Qian et al., 2012; Chatterji et al., 2013; Glaeser et. al., 2015). When both the convergence effects and the endogenous growth effects are present, the net effect of agglomeration on regional economic growth depends on the tradeoffs of these different forces.

Empirical studies on if and how clustering influences regional economic growth are mostly focused on identifying whether regional specialization or urbanization stimulates growth. And so far, there is a little consensus reached. Based on US data,

[8] Ruan and Zhang (2009) documents a typical case where nearly 12,000 small firms and over 70,000 people were engaged in the production of cashmere sweaters in the Puyuan Township of Zhejiang, which is the largest production and trading center for cashmere sweaters in China.

several studies find that the growth of employment, wage and entrepreneurship is positively correlated to clusters composed of firms from diverse industries (e.g., Glaeser et al., 1992; Feldman and Audretsch, 1999), supporting the argument of Jacobs externalities. Some other studies, however, find evidence that the clustering of firms in the same or related industries stimulates the growth of employment and wage, favoring the claims of MAR model (e.g., Porter, 2003; Delgado et al., 2014). At the same time, some studies find evidence for both the Jacobs and MAR externalities (Henderson et al., 1995; Rosenthal and Strange, 2003). Conversely, based on manufacturing data, Cingano and Schivardi (2004) and Dekle (2002) find no evidence for clustering externalities on regional employment growth. Similarly, using cross-country panel data for 70 countries, Henderson (2003) fail to observe growth-promoting effects from agglomeration in any means.

Growth and inequality are among the most important social welfare issues concerned by economists. Whereas there are extensive studies on the effect of clustering on economic growth, the general unanswered question is how specialization or urbanization affects inequality. Studies on growth and inequality are mainly focused on the relationship between the two or the factors influencing either of the two independently. The relationship between growth and inequality has been a debated subject since Kuznets (1955). Kuznets finds that the relationship between the two in the US is an inverted U-shape between 1770 and 1970 (Kuznets, 1963). The interpretation is that in the transition from a rural to an industrial economy, income inequality should increase during the early stages of development (because of urbanization and industrialization) and decrease later (because industries would have already attracted a significant fraction of the rural labor force). However, recent studies find high income-inequality is associated with the deceleration of economic growth in developed countries since the 1970s (Alesina and Rodrik, 1994; Persson and Tabellini, 1994; Perotti, 1996). At the same time, studies find various additional factors (such as human capital, social capital, capital mobility and institutions) that may affect either growth (e.g., Barro, 2000; Barro and Sala-i-Martin, 1995; McCleary and Barro, 2006) or inequality (e.g., Heckman and Hotz, 1986; Krugman and Venables, 1995). Finally, a good (bad) institution may simultaneously protect (violate) private property rights, promote (prevent) development, and reduce (widen) inequality. Factors which may simultaneously affect growth and inequality are still not sufficiently investigated except some recent studies on institutions (e.g., Engermann and Sokoloff, 1997, 2000; Acemoglu et al., 2002, 2005; Easterly, 2007).

As discussed before, a large proportion of entrepreneurial industrial clusters in today's China can be traced to locations with a concentration of TVEs, which were initially owned by rural residents. Such regions are normally those with the most active entrepreneurial activities and most developed private sector. We, therefore, expect to observe industrial clusters may drive local economic growth. Moreover, the rapid development of entrepreneurial clusters in China has brought business opportunities and created jobs for those officially defined as rural residents. Therefore, we expect that entrepreneurial clusters in China may help to reduce officially defined urban-rural inequality within the region.

Moreover, the effects of industrial clusters may be heterogeneous. As suggested by the new micro-geography literature, it is important to delve down to granular levels of geography in order to gain insightful understanding in the true pictures of the locational advantages and thereby explore the mechanisms (Feldman, 2014; Catalini, 2018; Mudambi et al., 2018). The potential functions of clusters may differ depending on the ecosystems of a region. Meanwhile, China is vast in size and regions vary significantly in institutions, economic structure, and the development level, among other aspects. We, therefore, expect to observe heterogeneity in the clustering effects.

4. Data and the Construction of DBI

4.1 Data Sources

A panel data consisting of 2,815 Chinese counties (including county-level districts in municipalities and county-level cities) is constructed by combining several datasets from 1998 to 2007. First, our key explanatory variables, including the existence and features of clusters, are constructed based on data in the Above-Scale Industrial Firm Panel (ASIFP), which covers all state- and non-state-owned industrial firms with annual sales of 5 million RMB or above, including information on industry, location, age, ownership, and financial information at firm level. The enterprises included in this database account for 90% of the total sales of all industrial firms in China.[9] ASIFP excludes non-state-owned firms with annual sales under 5 million RMB. Thus, the potential bias of our findings should be underestimating the impacts of entrepreneurial clusters. As a robustness check, we apply the same methodology to identify clusters using the Chinese Economic Census data in 2004, which includes industrial firms of all sizes. The identified clustering patterns with the census data are qualitatively consistent with those identified based on the ASIFP.

Second, data on county-level per capita GDP, per capita household income, and other general county-level economic and demographic variables (e.g., total GDP, rural and urban populations, and investment in fixed assets), are all from the China Socio-Economic Development Statistical Database. Per capita household income statistics include rural household per capita net income and urban household per capita disposable income in the said database. Rural household net income is defined as the total family income excluding the family business expenses, depreciation of productive fixed assets, taxes, and land contract fees. Urban household disposable income is the total family income minus personal income tax and expenditures on social security. According to the description of the database, the income data of rural and urban households are collected based on the surveys of randomly selected local residents, who have been residing in a place for more than 6 months, regardless of being migrant workers or permanent residents. The panel is unbalanced because of missing data for certain counties and years.

Third, we control a series of county-specific variables in empirical investigations. Specifically, we include *fraction of industrial outputs* to total GDP for capturing the local economic structure; *fraction of non-state owned firms* and *fraction of micro firms*[10] for controlling the effect of privatization and small businesses; *fraction of education expenditure* to GDP for capturing the human capital development; *fraction of investment in fixed assets* to GDP (including investment in infrastructure, renovation, and real estate among others) for controlling the local investment in physical capital; and *fraction of government expenditure* to GDP to control for government administrative expenditure. All the above ratios are in log form. Data on local fiscal expenditures come from the National Prefecture and County Public Finance Statistical Yearbooks for the same period. Furthermore, we construct a panel

[9] In the first Chinese Economic Census conducted in 2004, the amount of the total sales for all industrial firms was 218 billion RMB, whereas that of the total sales for all the ASIFP firms was 196 billion RMB.

[10] The fractions of non-state-owned and micro firms are derived from firm-level data from the ASIFP. For instance, for any county during the sample period, we calculate the total number of non-state-owned firms or micro firms and divide it by the total number of firms in the county in that year to obtain the fraction.

of officially designated "National Poor Counties".[11] Each year, officially designated poor counties received sizeable amounts of fiscal transfers from the central government. This subsidy may affect the local income and the urban-rural inequality that we aim to investigate. The list of the poor counties is obtained from the official website of the State Council. Finally, to differentiate the effect of clusters from that of Special Economic Zones (SEZs), we construct a panel that indicates the existence and number of provincial-level SEZs in each county from 1998 to 2007. The list of SEZs is obtained from the website of the Ministry of Commerce of the People's Republic of China.

Forth, we control the inflow of the migrant workers at the provincial level, measured by the percentage of inflow migrant rural labor over the total employment in each province between 1998 and 2007. The data for this variable is extracted from Fan et al. (2011). It is known that industrial clusters employ large numbers of migrants from other regions. Such inflow of migrant workers may have affected the economic growth, urban-rural income inequality and the development of industrial clusters simultaneously. However, there is no county-level panel data for migration available. We use the provincial level panel data for the inflow of migrant workers as a proxy to control such effects.

All the above data are deflated to 1998 price level when applicable. During our sample period, some counties changed their names or judiciary boundaries. New counties were established, while some existing counties combined to form larger ones or were elevated into cities. We identify the changes and convert the corresponding county codes into a benchmark system. China also modified its industry coding system in 2002 (from GB/T 4754-1994 to GB/T 4754-2002). The four-digit industry codes that have become either more disaggregated or more aggregated after 2002 were tracked and the aggregated codes are used to group the industries from 1998 to 2007.

All variables used in this study are defined in Appendix 1 (Table A.1).

4.2 Measuring Industrial Clusters in China

Constructing clustering indices to capture entrepreneurial clusters in China is a major challenge. As discussed, a key assumption in the literature on clustering or geographical agglomeration is that factors are mobile and firms can move and choose their locations freely. Under these (implicit) assumptions, the clustering indices constructed in existing studies focus either on regional specialization or inter-connectedness of local industries (Porter, 1990; Krugman, 1991a; Glaeser et al., 1992; Long and Zhang, 2011). Most studies on regional specialization apply the Herfindahl–Hirschman index (HHI), Gini coefficient (Gini), location quotient (LQ), or Krugman index to measure clustering.[12] Based on the revealed comparative

[11] Two rounds of the poverty reduction program (known as the 8-7 Plan) of the government were conducted in China during 1986–1993 and 1994–2000, aiming to promote local economic development through targeted public investments with fiscal transfer. In 1986 and 1994, the Poverty Reduction and Development Team supervised by the State Council (*Guo-wu-yuan Fu-pin Kai-fa Ling-dao Xiao-zu*) published two National Poor County lists. The 1994 list was modified further in 2006 and 2012. As of 2012, there were 592 national level poor counties in the list.

[12] For instance, Glaeser et al. (1992) focus on the contribution of a region's top five largest industries to the local economy to reveal the extent to which a given region is specialized or diversified, regardless of how the economic structure of the country as a whole evolves. The Gini measures how far away a country or region is from an equal distribution in which each industry produces the same share of output or value added. Midelfart–Knarvik et al. (2000) use Gini to explore industrial location changes in terms of spatial concentration in Europe. LQ is an analytical statistic that measures a region's industrial specialization relative to a larger geographic unit (usually the nation). Glaeser et al. (1992) apply LQ as a specialization measure of an industry in a city and test its effect on city-industry employment growth. Porter (2003) utilizes LQ as an important criterion in defining traded industries

advantage in product export, Hausmann and Klinger (2007) construct a proximity measure for all four-digit Standard International Trade Classification products. Long and Zhang (2011, 2012) employ this proximity index to measure clusters in China.

However, employing regional specialization or inter-connectedness measurements directly to study entrepreneurial clustering in China may not be the most suitable method for our purpose. This is because restrictions on factor mobility and location decisions of firms may create biases and potential measurement errors. At the onset of the economic reform, all firms in China were owned or controlled by national or local governments and their locations were chosen as administrative decisions. As such, the concentration of heavy industries in certain areas of China was driven mostly by political concerns, including those related to national security.

Today, in commanding heights sectors such as finance, energy, mining, railway, airlines, and communication, state ownership still dominates. These firms usually are large so that regions with such giant SOEs will be specialized, with high specialization scores measured by HHI, Gini, or LQ. For instance, oil refining and processing SOEs contributed 24.5% to the local industrial output in Daqing City in 2007. Four SOEs, in particular, dominated this industry and they accounted for 89.39% of the outputs of this industry. Changchun City is highly specialized in manufacturing transportation equipment, which contributed to 68.26% of the industrial output there in 2007, with 79.62% of the outputs coming from 13 gigantic SOEs. However, the co-location decisions of these firms have little to do with markets, and this kind of regional specialization is not of interest for this study.

As discussed in Section 2, the entrepreneurial clusters in China are characterized by the emergence of numerous "specialty towns," each of which produces some particular type of product. Each cluster consists of a large number of small firms and family workshops. Outputs of these clusters comprise significant shares of national or global markets. These observations suggest that in addition to specialization, the density of firms in an industry within a locality is one of the most important features of entrepreneurial clustering in China. Hence, we propose a density-based index (DBI) to measure entrepreneurial clusters in China.[13] For the DBI at the county level, we denote the number of firms in any 2-digit industry $j \in \{1, 2, \ldots J\}$ in county $i \in \{1,2, \ldots I\}$ at time t as $fn_{j,i,t}$. We define county i as "a county with an α cluster of industry j" if the number of firms in this county is among the top α percentile of all counties in this industry at time t. Formally, we define

$$c_{j,i,t} = \begin{cases} 1, \ if \ \ fn_{j,i,t} \geq (100-\alpha) \ \ percentile \ \ of \ \ \{fn_{j,1,t}, fn_{j,2,t}, \ldots, fn_{j,I,t}\}. \\ 0, \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases},$$

And

$$C_{i,t} = \sum_{j \in C_{it}} c_{j,i,t}.$$

In this paper, we focus on the top five percentile county-level clusters. Thus, for the remainder of this paper, the term cluster means α = 5, and we will omit to mention this unless a definition is specified.[14] We use the following dummy variable to capture the existence of the DBI cluster in any county i of any industry in year t.

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that form clusters. Krugman (1991a) constructs a dissimilarity index focuses on the deviation of a region's industry structure from the average industry structure of a regional reference group to reveal a region's comparative advantage.

[13] Ciccon and Hall (1996) study clusters by measuring labor intensity and physical capital.

[14] Our results stay robust when we assign other values for α, such as 3 and 8.

$$Cluster_{it} = \begin{cases} 1, & if \ \ C_{i,t} \neq \emptyset \\ 0, & otherwise \end{cases}$$

Identifying the strength of clusters is essential because counting the number of firms treats all the firms as the same, thus ignoring their differences. We define the output[15] strength of each cluster of industry *j* located in county *i* at time *t* by the ratio of its output contribution to the total industrial output over the national county average level. Specifically, the output strength of each cluster ji at time *t* is defined as $OutputStrength_{jit} = \frac{OutputShare_{jit}}{\frac{1}{I}\sum_{i=1}^{I} OutputShare_{jit}}$, where $OutputShare_{jit} = \frac{Output_{jit}}{Output_{jt}}$ is the output share of the cluster ji in the national total output of industry *j* in time *t*, and $\frac{1}{I}\sum_{i=1}^{I} Output\_Share_{jit}$ is the average number of all counties for industry *j* in time *t*. $OutputStrength_{jit} > 1$, if output strength of cluster ji at time *t* is larger than the national average; otherwise, $OutputStrength_{jit} \leq 1$. Similarly, we define the establishment strength of each cluster ji at time *t* as $EstablishmentStrength_{jit} = \frac{EstablishmentShare_{jit}}{\frac{1}{I}\sum_{i=1}^{I} EstablishmentShare_{jit}}$, where $EstablishmentShare_{jit} = \frac{Establishment_{jit}}{Establishment_{jt}}$ is cluster ji's share in the national total establishments of industry *j*, and $\frac{1}{I}\sum_{i=1}^{I} EstablishmentShare_{jit}$ is the national average establishment share of industry *j* in each county.

To measure the cross-industry aggregate strength of clustering in each county *i* based on the strength ratios defined above, we construct the overall strengths of clusters in the following. The overall output strength of the clusters in county *i* is defined as the weighted average of the strength of each cluster (if any):

$$OutputStrength_{it} = \begin{cases} \frac{\sum_{j\in c_{jit}} Output_{jit} OutputStrength_{jit}}{\sum_{j\in c_{jit}} Output_{jit}}, & if \ \ C_{it} \neq \emptyset \\ 0 \ , & if \ \ C_{it} = \emptyset \end{cases}.$$

Similarly, the overall establishment strength of the clusters in county *i* is defined as

$$EstablishmentStrength_{it} = \begin{cases} \frac{\sum_{j\in c_{jit}} Establishment_{jit} EstablishmentStrength_{jit}}{\sum_{j\in c_{jit}} Establishment_{jit}}, & if \ \ C_{it} \neq \emptyset \\ 0 \ , & if \ \ C_{it} = \emptyset \end{cases}.$$

To capture the development of entrepreneurial clusters, we calculated two indices based on the ownership structure of clusters in county *i* at time *t*. First, we measure the share of non-state firms'[16] outputs in the total outputs of clusters in county *i* at time *t* as the following,

$$OutputNonstate_{it} = \begin{cases} \frac{\sum_{x\in X_{it}} \sum_{j\in c_{jit}} Output_{xjit}}{\sum_{j\in c_{jit}} Output_{jit}}, & if \ \ C_{it} \neq \emptyset \\ 0 \ , & if \ \ C_{it} = \emptyset \end{cases},$$

[15] The output and establishment data used in calculating cluster strength indices are based on the firm-level data from the ASIFP. For our county level cluster measurement, the output of a given county in a given year is the aggregated output of all firms located in the county in that year.

[16] Non-state-owned firms refer to firms where state capital constitutes less than 50% of the total paid-in capital.

where $\boldsymbol{X_{it}}$ is the set of non-state firms in county *i* at time *t*. This index captures the development of non-state firms within the clusters. Similarly, we calculate $EstablishmentNonstate_{it}$ as the share of non-state firms in the total establishments of the clusters in county *i* at time *t*:

$$EstablishmentNonstate_{it} = \begin{cases} \dfrac{\sum_{x \in X_{it}} \sum_{j \in c_{jit}} Establishment_{xjit}}{\sum_{j \in c_{jit}} Establishment_{jit}}, & if \ \ C_{it} \neq \emptyset \\ 0\ , & if \ \ C_{it} = \emptyset \end{cases}.$$

Table 1 presents the summary statistics of DBI clusters. Taking the year 2007 as an example, among 2,734 counties, 739 (about 27%) have clusters. The total number of industrial clusters is 2,213, which accounts for 5% of the 44,175 county-industry observations, given that we assign the value of 5 to α. These clusters contribute to 38% of the total national outputs and 37% of the total national employment. On average, the output strength of cluster(s) is about 6.5 times that of an average local industry within a county. Also, the number of establishments in the cluster(s) is about 5.9 times that of the national average number. On average, about 80% of the clusters' outputs are from non-state firms, and more than 83% of firms in the clusters are non-state owned.

Table 1 also shows the dynamics of cluster development in Chinese counties. In our sample period (1998–2007), 294 counties (about 10% of all the counties) always have some clusters in at least one industry. Conversely, 1,576 counties (about 56% of all the counties) have never developed any industrial cluster. A total of 317 counties initially did not have clusters in 1998, but they developed industrial clusters by 2007. Out of these counties, 52 are from Shandong, and 25 are from Fujian. By contrast, 292 counties had clusters operating in 1998, but clusters in these counties disappeared by 2007. Most of these backward developments occurred in inland areas.

Table 2 presents comparisons between provincial level DBI cluster indices and some standard cluster indices used in the existing literature. All measurement results are based on the 2007 ASIFP data. Measured by DBI cluster count, the top five provinces are Zhejiang, Jiangsu, Guangdong, Shandong, and Shanghai. Measured by DBI output strength, the top five provinces (in descending order) are Shanghai, Tianjin, Zhejiang, Shandong, and Jiangsu. Finally, when measured by the DBI establishment strength, the top five provinces are Zhejiang, Shanghai, Jiangsu, Shandong, and Tianjin. The strongest five provincial regions in DBI non-state cluster indices (in descending order, measured either by output volume or by establishments) are Zhejiang, Shanghai, Jiangsu, Shandong, and Tianjin. The common feature shared by all the results above is that the top provinces are all coastal regions. Note that this common feature is consistent with the general perceptions of spatial distributions of entrepreneurial clusters in China.[17]

In contrast, applying standard measurements to Chinese data tends to capture agglomerations of highly specialized large SOEs, many of which are located in interior regions. For example, measured by HHI, the top 5 provincial regions will be Xinjiang, Shanxi, Hainan, Jilin, Gansu; or Xinjiang, Qinghai, Gansu, Yunnan, Hainan if measured by Gini; or Tibet, Ningxia, Xinjiang, Qinghai, Yunnan if measured by LQ; and Shanxi, Tibet, Xinjiang, Qinghai, Yunnan if measured by Krugman Index. Except for Tibet (which is one of the most under-developed regions in China), all these

[17] For instance, studies have documented clusters along the coastal areas in Wenzhou City (Huang et al., 2008), Tongxiang County (Ruan and Zhang, 2009), and Wuxing County (Sonobe et al., 2002), etc.

provinces are known for a concentration of SOEs and their weakness regarding entrepreneurial activities. Some of the provincial level cluster measurements shown in Long and Zhang (2011), which apply the Industrial Proximity measurement (Hausmann and Klinger, 2007), are close to ours; but some other results reflect noises. The top five provincial regions by their measurement are Tibet, Beijing, Jilin, Zhejiang, and Ningxia. We further compare the average weights of SOEs in the regions defined by different clustering measurements as shown in Table A.2 The comparison further confirms that standard clustering measurements tend to capture the specialization or concentration of SOEs under the centrally planned economy.

Figure 1.a and Figure 1.b illustrate how standard approaches and DBI capture China's clusters geographically by showing maps of clustering levels at the prefectural level. The map shows that the DBI clusters are concentrated heavily along coastal line regions, which is highly consistent with a satellite night vision of China (Figure 2). By contrast, coastal line regions are not captured adequately by standard clustering measurements.

Table 3(a) presents the summary statistics of the dependent variables for counties with and without DBI clusters. Compared with counties without clusters, on average, counties with clusters grow faster and have lower urban-rural income inequality. Between 1998 and 2007, the average growth rate of the counties with clusters is 1.3% higher than other counties, whereas the urban-rural per capita income ratio in counties with clusters is lower by about 20% than other counties. Table 3(b) provides the summary statistics of other characteristics of counties with and without DBI clusters. On the one hand, counties with clusters have higher per capita and total GDP on average, are more industrialized and have more private firms than other counties. On the other hand, government and education expenditures in counties with clusters are about only half of those in other counties.

5. Clustering, Regional Economic Growth, and Urban-Rural Inequality

In this section, we present the estimations for the effects of clustering on regional growth and urban-rural inequality within a region, with identification issues addressed.

5.1 Clustering and Regional Growth

Our hypothesis is that clusters should be positively and significantly associated with economic growth. Concretely, we expect counties with clusters should have higher growth rates than others. Moreover, they should grow faster if their clusters are stronger, or if their clusters are entrepreneurial ones. We test this hypothesis by estimating a type of Barro growth model (Barro, 2000) as follows:

$$\ln\left(\frac{GDPpercapita_{it+1}}{GDPpercapita_{it}}\right) = \alpha + \beta Clustering_{it} + \gamma \ln(GDPpercapita_{it}) + \mu[\ln(GDPpercapita_{it})]^{2} + \tau \ln\left(CPI_{pt}\right) + \boldsymbol{\delta Z_{it}} + \varepsilon_{it} \quad (1),$$

where $GDPpercapita_{it}$ is the per capita GDP of county i at year t, and the dependent variable represents a county level annual growth rate of per capita GDP. Our major explanatory variables are $Cluster_{it}$, which is a dummy variable that equals to one if at least one cluster operates in county i in year t and zero otherwise; the strength of clusters ($OutputStrength_{it}$, and $EstablishmentStrength_{it}$); and the ownership structure of clusters ($OutputNonstate_{it}$ and $EstablishmentNonstate_{it}$). The initial level of per capita GDP controls for any convergence or divergence effect, and the square term of per capita GDP controls the speed of convergence or divergence. Provincial level consumer price index (CPI) is included to control for the inflation effects. $\boldsymbol{Z_{it}}$ is a vector of other control variables. County and year fixed effects are controlled in the panel analysis to address county- and time-specific effects. Meanwhile, as each county's observations in the panel data are auto-correlated, following Peterson (2009), we group the standard errors within counties.

The major estimation results are presented in Table 4. Panel A reports the baseline estimations. Column (1) of Panel A indicates that the coefficient of *Cluster* is positive and significant, indicating that the existence of industrial clusters has a positive impact on local economic growth. Moreover, Columns (2) and (3) indicate that the strengths of clusters (*OutputStrength* and *EstablishmentStrength*) are also positively and significantly associated with growth. A 1% increase in the clusters' output strength will result in about a 1% increase of per capita GDP growth. Finally, Columns (4) and (5) demonstrate that entrepreneurial clusters, i.e., clusters dominated by non-state firms (measured by *OutputNonstate* or *EstablishmentNonstate*) are positively and significantly associated with economic growth. A 1% increase in the contribution of the non-state sector (either in output or establishment) will result in approximately 1.6% increase in the per capita GDP growth.

For all regressions, both initial levels of per capita GDP and the squared term of per capita GDP are significantly and negatively associated with growth, suggesting a mean convergence in the economic growth among Chinese regions, and the convergence accelerates over time. Regarding the structure of the local economies, estimated coefficients of *fraction of industrial output* and *fraction of non-state firms* are all significant and positive, thereby implying that counties with higher levels of industrialization and more non-state firms experience higher economic growth rates. Furthermore, expenditures for education and fixed investments are significantly and positively correlated to local economic growth, indicating that regions that invest more in human and physical capitals experience higher economic growth. Local government expenditure is positively correlated to growth, which denotes a positive correlation between the size of the government and growth rate. Lastly, the presence of SEZ (special economic zone) within a county is positively correlated with growth.

Our baseline regressions demonstrate strong statistical associations between industrial clusters, particularly strong and entrepreneurial clusters, and economic growth. However, the causalities for the relationships are yet to be established because the clustering might be a result rather than a cause of economic growth. Moreover, the existence of clusters or the features of clustering might coincide with other unobservable variables that might influence local economic growth. To address identification concerns, we employ two empirical strategies: the two-stage estimations and Granger test of causalities.

First, we employ the two-stage least squares estimation procedure with an IV to identify the clustering effects on growth. The IV, per capita mining output, is the per capita mining output in each province obtained from the China Mining Yearbook (2001–2007). We believe per capita mining output is relevant to the existence of clusters and the strength and the ownership structure of clusters, because we expect provinces with higher per capita mining outputs to have weaker industrial clusters and a smaller share of the private sector in the clusters. This anticipation is based on an observation that mine-rich regions are often dominated by large companies due to large fixed investments and scale economies in the mining industry. Thus, smaller businesses are often crowded out, and entrepreneurship is often depressed as argued by Chinitz (1961)[18] and as supported by empirical evidence (e.g., Rosenthal and Strange, 2003; and Glaeser et al., 2010, 2015). Moreover, given the state-ownership of mining rights in China, mine-rich regions should have higher shares of the state sector, which in general would affect all industries in those regions. We also believe that the per capita mining output of a province is exogenous because the mine-richness of a region is geologically determined, and thus by itself is exogenous to regional economic growth. Given our panel data is at the county level, whereas this particular IV is at the provincial level, it should not be directly correlated to county-level economic growth.[19]

Panel B of Table 4 presents the regression results of the two-stage estimations for economic growth when clustering variables are instrumented. Columns (1) to (5) report the first-stage estimations, showing that the per capita mining output is, as expected, significantly and negatively associated with the existence, the strength, and the non-state ownership of clusters within a county. Columns (6) to (10) show the second-stage estimation results. Consistent with our baseline OLS regression results, the instrumented clustering variables remain significantly and positively associated with economic growth. These outcomes confirm that the presence of industrial clusters, particularly strong clusters and entrepreneurial clusters drive local economic growth.

Besides the two-stage estimations, we further conduct a Granger causality test to identify the dynamic causal relationships between industrial clustering and economic growth. Being first proposed by Granger (1969), Granger causality test initially focuses on examining the predicting power of one time series for another through T-tests and F-tests on lagged values of relevant variables. As we are dealing with panel data, we follow the Dumitrescu and Hurlin (2012) procedure for panel data analysis. Ideally, we should find out the lag value to make the average value of the Akaike, the Bayesian, or the Hannan-Quinn information criteria be minimized. However, the largest number of lags is constrained by the length of a panel (T) where: $T>5+3\times lag$. Given that we have a ten-year panel, the only lag we are able to choose is one year. The results of the Granger causality tests are presented in Panel A of Table 5. As shown in the table, the null hypothesis that industrial clustering (including all variables that measure the existence, strength and non-state ownership of clustering) does not lead to economic growth is rejected. In other words, industrial clustering does have predictive power for the economic growth of counties between 1998 and 2007.

5.2 Clustering and Urban-Rural Income Inequality within a County

In this subsection, we examine the relationship between clustering and urban-rural income inequality and explore how clustering affects household income of urban and rural residents within a county. We use urban-rural household per capita income ratio as a proxy for urban-rural inequality (we do not have the data for constructing other measurements of inequality). In our sample, the county-level

[18] Chinitz (1961) also argues that when a region is dominated by large mining companies, the culture of entrepreneurship is weak because the executives of large companies in regions with large mining companies are less likely to transfer entrepreneurial knowledge to the next generations. Moreover, in such regions, the financial and labor constraints for entrepreneurial firms may be severe, because both financial institutions and labor may easily access large firms with low levels of risks and uncertainty. Furthermore, large companies are more likely to internalize supplies or source them outside the region to enjoy low costs, which consequently depresses the local supply development of small entrepreneurial firms.

[19] Indeed, even in the case of dealing with the relationship between provincial level mining and provincial economic growth, evidence provided in the literature (e.g. Glaeser et al., 2015) still supports our conjecture.

urban-rural income ratio increased from 2.08 to 2.69 (on average) from 1998 to 2007. Our hypothesis is that industrial clustering, measured by different DBIs, should be negatively and significantly associated with urban-rural income ratio. Our baseline regression model of urban-rural inequality vs. clustering is the following equation:

$$\ln(Ratio_{it}) = \alpha + \beta Clustering_{it} + \boldsymbol{\delta W_{it}} + \varepsilon_{it} \quad (2),$$

where $Ratio_{it}$ refers to the urban-rural household income inequality measured by the ratio of urban over the rural household per capita income in county i in year t. The clustering variables and major control variables $\boldsymbol{W_{it}}$ are the same as those in Equation (1) except for the inclusion of the total GDP of the county and dropping the square term of the per capita GDP and CPI.

The estimation results are reported in Table 6. Panel A presents the baseline estimations. Columns (1), (2), and (3) of the table indicate that by pooling all clusters together without differentiating the ownership structure of clusters, the cluster is negatively but insignificantly associated with local urban-rural inequality. The correlation becomes statistically significant only when we focus on entrepreneurial clusters which are dominated by non-state firms, as shown in Columns (4) and (5). These findings indicate that an increase of 1% in the number and outputs of non-state firms within clusters is associated with a 3% reduction in the urban-rural inequality in the county. Furthermore, in all five columns, investments in both fixed assets and education and the presence of SEZs are positively and significantly correlated to urban-rural inequality, while the inflow of migrants within the province is negatively and significantly associated with urban-rural inequality.

In order to establish the causalities of the relationships between entrepreneurial clustering and urban-rural income inequality, we conduct two-stage estimations and the Granger causality tests. We use two IVs for the two-stage estimations. The first IV we use is the per capita number of Christian churches of a county in a given year. Christianity culture plays an important role in fostering trade and entrepreneurship, which is essential for cluster formation in modern China. Christian missionaries brought the ideas of modern commerce and trade to China a century ago. Meanwhile, religious activities organized by churches serve as a mechanism for the local people to communicate and coordinate with each other. Although religious activities were banned during 1950 and 1980, they were revived since the post-Mao reform. Arguably, the formation of industrial clusters is rooted in the entrepreneurship culture and coordination capacity of the local people. We, therefore, expect that the local density of churches is related to our clustering measurements. On the other hand, however, religions in China do not play any roles in wealth distribution as the scale of the activities or organizations is tightly controlled by the government. We hence do not expect Christian activities to be directly related to the urban-rural income inequality in a county, unless through the related economic activities.

The second IV is the per capita length of classified highways[20] in a city. The so-called city here is an admin level within the government hierarchy. Typically a city government controls a dozen counties, but itself is under the control of a provincial government. Access to the transportation network is expected to be related to the development of clusters because of several reasons. First, transportation infrastructure reduces the trade and shipping costs for the firms within the region that is ultimately important for clustering of firms. Second, with reduced transportation costs, the scale

[20] Classified highways here refer to National and provincial level highways. These highways are planned, financed and constructed by national and provincial level governments.

and scope of the market may be increased that more firms within the region may benefit. Third, with better transportation infrastructure, technology and knowledge may be transferred more easily that helps firms' specialization and development within the region. We, therefore, expect that the density of classified highways to be correlated to the probability of a county to have industrial clusters. However, the construction of classified highways in China is the decisions made at the national and provincial levels of governments, and intra-county inequality issue cannot be their major concern. County governments do not have a voice in such decisions. Hence, the per capita length of classified highways at city level should not have a direct relationship with the urban-rural income inequality at the county level, unless through the economic activities within the county.

The two-stage estimations for the clustering effects on urban-rural income inequality with the two IVs are presented in Panel B of Table 6. Our focus is the effects of entrepreneurial clusters while ignoring the effects of other measurements of clusters, such as *OutputStrength* and *EstablishmentStrength,* as they are statistically insignificant in baseline OLS regressions (Table 6 Panel A). Columns (1) to (2) report the first-stage estimation results while Columns (3) to (4) report the second-stage estimation results, respectively. As shown in the table, both per capita number of Christian churches and per capita length of the classified highways in a city are significantly and positively associated with entrepreneurial clusters measurements. Thus, these two IVs are relevant. Moreover, the Sargan tests indicate that the IVs are jointly exogenous. Finally, the second-stage estimations show a negative and significant relationship between the development of entrepreneurial clusters and urban-rural income inequality, confirming the causality between the two.

Besides, we conduct Granger tests to further identify the clustering effects on urban-rural income inequality. The results are reported in Panel B of Table 5. As shown in the table, the null hypothesis that there is no causal relationship between cluster measurements and urban-rural income inequality within the county is rejected. Such results further confirm the causal relationship between the entrepreneurial clustering and reduced urban-rural inequality within the county.

A positive association between growth-enhancing efforts and the widening of inequality may be unsurprising. However, the negative association between entrepreneurial clusters and inequality might be counter-intuitive, as it is a popular view that a market economy dominated by privately owned firms tends to worsen inequality and one of the benefits of maintaining state-owned firms is to contain inequality. To understand the mechanism of how the development of non-state firms in clusters might reduce inequality, we subsequently study impacts of clusters to rural and urban income separately.

Noticing that today's entrepreneurial clusters are mostly located in areas with active TVEs in the 1990s, it is likely that entrepreneurial clusters create more business opportunities for rural residents (Long and Zhang, 2012) and employ more rural laborers, which contributes to the rural residents' income and reduces urban-rural inequality. The 2007 Chinese Household Income Project (CHIP) database, which covers 92 rural counties in China, reveals that in counties with clusters, individuals' average non-agricultural income is about 8% (1,398RMB vs. 1,293RMB in Table A.3.1) higher than that in counties without clusters, and the ratio of individuals engaged in non-agricultural activities in counties with clusters is about 20% (42.76% vs. 35.58% in Table A.3.1) higher than that in counties without clusters. Additionally, using 2004 and 2008 economic census data which include enterprises of all sizes to calculate the entry of new businesses in counties with and without clusters, we find that clusters create significantly more new business opportunities for local people. As shown in Table A.3.2, on average, in counties with clusters, the number of new businesses established between 2004 and 2008 is 821.55 comparing to 186.74 in counties without clusters. Moreover, the survival rate of businesses in counties with clusters is much higher than that in counties without clusters in the same period. The results presented in Table A.3.1 and Table A.3.2 to some extent suggest that clustering lowers the entry barriers for starting up new businesses for rural residents and creates more non-farming jobs for the local people. Therefore, we hypothesize that clustering lifts rural residents' income, which reduces the urban-rural income inequality.

Our baseline regression models for testing this hypothesis are as follows:

$$\ln(Rural\ \ household\ \ income_{it}) = \alpha + \beta \frac{OutputNonstate_{it}}{EstablishmentNonstate_{it}} + \boldsymbol{\delta W_{it}} + \varepsilon_{it} \qquad (3)$$

$$\ln(Urban\ \ household\ \ income_{it}) = \alpha + \beta \frac{OutputNonstate_{it}}{EstablishmentNonstate_{it}} + \boldsymbol{\delta W_{it}} + \varepsilon_{it} \qquad (4),$$

where $Rural\ or\ Urban\ household\ income_{it}$ are the rural or urban household per capita income in each county during our sample period. $OutputNonstate_{it}$ and $EstablishmentNonstate_{it}$ are the entrepreneurial cluster measurement and $\boldsymbol{W_{it}}$ are the same control variables as those in Equation (2).

The regression results are summarized in Panel A of Table 7. Columns (1) and (2) show that, in the OLS model, the development of non-state firms in clusters measured by both output and establishment is significantly and positively associated with the rural household per capita income, suggesting that local rural residents' income is positively associated with entrepreneurial clusters. Everything else being equal, a 1% increase in the non-state firms' output or establishment number within clusters is associated with 3% increase of the rural household per capita income. By contrast, Columns (3) and (4) indicate that the development of non-state sectors in the clusters is not statistically related to urban household income. This finding suggests a potential mechanism through which entrepreneurial clusters reduce urban-rural income inequality.

Table 7 also shows that the share of the private sector, the total GDP, the investments in fixed assets and education, and provincial inflow of migrants are all significantly and positively correlated to rural household income. Our regressions also control for some competing government policies, including 1) the policy of special economic zones or development zones for attracting FDI and developing export-oriented industries (the number of SEZ in regressions); 2) the poverty eradication policy by subsidizing officially identified or recognized national Poor Counties ("Poor" in regressions); and 3) the administrative expenditure in general. Interestingly, government policies on special economic zones are negatively correlated with rural household income and poverty eradication does not demonstrate any statistical significance on rural household income. Furthermore, the expenditures on administration seem to have a negative effect on rural household income but positively affect its urban counterpart.

Finally, we conduct two-stage estimations for the clustering effects on per capita income of rural households. The IVs and the specifications are the same as those in the two-stage estimations for the clustering effects on inequality. The estimation results are reported in Table 7, Panel B. Columns of (1) to (2) present the first-stage estimation results, and the under-identification and the weak identification tests confirm the relevance of the two IVs in general. Second-stage estimations from Columns (3) and (4) confirm that the development of non-state firms in the clusters (measured by *OutputNonstate* and *EstablishmentNonstate*) is significantly and positively correlated with rural household per capita income after these independent variables are instrumented. The estimations verify that clusters with more non-state firms lead to a higher income of rural residents, which confirms that entrepreneurial clusters reduce urban-rural income inequality (Table 6) by increasing the income of rural residents.

5.3 Additional Robustness Checks

Besides the identification estimations, we conduct some additional robustness checks to test the reliability of our results of clustering effects. Above all, as we have discussed, the economic activities in China have been concentrated in the coastal regions, whereas there are fast-growing megacities in these regions as well, such as Beijing, Shanghai, Guangzhou, and Shenzhen. In our baseline and two-stage estimations, we have controlled county fixed effects. However, if megacities' impacts on economic activities, such as creating a huge inflow of FDI or other public policies, are so large that they overwhelm the county fixed effects, the estimation results we obtained from the baseline estimations might be biased. In addressing such concerns, we control the megacity effects (measured by the megacity population) for the estimations. As shown in Table A.4, the effects of clustering variables stay robust after controlling for megacity population.

Additionally, industrial profile varies considerably across locations and might affect local growth and urban-rural inequality as well as the development of clusters substantially. Such concerns are relevant in our case as we did not consider regional specialization in certain industries. To address such concerns, we control the local industry profile by identifying the three largest industries in each county in a given year. As shown in Tables A.5a and A.5b, after controlling these largest industries in the county, the clustering effects on growth and income inequality stay robust.

To summarize, by employing different identification strategies and exercising robustness checks, our estimations confirm the positive effects of industrial clustering on regional economic growth as well as the effect of entrepreneurial clustering on the reduction of intra-region urban-rural income inequality in China.

5.4 Clustering Effects under Different Urbanization Levels

As all Chinese large cities are national or regional political centers, and the driving forces of these cities' expansions are more of political powers, including SOEs, than markets (Bai and Jia, 2018). City boundaries (sizes) and entitlement of city residents are assigned and defined administratively rather than by business activities. Strong distortions and restrictions (e.g., *Hukou* in these cities) associated with political powers might overwhelm the benefits of agglomeration. Furthermore, in rural areas, where agricultural activities were the major household activities, clusters may evolve as the most prominent industrial force of a county that have significant impacts on the society from various aspects including the economic growth and urban-rural income inequality. On the contrary, in highly urbanized regions and especially megacities, manufacturing activities are much more diverse and the service sector has increasing impacts on the local economy and society. The Jacobs-type effects of urbanization are likely to overwhelm the clustering effects under complicated landscapes. Combining both the factors discussed above, we expect that clusters in highly urbanized areas or megacities have less significant effects than those in less urbanized areas or non-megacities.

In order to examine clustering effects in regions with different urbanization levels, we first compare regions at the highest urbanization level, i.e. megacities, with the rest of regions. We divide our county samples into two groups: those located in megacities, and those not located in megacities. Our estimations of the baseline regression model for the two subsamples (Table 8) show that in non-megacity counties, the impacts of clusters on growth and urban-rural inequality (Table 8a) are qualitatively the same as our full sample estimations (Tables 4A and 6A): the existence of clusters, entrepreneurial clusters and strong clusters are significantly and positively associated with the county's growth; and the existence of entrepreneurial clusters is significantly and negatively associated with the urban-rural income inequality within the county. However, for megacity counties, clusters have no significant relationship with growth or with urban-rural income inequality (Table 8b).

Then we compare relatively more urbanized regions with less urbanized regions. We divide all the counties in our sample into two groups based on the ratio of urban population to the total population, using the median value as the cutoff threshold. We then conduct our baseline regressions on economic growth and urban-rural income inequality for the two subsamples separately. Our regression results (Table 9) show that in the sub-sample of less urbanized counties, stronger clusters and entrepreneurial clusters have significant and positive effects on growth; and entrepreneurial clusters are correlated with significantly lower urban-rural inequality (Table 9a). However, clusters located in more urbanized regions are insignificantly related to growth; while entrepreneurial clustering in these regions is still significantly associated with a reduction of urban-rural income inequality (though the effect is only significant for *OutputNonstate*) (Table 9b).

The results presented in Tables 8 and 9 confirm our conjecture that the clustering effects on growth and urban-rural intra county income inequality vary depending on the urbanization level of a region. In counties located in more urbanized regions, the clustering effects are weaker.

6. Conclusion

In this study, we develop an industrial cluster measurement, density-based index (DBI), which captures institutionally constrained industrial clusters, particularly entrepreneurial clusters in China. Combining both firm- and county-level data, we create a county-level DBI cluster panel, and find that industrial clustering enhances regional economic growth. Moreover, entrepreneurial clusters reduce urban-rural intra-region income inequality by increasing rural residence income, which is qualitatively different from the impacts of clusters of SOEs on income inequality. We also find that the clustering effects on growth and reduction of intra-region inequality are insignificant in highly urbanized regions, and particular in megacities. To our knowledge, this is the first study of this kind in the literature.

We carefully address identification concerns through the two-stage least squares approach and Granger causality test. For investigating the effects of clustering on economic growth, we use local per capita mining outputs as an IV. Concerning urban-rural inequality and the income of rural residents, we use the per capita length of classified highways in a city and the number of Christian churches in a county as IVs.

This study contributes to the literature on development economics, growth, inequality, and economic geography. Several challenging questions arising from our discoveries require further research. One of our major findings is that entrepreneurial industrial clusters enhance economic growth and reduce intra-region urban-rural inequality effectively. However, such clusters are only concentrated in some regions and certain industries, and entrepreneurial clusters are non-existent in many provinces. Why is this so? What barriers prevent the creation of entrepreneurial clusters? Evidence on the simultaneous existence of the strong growth-enhancing effect and inequality-reducing effect of entrepreneurial industrial clusters indicates a possibility that Schumpeterian growth mechanism (e.g., Aghion, 2002) is at work. Determining the mechanisms and addressing why particular mechanisms are more prevalent than others in certain regions require much more research. These future research directions promise further contribution to the literature on economic development and institutions (e.g., Acemoglu et al., 2002, 2005; Engermann and Sokoloff, 1997, 2000; Easterly, 2007), and knowledge on growth and inequality, economic geography, urban economics, and the economic development of China.

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