The effects of innovation on income inequality in China[1]

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Abstract

Innovation can play a role in the economic development of developing countries, and can also impact income inequality. This paper examines the impact of innovation on income inequality in China. We use an instrumental variables model and apply it to panel data over the period 1995 to 2011. Results show that there is a U-shaped relationship between the innovation level and the ratio between urban and rural income, which means that while small amounts of innovation can decrease income inequality and contribute to income equality, large amounts of innovation may increase income inequality. We find that both industrialization and urbanization increase income inequality. Our results also show that there is an inverse U-shaped relationship between innovation and the proportion of the population that is high-skilled.

Keywords: innovation; income inequality; China
JEL codes: O30, O53

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1. Introduction

Innovation can play a role in economic development, particularly for developing countries. According to endogenous growth theory, a major driving force for economic growth is technological progress. In recent years the Chinese government has regarded technological progress and innovation as important for accelerating economic development. As a consequence, China has invested heavily in innovation and technology, which has led to increases in innovation and the potential for increases in economic growth in China. However, China has also become one of the countries in the world with the greatest income inequality, and the inequality of income between urban and rural residents is the main source of its income inequality (Lu and Chen, 2005).

Innovation not only plays a role in the economic development of developing countries, but can also impact income inequality. While there is ample literature studying income inequality in China, there is less concern about the impact of the innovation level on income inequality. However, high skilled workers working in innovative regions or cities tend to benefit more from innovations than low skilled workers do; as a consequence, innovation might cause an increase in income inequality. In China, policymakers see investing in innovation processes as essential to maintaining a competitive advantage, increasing productivity and creating new jobs, but whether these processes result in the decrease of income inequality may depend on the particular socio-economic and institutional context.

Much of the theoretical literature on innovation and income inequality has focused on skill premia rather than the distribution of skill in the population (Lee and Rodriguez-Pose, 2013). Nevertheless, the four mechanisms by which innovation can impact skill premia explored in this literature are also relevant for the effects of innovation on income inequality. The first mechanism by which innovation can impact skill premia and therefore income inequality is that higher skilled workers tend to earn higher returns in higher innovation regions, which is supported by several papers that find that people working at the innovative city often command a higher wage (Van Reenen, 1996; Faggio, Salvanes and Van Reenen, 2007; Echeverri-Carrol and Ayala, 2009).

The second mechanism by which innovation can impact skill premia and therefore income inequality is through knowledge spillovers. Knowledge spillovers may allow those workers with fewer skills to learn from the highly skilled and increase their productivity (Glaeser, 1999), which is conducive to technological innovation, and also to decreasing income inequality. Some researchers believe that in innovative, knowledge-rich environments, those with lower skill levels may learn more and gain from innovation, but others believe that it is not clear that the knowledge from innovation is of sufficiently wide use to raise productivity for low-skilled groups, and therefore that low-skilled workers will not be in occupations in which they can benefit from this new knowledge.

The third mechanism by which innovation can impact skill premia and therefore income inequality is through the spatial agglomeration effects of innovation. Innovation can produce great gains which are likely to attractive to those with complementary skills or those working in innovative sectors (Van Reenen, 1996; Faggio et al., 2007; Echeverri-Carroll and Ayala, 2009), resulting in labor migration. But the impact of migration on overall inequality is ambiguous. For cities which have few highly skilled residents but experience high-skilled in-migration, innovation may first increase inequality, but after a certain threshold level it may begin to reduce inequality. Traditional models of labor markets imply that this process of migration will reduce wages for the highly skilled. In contrast, more recent models based on increasing returns suggest that there will be increasing returns to scale when the highly skilled migrants cluster, with more highly skilled migrants leading to even greater increases in innovation (Puga, 2002). The cluster of affluent innovators in the labor market will alter both the occupational structure and wages for those with low skill levels, because affluence for one group may skew the labor market for others, creating jobs in personal service employment with low wages (Manning, 2004; Kaplanis, 2010), and ultimately changing the overall level of income inequality.

The fourth mechanism by which innovation can impact skill premia and therefore income inequality is that technological advances may change the employment shares and wages for the different skill groups. The theory of skill-biased technological change posits that technology will substitute for low-skilled labor, reducing employment shares for the low skilled and also their wages, while increasing wages and employment shares for the highly skilled. Autor, Levy and Murnane (2003) believes that technology will replace some of the routine work in semi-skilled employment, but since routine non-skilled employment, such as cleaning, is difficult to automate, technological change will lead to a polarization of the labor market into high-skilled and low-skilled employment. Autor and Dorn (2013) find that in the United States, local labor markets that specialized in routine tasks adopted information technology that displaced low-skilled labor, which was reallocated into service occupations. Machin and Van Reenen (1998) find that technical change is closely linked to the growth in the importance of more highly skilled workers in seven OECD countries. Acemoglu, Gancia and Zilibotti (2012) develop a model in which innovation takes the form of the introduction of new goods whose production requires skilled workers, and is followed by standardization, whereby these new goods are adapted to be produced using unskilled labor.

Based on the above four mechanisms, it is possible for innovation to either increase or decrease the overall inequality, as the impact of innovation on income inequality depends on labor skill structure, the scale of the labor market and other factors. In this paper we analyze the effects of innovation on income inequality in China. We use an instrumental variables model and apply it to panel data on Chinese provinces over the period 1995 to 2011.

For our measure of income inequality, we focus on the inequality of income between urban and rural residents, the main source of China's income inequality (Lu and Chen, 2005). In 2014, the ratio between urban and rural income was 2.03. In China, rural residents tend to have lower skill and education levels than urban residents do, and thus the income levels of urban and rural residents may be differentially impacted by innovation. In addition to the ratio between urban and rural income, we also analyze the effects of innovation on another possible measure of inequality: the skill composition of the workforce.

Our results show that there is a U-shaped relationship between the innovation level and the ratio between urban and rural income, which means that while small amounts of innovation can decrease income inequality and contribute to income equality, large amounts of innovation may increase income inequality. We find that high-skilled labor can decrease income inequality, while both the industrialization rate and the urbanization rate increase income inequality. Our results also show that there is an inverse U-shaped relationship between innovation and the proportion of the population that is high-skilled.

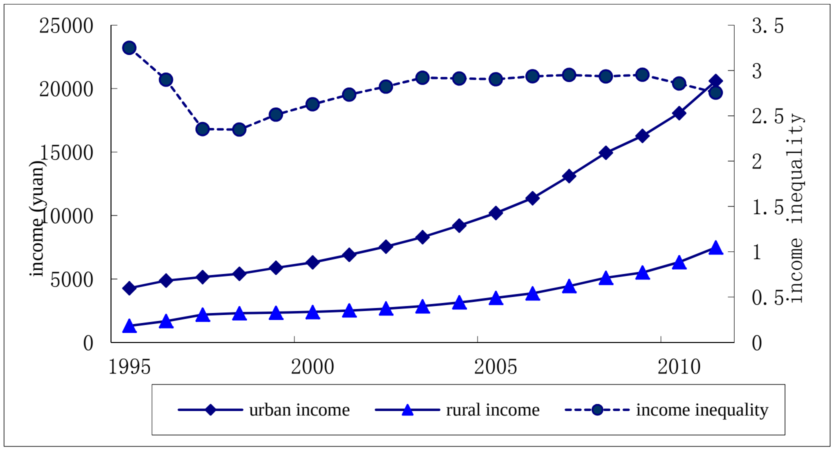
The remainder of this paper is organized as follows. Section 2 summarizes the spatial and temporal characteristics of innovation and income inequality in China over the period 1995 to 2011. We present our empirical model in Section 3 and describe our data in Section 4. Section 5 presents our results. Section 6 concludes.

2. Innovation and Income Inequality in China

2.1. Spatial and temporal characteristics of income inequality

Since income inequality in China is largely due to the gap between urban and rural income, we use the ratio between urban and rural income as our measure of income inequality. Figure 1 plots the trends in urban income, rural income and income inequality in China over the period 1995 to 2011. Both urban and rural incomes exhibit an increasing trend, with urban income growing faster than rural income. Income inequality reaches a peak of 3.5 in 1995. The lowest value of income inequality, 2.092, appeared in 1998 and was caused by the financial crisis. Since then, income inequality has exhibited an upward trend until 2007, after which income inequality was decreased by regional coordination of economic policies and the global financial crisis of 2007-2008.

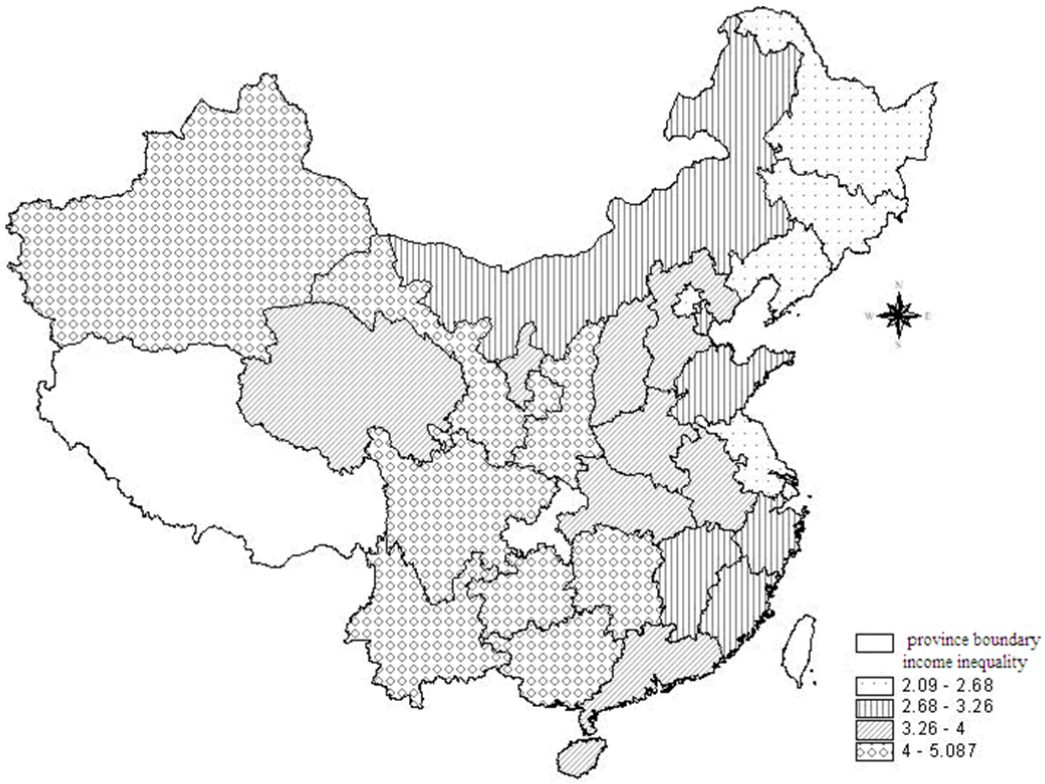
Figure 1. Urban income, rural income, and income inequality in China, 1995-2011



Note: Income inequality is measured by the ratio between urban and rural income.
Source: China Statistical Yearbook (1996-2012)

Figures 2 and 3 plot the spatial distribution of income inequality in China in 1995 and 2011, the first and last years of our data set, respectively. Income inequality ranged from 2.092 to 5.087 in 1995, with the higher values above 3.23 mainly concentrated in the central and western provinces of China, and also in some eastern provinces, including Shandong, Hebei and Guangdong provinces. In 2000, income inequality ranged from 1.891 to 5.579, the spatial distribution of income inequality changed little compared to 1995, and the maximum value of 5.579 appeared in Tibet. In 2011, the income gap ranged from 2.067 to 3.979. The values of income inequality in the western provinces are still high in 2011. Income inequality in the Shandong, Guangdong and Fujian provinces have values that are higher than 3.38.

Figure 2. Spatial distribution of income inequality in China, 1995



Notes: Income inequality is measured by the ratio between urban and rural income. There is no official data for Tibet in 1995.
Source: China Statistical Yearbook (1996-2012)

Figure 3. Spatial distribution of income inequality in China, 2011

Note: Income inequality is measured by the ratio between urban and rural income.
Source: China Statistical Yearbook (1996-2012)

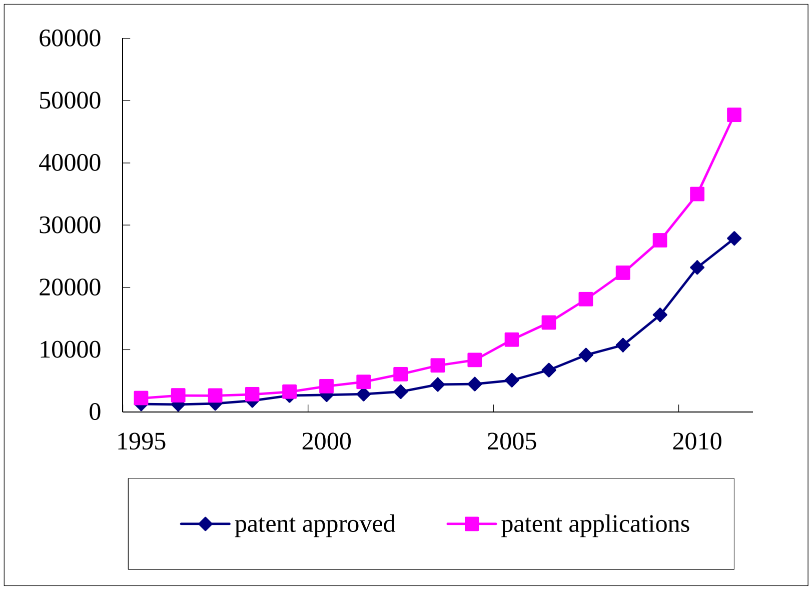
2.2. Spatial and temporal characteristics of innovation

We use the number of patent applications and the number of patents approved as our measure of innovation. The number of patent applications and the number of patents approved in each province reflect the output of the regional research and development, and therefore reflect innovation.

Figure 4 shows the exponential growth of the total number of patents applications and patents approved in China from 1995 to 2011. Particularly after 2001, both measures of patenting activity increased rapidly.

Table 1 presents the number of patents approved and the number patents per 10,000 people for each province for the years 1995, 2000, 2005, and 2011. Innovation varies spatially. In 2011, the top six provinces in patents approved are located in the economically developed eastern coastal regions, and comprise about 65% of total patent applications and patents approved. The provinces in the central and western regions account for only about a quarter of number of patents approved in the whole country. There is a large gap between the innovation levels in the central and western regions and the innovation levels in the eastern region. In 2011, Jiangsu, Zhejiang and Guangdong are the top three provinces in innovation level, and the bottom three are Ningxia, Qinghai and Tibet. The quotient of maximum over minimum number of patents approved is 196.25 in 2011, but in 1995 it is 2305.5, so the quotient has decreased over time. In terms of patents approved per 10,000 people, the top three provinces are Jiangsu, Zhejiang and Shanghai, and the bottom three provinces are Tibet, Hainan and Yunnan.

Figure 4. Number of patents approved and patent applications in China, 1995-2011



Source: China Energy Statistical Yearbook, 1996 to 2011.

Table 1. Numbers of patents approved by province in China

	Number of patents approved				Number of patents approved per 10,000 people			
Province	1995	2000	2005	2011	1995	2000	2005	2011
Anhui	574	1482	1939	32681	0.095	0.236	0.317	5.476
Beijing	4025	5905	10100	40888	3.217	4.352	6.567	20.252
Chongqing	4041	1158	3591	15525		0.375	1.283	5.319
Fujian	933	3003	5147	21857	0.288	0.881	1.456	5.876
Gansu	257	493	547	2383	0.105	0.193	0.211	0.929
Guangdong	4611	15799	36894	128413	0.671	2.050	4.013	12.224
Guangxi	665	1191	1225	4402	0.146	0.251	0.263	0.948
Guizhou	274	710	925	3386	0.078	0.189	0.248	0.976
Hainan	108	320	200	765	0.149	0.406	0.242	0.872
Hebei	1580	2812	3585	11119	0.245	0.421	0.523	1.536
Henan	1145	2766	3748	19259	0.126	0.292	0.400	2.051
Heilongjiang	1403	2252	2906	12236	0.379	0.592	0.761	3.191
Hubei	1017	2198	3860	19035	0.176	0.369	0.676	3.306
Hunan	1515	2555	3659	16064	0.237	0.389	0.578	2.435
Jilin	824	1650	2023	4920	0.318	0.615	0.745	1.790
Jiangsu	2413	6432	13580	199814	0.341	0.878	1.817	25.296
Jiangxi	509	1072	1361	5550	0.125	0.258	0.316	1.237
Liaoning	2745	4842	6195	19176	0.671	1.157	1.468	4.375
Neimenggu	415	775	845	2262	0.182	0.327	0.354	0.911
Ningxia	111	224	214	613	0.216	0.404	0.359	0.959
Qinghai	65	117	79	538	0.135	0.226	0.145	0.947
Shandong	2861	6962	10743	58844	0.329	0.774	1.162	6.106
Shanxi	569	968	1220	4974	0.185	0.298	0.364	1.384
Shannxi	1085	1462	1894	11662	0.309	0.401	0.509	3.116
Shanghai	1436	4050	12603	47960	1.015	2.468	7.088	20.435
Sichuan	2019	3218	4606	28446	0.178	0.374	0.561	3.534
Tianjin	1034	1611	3045	13982	1.098	1.609	2.919	10.319
Tibet	2	17	44	142	0.008	0.066	0.159	0.469
Xinjiang	312	717	921	2642	0.188	0.388	0.458	1.196
Yunnan	569	1217	1381	4199	0.143	0.287	0.310	0.907
Zhejiang	2131	7495	19056	130190	0.493	1.631	3.891	23.831
Mean	1330.6	2757.2	5101.2	27868.6	0.395	0.747	1.296	5.555

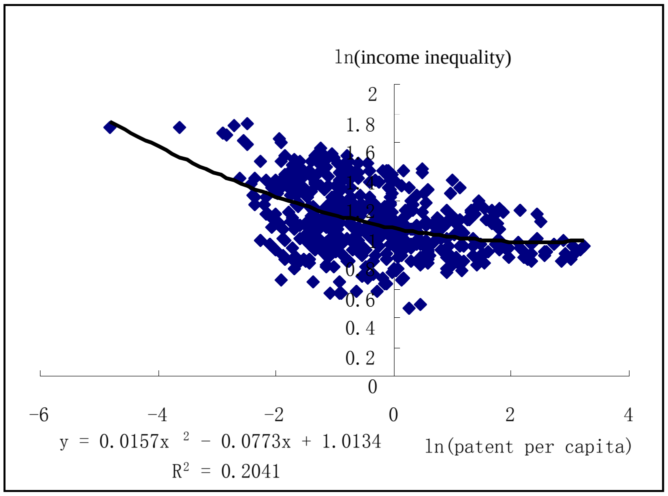
Source: China Energy Statistical Yearbook, 1996 to 2011.

2.3. Scatter plot of innovation and income inequality

To examine the relationship between innovation and income inequality, Figure 5 presents a scatter plot of innovation (measured by the log of the patents approved per 10,000 people) and income inequality (measured by the log of the ratio between urban and rural income) using panel data and the results from fitting a curve between these two variables. We find that there is a U-shaped relationship between these two variables: income inequality decreases as innovation increases for low levels of innovation, but after the number patents approved per 10,000 people reaches 11.744, increases in innovation are associated with increases in income inequality.

However, income inequality is caused by a variety of factors not accounted for in the scatterplot in Figure 5. We now proceed to our empirical analysis, which examines the impact of innovation on income inequality while controlling for these other factors.

Figure 5. Scatter plot of log income inequality and log patents approved per 10,000 people in China, 1995-2011



Note: Income inequality is measured by the ratio between urban and rural income.

3. Empirical Model

In order to empirically analyze the impact of innovation on income inequality in China, we use a model based on Lee and Rodriguez-Pose (2013), who model income inequality as a function of innovation, labor education, labor density, and the regional development level. Other factors influencing the income inequality include the urbanization level and industrialization level. In China, rapid urbanization and industrialization have given many farmers more opportunities to work in urban cities, thus affecting the income gap between rural and urban regions.

We use the following econometric model:

$$\ln(inequality_{it}) = \beta_0 + \beta_1 \ln(patent_{it}) + \beta_2 (\ln(patent_{it}))^2 + x_{it}'\gamma + \alpha_i + \nu_t + \theta_{it} + \varepsilon_{it}, \quad (1)$$

where $inequality_{it}$ is the ratio of per capita disposable income of residents in urban areas to per capita net income of farms in rural areas in province *i* in year *t*; $patent_{it}$ is the number of patents approved per 10,000 people in province *i* in year *t*; x_{it} are covariates, α_i is a province fixed effect, ν_t is a year effect, θ_{it} is a region-year effect, and ε_{it} is an error term.

We include a number of covariates x_{it} for each province *i* for each year *t* in our model. The first covariate we include is the high-skilled population proportion, which we define as number of people with a higher education degree or above per 100,000 people in the province. The proportion of the population with a higher education degree or above is a measure of human capital and reflects the workforce skill structure of the province. The greater the proportion of the population with a higher education degree or above, the greater the proportion of high-skilled labor in the province.

The second covariate we include is population density, which we define as the number of people per square kilometer. Population density is a measure of urban scale and represents the size of the region's labor force. Population density also reflects the intensity of regional economic activity.

The third covariate we include is GDP per capita, which measures the state of the economy and reflects the economic development of the region.

The fourth covariate we use is an urbanization index, which we calculate as the ratio between the employed population in urban areas and the total employed population. The urbanization index can reflect the mobility of agricultural labor to urban areas.

The fifth covariate we use is an industrialization index, which we calculate as the ratio between the industrial sector value added and total GDP, and which measures the degree of industrialization.

In a regression of log income inequality on log number of patents approved per 10,000 people, log high-skilled population proportion, log population density, log GDP per capita, log industrialization, and log urbanization, one may worry that some of the regressors may be endogenous to income inequality. For example, the high-skilled population proportion may be endogenous if areas with high income inequality are also areas with a poor and/or unequal educational system, so that high income inequality may lead to lower high-skilled population proportion levels.

To address any potential endogeneity of the regressors, we use lagged values of the regressors as instruments for each respective regressor. We assume that the lagged value of each of our regressors is correlated with the endogenous regressor but uncorrelated with income inequality except through its correlation with the endogenous regressor. In one set of specifications, we use the 1-year lagged values of the regressors as instruments for each respective regressor. In order to address the possible concern that the 1-year lagged values of the regressors may affect income inequality directly, and therefore do no serve as good instruments since they do not satisfy the exclusion restriction, we also run a set of specifications using the 3-year lagged values of the regressors as instruments instead.

To test for the endogeneity of the regressors, we run an IV regression of equation (1) using 3-year lagged values of the regressors as instruments. Under the null hypothesis that the specified endogenous regressors can actually be treated as exogenous, the test statistic in our endogeneity test is distributed as chi-squared with degrees of freedom equal to the number of regressors tested. The test statistic is based on the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments, where the suspect regressor(s) are treated as endogenous, and one for the equation with the larger set of instruments, where the suspect regressors are treated as exogenous. Under conditional homoskedasticity, this endogeneity test statistic is numerically equal to a Hausman test statistic (Hayashi, 2000; Baum, Schaffer and Stillman, 2007). Unlike the Durbin-Wu-Hausman tests the test statistics we use are robust to various violations of conditional homoscedasticity (Baum, Schaffer and Stillman, 2007).

According to the results of our endogeneity test, the p-values for the log patents approved per 10,000 people (p-value = 0.5436), log patents approved per 10,000 people squared (p-value = 0.3627), log population density (p-value = 0.1212), log GDP per capita (p-value = 0.1685), log industrialization (p-value = 0.1320), and log urbanization (p-value = 0.7470) are all greater than 0.05, so we do not reject the null hypothesis that these varaibles are exogenous. However, we reject the null hypothesis that the log high skill population proportion is exogenous at a 0.1% level (p-value = 0.0000). Since we reject the null hypothesis that the log high skill population proportion is exogenous and since it is likely that the other regressors are endogenous to income inequality, we use either the 1-year or 3-year lagged values of the regressors as instruments.

In addition to using instruments for each regressor, we also address potential endogeneity by including province fixed effects, year effects, and region-year effects to control for time-invariant province-level unobservables, nation-wide shocks that vary year by year, and region-wide shocks that vary year by year, respectively.

To find where log income inequality reaches its maximum or minimum, we set the partial derivative of log inequality in equation (1) with respect to log patent equal to 0, and then solve for the turning point level of number of patents approved per 10,000 people:

$$\frac{\partial \ln inequality}{\partial \ln patent} = \beta_1 + 2\beta_2 \ln patent = 0$$
$$=> \ln patent = -\beta_1 / (2\beta_2)$$
$$=> patent^* = \exp((-\beta_1) / 2\beta_2) \ . \qquad (2)$$

4. Data

We use annual province-level panel data over the years 1995 to 2011. The data in this study are from the China Statistical Yearbook, the China Energy Statistical Yearbook and the China Labor and Population Statistics Yearbook. Table 1 presents summary statistics of the variables in our data set. Over the period 1995 to 2011, China's income gap ranges from 1.599 to 5.60, with an average of 2.99. The number of patents approved per 10,000 people varies greatly by region; its average value is 1.689. There is also great spatial disparity in the proportion of the population with a higher education degree or above: the maximum value is 31,499, but the minimum is only 80.05. The average values for the level of urbanization and the level of industrialization are 0.343 and 0.601, respectively. For the population density, there is a large gap between the maximum value and the minimum value: the minimum value of 1.953 appeared in Tibet in 1995, and the highest value of 3701.893 occurred in Shanghai in 2011.

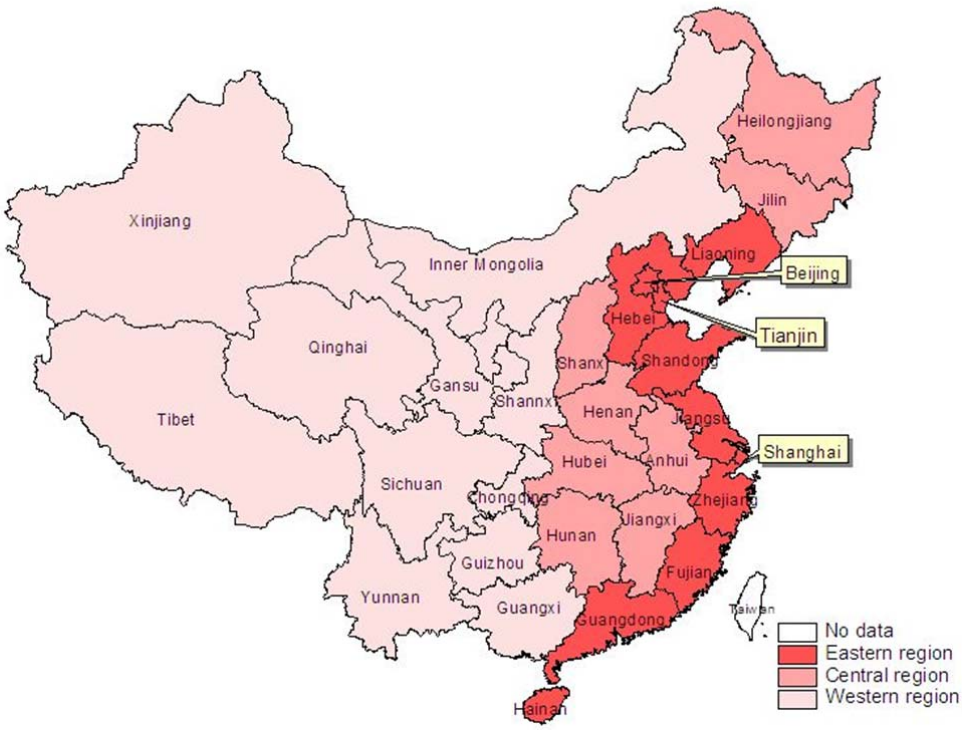
Although GDP per capita, industrialization, and urbanization are correlated, they are not highly correlated. The correlation between log GDP per capita and log industrialization is 0.3862. The correlation between log GDP per capita and log urbanization is 0.5514. The correlation between log industrialization and log urbanization is 0.1034. Thus, because GDP per capita, industrialization, and urbanization may each potentially affect income inequality, and because they are not highly correlated with each other, it makes sense to include all three variables as potential determinants of income inequality in our regressions.

For the region-year effects in our model, we classify the provinces in China into 3 regions: the eastern region, the central region and the western region. The regions are mapped in Figure 6. The eastern region includes the following 11 provinces: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes the following 8 provinces: Shanxi, Heilongjiang, Jilin, Anhui, Jiangxi, Henan, Hunan, and Hubei. The western region includes the following 12 provinces: Sichuan, Guizhou, Shaanxi, Inner Monglia, Yunnan, Qinghai, Ningxia and Xinjiang, Guangxi, Sichuan, Chongqing, and Tibet. Owing to limits on data availability, and because they are separate from mainland China, Macao, Taiwan and Hong Kong are not included in any region nor in any regression.

Table 2. Summary statistics

	# Obs	Mean	Std. Dev.	Min	Max
Income inequality (ratio between urban and rural income)	522	2.994	0.714	1.599	5.605
Number of patents approved per 10,000 people	525	1.689	3.321	0.008	25.296
High-skilled population proportion (number with higher education degree or above per 100,000 people)	525	5460.07	4492.06	80.046	31499
Population density (people/km^2)	525	378.446	501.340	1.954	3701.89
GDP per capita (yuan)	525	1.599	1.481	0.181	8.345
Urbanization index (ratio between employed population in urban areas and total employed population)	527	0.344	0.151	0.119	0.833
Industrialization index (ratio between the industrial sector value added and total GDP)	527	0.601	0.074	0.239	0.723

Figure 6. Regions in China



Notes: The eastern region includes the following 11 provinces: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes the following 8 provinces: Shanxi, Heilongjiang, Jilin, Anhui, Jiangxi, Henan, Hunan, and Hubei. The western region includes the following 12 provinces: Sichuan, Guizhou, Shaanxi, Inner Monglia, Yunnan, Qinghai, Ningxia and Xinjiang, Guangxi, Sichuan, Chongqing, and Tibet. Macao, Taiwan and Hong Kong are not included in any region.

5. Results

The results of our instrumental variables model with province fixed effects and year effects are reported in Table 3; specification (8), our preferred specification, includes region-year effects as well. As reported in Table 3, all the first-stage F-statistics are greater than 10. We also conduct an under-identification test and a weak-instrument-robust inference test and their results are also presented in Table 3. In all our regressions, we reject under-identification and pass the weak-instrument-robust inference test.

According to the results in Table 3, the coefficient on the log of the number of patents approved per 10,000 people is negative and significant in specifications (1),(6) and (8), which means that innovation can decrease income inequality. Moreover, the coefficient on the log of the number of patents approved per 10,000 people squared is significant and positive in all specifications, which means that the relationship between the innovation level and income inequality is not linear but U-shaped. While small amounts of innovation can decrease income inequality and contribute to income equality, large amounts of innovation may increase income inequality.

Table 3 also reports the turning point levels of number of patents approved per 10,000 people. Income inequality decreases with the number of patents approved per 10,000 people when the number of patents approved per 10,000 people is lower than these turning point levels, but decreases with the number of patents approved per 10,000 people once the number of patents approved per 10,000 people exceeds these turning point levels. The turning point level of the number of patents approved per 10,000 people in specification (8), which includes region-year effects in addition to province fixed effects and year effects, is 4.819.

The coefficient on log high-skilled population proportion is significant and negative, which means that increases in human capital can decrease income inequality. When high-skilled population proportion is dropped from the regression in specification (6), the coefficient on the number of patents approved per 10,000 people becomes more negative. Excluding high-skilled population proportion from the regression leads to omitted variable bias because human capital directly affects the ability of the labor force to absorb innovation and new technology (Durlauf and Quah, 1998). Moreover, through knowledge spillovers human capital can decrease income inequality.

The coefficient on population density is negative and significant in most specifications, including our preferred specification (8) that includes region-year effects, which is evidence that a greater population density decreases income inequality. The coefficient on the number of patents approved per 10,000 people is robust to whether or not population density is included in the regression, indicating that labor density and innovation might not be closely related.

The coefficient on industrialization is positive and significant in most specifications including our preferred specification (8) that includes region-year effects; the greater the industrialization, the greater the income inequality. Since innovations in China are mainly in the production processes of the industrial sector, a high industrialization level could improve ability of innovation. However, for most of industrial enterprises, increases in industrialization level do not necessarily result in increases in the ability to adapt to new innovation, thus limiting any increase in the wages of low-skilled labor and therefore resulting in greater income inequality.

The coefficient on urbanization is positive and significant in most specifications including our preferred specification (8) that includes region-year effects; the greater the urbanization, the greater the income inequality. Urbanization provides job opportunities for low-skilled labor, but China's household registration system restricts rural labor from flowing freely to the city, causing a separation between the urban and rural labor market and resulting in greater income inequality (Pan, 2010; Lu and Chen, 2004).

The coefficient on per capita GDP is positive and significant. As income increases, income inequality increases as well. Comparing results in specification (5) and specification (2), we find that the turning point levels of number of patents approved per 10,000 people is higher when we control for per capita GDP.

In order to address the possible concern that the 1-year lagged values of the regressors may affect income inequality directly, and therefore do no serve as good instruments since they do not satisfy the exclusion restriction, we also run a set of income inequality regressions using the 3-year lagged values of the regressors as instruments. The results are shown in Table 4. As reported in Table 4, all the first-stage F-statistics are greater than 10. In all our regressions, we reject under-identification and pass the weak-instrument-robust inference test.

When using 3-year lags as instruments, the coefficients on log patents approved per 10,000 people are significant and negative and more negative than they were when the 1-year lags were used as instruments, which means that innovation can more significantly decrease income inequality. Moreover, the coefficient on the log of the number of patents approved per 10,000 people squared is significant and positive in all specifications except specification (7), which means that the relationship between the innovation level and income inequality is a robust U-shape.

Most of the signs and significances of the other covariates are robust to whether 1-year lags or 3-year lags are used for the instruments. The exception is the coefficient on the high-skilled population proportion, which is no longer significant when 3-lags are used as instruments. The turning point level of the number of patents approved per 10,000 people in our preferred specification (8), which includes region-year effects in addition to province fixed effects and year effects, is 12.68.

The provinces with the 4 primary cities in China -- Beijing, Shanghai, Tianjin, and Chongqing -- are likely to be outliers because they are more metropolitan and have a lower proportion of rural residents than the other provinces in China. We therefore also run our preferred specification (8) using only those provinces with the 4 primary cities in China -- Beijing, Shanghai, Tianjin, and Chongqing -- as well as using all the provinces except the ones with these 4 cities. The results are shown in Table 5. According to the results for the provinces with Beijing, Shanghai, Tianjin, and Chongqing in specifications (9a) and (9b), neither log patents nor log patents squared is significant at a 5% level. In contrast, according to the results for the remaining provinces in specifications (10a) and (10b), the relationship between the innovation level and income inequality is a robust U-shape. Thus, our result that the relationship between the innovation level and income inequality is

U-shaped is robust to the removal of the outlier provinces with Beijing, Shanghai, Tianjin, and Chongqing.

In addition to the gap between urban and rural income, another possible measure of inequality is the skill composition of the workforce. We therefore run a regression of our inequality equation (1) using the high-skilled population proportion as the dependent variable and 3-year lagged value as instruments for the regressors. According to our results in Table 6, the coefficient on log patents approved per 10,000 people is significant and negative, which suggests that there is an inverse U-shaped relationship between innovation and human capital. As innovation increases, human capital increases initially but then decreases with innovation when innovation is high. However, the turning point level of innovation after which human capital declines with innovation is high; in specification (2), which includes region-year effects in addition to province fixed effects and year effects, the turning point level of the number of patents approved per 10,000 people is approximately 14 times higher than the mean number of patents approved per 10,000 people, and only slightly lower than the maximum number of patents approved per 10,000 people. Thus, for most provinces, the level of innovation has not yet reached the turning point level.

Table 3. IV Results for income inequality using 1-year lags as instruments

	Dependent variable is log income inequality							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log patents approved per 10,000 people	-0.0383**	-0.0268	-0.0307	-0.0214	-0.0218	-0.0563***	-0.0263	-0.04026**
	(0.0129)	(0.0174)	(0.0164)	(0.0163)	(0.0173)	(0.0138)	(0.0173)	(0.0161)
(log patents approved per 10,000 people)^2	0.0119***	0.0189***	0.0143***	0.0186***	0.0194***	0.0190***	0.0174***	0.0128***
	(0.00176)	(0.00273)	(0.00230)	(0.00256)	(0.00277)	(0.00232)	(0.00260)	(0.00291)
log high skill population proportion		-0.199***	-0.161**	-0.149**	-0.203***		-0.188***	-0.1753***
		(0.0573)	(0.0492)	(0.0461)	(0.0578)		(0.0566)	(0.0526)
log population density		-0.177*	-0.206*	-0.147	-0.256**	-0.166*		-0.1854**
		(0.0896)	(0.0850)	(0.0828)	(0.0867)	(0.0758)		(0.0886)
log GDP per capita		0.111*	0.156***	0.108*		0.154***	0.142**	0.2106**
		(0.0497)	(0.0439)	(0.0467)		(0.0413)	(0.0469)	(0.0483)
log industrialization		0.225**		0.192**	0.270***	0.0802	0.238**	0.1274**
		(0.0763)		(0.0692)	(0.0722)	(0.0547)	(0.0755)	(0.0705)
log urbanization		0.101*	0.0862*		0.0961*	0.0399	0.0919*	0.111**
		(0.0439)	(0.0407)		(0.0446)	(0.0317)	(0.0430)	(0.0412)
constant	1.062***	3.858***	3.459***	3.128***	4.478***	1.851***	2.792***	3.598***
	(0.0175)	(0.789)	(0.708)	(0.631)	(0.728)	(0.426)	(0.566)	(0.7776)
province fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
year effects	Y	Y	Y	Y	Y	Y	Y	Y
region*year effects	N	N	N	N	N	N	N	Y
Number of observations	492	492	492	492	492	492	492	492
Number of provinces	31	31	31	31	31	31	31	31
First-stage F-statistics for:								

log patents approved per 10,000 people	5732	2760.93	3067.77	3156.21	2733.06	3139.83	2742.05	1050.69
(log patents approved per 10,000 people)^2	722.4	392.81	431.37	446.97	328.64	446.59	441.64	222.46
log high skill population proportion		373.21	429.55	412.91	420.62		433.79	326.02
log population density		6.6e+05	7.4e+05	7.5e+05	8.6e+05	7.4e+05		2.3e+05
log GDP per capita		12950.04	14570.14	15094.92		13975.57	14955.36	5077.25
log industrialization		2683.46		3066.20	2462.28	3069.92	3109.19	2160.20
log urbanization		2875.67	3098.68		2786.07	2461.91	3190.43	1992.84
p-value from under-identification test	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
p-value from weak instrument-robust inference test	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Turning point level of number of patents approved per 10,000 people	4.999	2.032	2.925	1.778	1.754	4.400	2.129	4.819

Notes: Standard errors in parentheses. We use 1-year lagged values of the regressors as instruments for each respective regressor. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. IV results for income inequality using 3-year lags as instruments

	Dependent variable is log income inequality							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log patents approved per 10,000 people	-0.266***	-0.249**	-0.314**	-0.129*	-0.296*	-0.260***	-0.545	-0.255*
	(0.0701)	(0.0947)	(0.0965)	(0.0531)	(0.131)	(0.0565)	(0.387)	(0.110)
(log patents approved per 10,000 people)^2	0.0384***	0.0538***	0.0575***	0.0421***	0.0622***	0.0551***	0.0840	0.0502**
	(0.00684)	(0.0120)	(0.0138)	(0.00796)	(0.0172)	(0.00830)	(0.0437)	(0.0170)
log high skill population proportion		-0.0180	0.0779	-0.139	0.0304		0.207	0.0119
		(0.120)	(0.115)	(0.0910)	(0.157)		(0.373)	(0.140)
log population density		-0.742**	-0.925***	-0.392*	-1.164*	-0.767***		-0.656**
		(0.251)	(0.250)	(0.156)	(0.454)	(0.201)		(0.237)
log GDP per capita		0.288*	0.404***	0.100		0.300**	0.758	0.357*
		(0.133)	(0.121)	(0.0836)		(0.105)	(0.536)	(0.139)
log industrialization		0.232		0.441**	0.357*	0.215	0.333	0.103
		(0.166)		(0.135)	(0.160)	(0.141)	(0.317)	(0.183)
log urbanization		0.309*	0.391*		0.380	0.315*	0.835	0.411*
		(0.152)	(0.164)		(0.204)	(0.142)	(0.637)	(0.187)
constant	1.241***	5.407***	5.366***	4.589***	7.780***	5.371***	-0.233	4.631***
	(0.0634)	(1.136)	(1.331)	(0.884)	(1.801)	(1.130)	(3.199)	(1.217)
province fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
year effects	Y	Y	Y	Y	Y	Y	Y	Y
region*year effects	N	N	N	N	N	N	N	Y
Number of observations	433	431	431	431	431	431	431	431
Number of provinces	31	31	31	31	31	31	31	31
First-stage F-statistics for:								

log patents approved per 10,000 people	402.13	706.62	706.62	797.66	471.21	757.96	745.70	285.07
(log patents approved per 10,000 people)^2	53.00	19.35	19.35	21.34	22.29	20.21	23.26	27.41
log high skill population proportion		281.36	281.36	325.86	252.93		315.86	210.94
log population density		1.7e+05	1.7e+05	2.1e+05	1.5e+05	1.8e+05		75062.96
log GDP per capita		2755.35	2755.35	2945.33		2783.29	3208.98	1031.62
log industrialization		576.81		674.34	665.74	657.41	653.98	486.33
log urbanization		618.80	618.8		597.41	695.96	667.90	430.76
p-value from under-identification test	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
p-value from weak instrument-robust inference test	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Turning point level of number of patents approved per 10,000 people	31.93	10.12	15.34	4.63	10.80	10.58	25.64	12.68

Notes: Standard errors in parentheses. We use 3-year lagged values of the regressors as instruments for each respective regressor. Significance codes: * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 5. IV Results for provinces with and without large cities

	Dependent variable is log income inequality			
	Provinces with Beijing, Shanghai, Tianjin, and Chongqing		Provinces without Beijing, Shanghai,Tianjin, and Chongqing	
Instruments	1-year lags	3-year lags	1-year lag	3-year lags
	(9a)	(9b)	(10a)	(10b)
log patents approved per 10,000 people	0.309	0.231	-0.0623***	-0.272*
	(0.184)	(0.461)	(0.0172)	(0.115)
(log patents approved per 10,000 people)^2	-0.0640	0.120	0.00957**	0.048*
	(0.103)	(0.475)	(0.00295)	(0.0189)
log high skill population proportion	-0.481	-0.439	-0.153**	0.0195
	(0.554)	(0.899)	(0.0507)	(0.136)
log population density	1.086	-1.092	-0.126	-0.873*
	(0.698)	(7.935)	(0.109)	(0.358)
log GDP per capita	-0.330	0.748	0.338***	0.479**
	(0.723)	(3.354)	(0.0542)	(0.153)
log industrialization	0.231	-0.476	0.0317	0.130
	(0.241)	(4.063)	(0.0869)	(0.204)
log urbanization	-0.569	0.458	0.122**	0.428**
	(1.031)	(2.289)	(0.0427)	(0.197)
constant	-2.016	9.794	2.842***	5.471**
	(6.222)	(51.22)	(0.849)	(1.664)
province fixed effects	Y	Y	Y	Y
year effects	Y	Y	Y	Y
region*year effects	N	N	Y	Y

Number of observations	62	54	430	377
Number of provinces	4	4	27	27
First-stage F-statistics for:				
log patents approved per 10,000 people	374.27	168.10	798.04	180.69
(log patents approved per 10,000 people)^2	259.70	95.96	208.20	17.12
log high skill population proportion	196.74	242.28	99.80	70.11
log population density	7348.08	3804.77	2.9e+05	93451.44
log GDP per capita	2401.05	908.05	3500.21	547.33
log industrialization	697.78	249.54	1655.63	388.88
log urbanization	246.77	50.58	1293.56	271.28
p-value from under-identification test	0.0305*	0.9636	0.000***	0.0016**
p-value from weak instrument-robust inference test	0.000***	0.0000***	0.000***	0.000***
Turning point level of number of patents approved per 10,000 people	NA	NA	25.9186	17.002

Notes: Standard errors in parentheses. We use either the 1-year or 3-year lagged values of the regressors as instruments for each respective regressor. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6. IV results for high-skilled population proportion using 3-year lags as instruments

Dependent variable is log high-skilled population proportion		
	(1)	(2)
log patents approved per 10,000 people	0.799***	0.824***
	(0.184)	(0.193)
(log patents approved per 10,000 people)^2	-0.106***	-0.131***
	(0.0262)	(0.0341)
log population density	1.919**	1.500*
	(0.657)	(0.668)
log GDP per capita	-0.811*	-0.686
	(0.359)	(0.384)
log industrialization	0.802	0.811
	(0.483)	(0.502)
log urbanization	-0.519	-0.754
	(0.484)	(0.556)
constant	-0.852	0.995
	(3.696)	(3.746)
province fixed effects	Y	Y
year effects	Y	Y
region*year effects	N	Y
Number of observations	432	432
Number of provinces	31	31
First-stage F-statistics for:		
log patents approved per 10,000 people	761.38	327.36
(log patents approved per 10,000 people)^2	23.95	31.68
log population density	1.9e+05	81298.95
log GDP per capita	2764.39	1139.65
log industrialization	654.81	567.41
log urbanization	733.97	465.23
p-value from under-identification test	0.000***	0.000***
p-value from weak instrument-robust inference test	0.000***	0.000***
Turning point level of number of patents approved per 10,000 people	43.33	23.22

Notes: Standard errors in parentheses. We use 3-year lagged values of the regressors as instruments for each respective regressor. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6. Conclusion

This paper examines the impact of innovation on income inequality in China. Our results show that the innovation level has a significant effect on income inequality and moreover that the relationship between innovation level and income inequality in China is not linear, but U-shaped. Because innovation can impact income inequality, it will be important for the Chinese government to pay attention to the relationship between innovation and income inequality in the long run. In particular, China should consider the effects of innovation on income inequality when distributing research investment efforts and funding among provinces and industries.

Urbanization and industrialization create opportunities for labor mobility, so that labor can flow from the agricultural sector non-agricultural sectors, and from agriculture to manufacturing and service sectors, leading to changes in the employment shares of different sectors. However, urbanization and industrialization can increase income inequality because of China's household registration system. Currently, most areas in China still practice a policy of *hukou* registration, making it difficult for workers from rural areas to enter the urban labor market and enjoy the benefits of urbanization, and therefore leading to higher income inequality (Au and Henderson, 2006).

In addition to the ratio between urban and rural income, we also analyze the effects of innovation on another possible measure of inequality: the skill composition of the workforce. According to our results there is an inverse U-shaped relationship between innovation and human capital. As innovation increases, human capital increases initially but then decreases with innovation when innovation is high. However, the turning point level of innovation after which human capital declines with innovation is high.

Our research suggests several possible future avenues for research. In this paper, we use the number of patents approved per 10,000 people to represent the regional innovation level, without considering the "quality" of the patents approved and without disaggregating the patents by sector. Because data on patents from specific sectors such as agriculture, high technology, biotechnology are not available, we were unable to analyze the effects of innovation from different industries on income inequality. In future work we hope to find and use measures of the quality of patents approved and also measures of the innovation levels of different sectors.

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