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Understanding Inter-industrial Wage Differentials in Urban China

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Understanding Inter-industrial Wage Differentials in Urban China

Zhao Chen, Ming Lu and Hiroshi Sato[1]

Abstract: An entry barrier in the labor market can be an important source of wage inequality. This paper finds that social networks, father's education and political status, and urban household registration status (*hukou* identity), as well as their own education, experience, age, and gender, help people enter high-wage industries. When contrasting coastal and inland samples, after instrumenting social networks by household political identity (based on classifications during the land reform in the 1950s), we find that social networks are more helpful for entering high-wage industries. The implication of this paper is: breaking industrial entry barriers in the urban labor market is an essential policy in order to control inter-industrial wage inequality in urban China.

Key Words: inter-industrial wage differentials, industry monopoly, entry barrier, labor market, social networks, CHIPS data
JEL Classification Codes: J31, J42, Z1

1. Introduction

When discussing inter-industrial income inequality, there is a tendency to focus on monopoly in the product market, while overlooking entry barriers in the labor market. In fact, both aspects are necessary conditions for inter-industrial income inequality. Monopoly in the product market generates excess profit, and an entry barrier in the labor market is fundamental to unfair competition that enables workers in monopoly industries to share excess profit. In order to deepen the study of inter-industrial income inequality, we need to ask key questions: Who can enter high-wage industries? How are they able to enter? The critical step for alleviating such inter-industrial wage inequality is to find the determinants of entry barriers in the labor market.

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Our research shows that, in China, inter-industrial wage inequality is not always generated by differences in productivity. The causes of inter-industrial wage inequality have long been debated among scholars. Some literature refers to the mechanism of efficiency wages (Chen and Edin, 2006), while other research regards the disparity as a kind of industry rent induced by non-competitive factors (Krueger and Summers, 1988; Katz and Summers, 1989). Few of these studies consider entry barriers in the labor market from the perspective of non-market factors. Therefore, our research provides a new perspective to understand widespread inter-industrial wage inequality. In particular, this paper provides important evidence for the future evolution of China's urban labor market. If non-market forces construct entry barriers in the labor market, then breaking such entry barriers and promoting fair competition in the urban labor market are essential policies to reduce China's urban wage inequality.

Section 2 is a brief review of the literature related to our research. Section 3 introduces the data and the basic model. Section 4 extends the model by introducing the instrumental variable, and Section 5 compares differences in entry barriers in the labor markets of different areas. Section 6 concludes and provides some policy implications.

2. Inter-industrial Wage Inequality and Labor Market Segmentation

For people who believe in the ideal of a free market economy, inter-industrial wage inequality is a confusing phenomenon. If the market is sufficiently competitive, the industry in which a person works should have no significant influence on personal income, assuming factors affecting productivity (such as education and experience) are accounted for. However, in reality, inter-industrial wage inequality is a worldwide phenomenon. Researchers have shown that even after controlling variables representing productivity, or using sibling data or panel data to control time-invariant unobserved fixed effects, inter-industrial wage inequality remains. Details can be found in Björklund *et al*. (2004)'s research on the U.S. and northern Europe, Haisken-DeNew and Schmidt (1999)'s comparison between Germany and the U.S., and Pinheiro and Ramos (1994) which provides evidence about Brazil. In countries that are going through economic transformation, such as Russia, inter-industrial wage inequality is widening (Lukyanova, 2006). In China, Démurger *et al.* (2006) have shown that the average income gap between monopoly industries and competitive industries is significant. Aside from region, education, ownership, occupation, secondary job, full/partial employment, and age, inter-industrial wage inequality has increasingly contributed to income inequality. During 1995–2002, the increasing contribution of inter-industry wage differentials to income inequality was mainly related to state-owned monopoly industries (Chen, Wan and Lu, 2008).

One explanation of higher wages in some industries is that these industries are willing to pay wages above the market clearing level in order to achieve higher productivity. This mechanism is known as “efficiency wages.” Evidence provided by Chen and Edin (2006) supports the efficiency wage hypothesis. Arbache (2001) uses comparable and measurable productivity characteristics to explain wage differentials. He does not find evidence to support compensatory wages, but shows the existence of an efficiency wage mechanism in the manufacturing sector. Another explanation is that non-competitiveness in the product market and labor market is an important factor for inter-industry wage differentials. Monopoly power in the market helps enterprises to obtain excess profits. If there is no premise of excess profits, there is no source for an inter-industry wage differential. However, the labor market’s non-competitiveness is the other condition necessary for the existence of an inter-industry wage differential. If there were no entry barriers in the labor market, which means perfect competition among labor, then industry monopolies would not lead to inter-industry wage differentials. Krueger and Summers (1988) find that, even after the controlling of labor quality, working conditions, excess welfare, short-term demand shocks, unionization threats, collective bargaining, the enterprise’s scale, *etc.*, there are still inter-industry wage differentials. They also find that higher wages are related to lower labor turnover in the industry, which demonstrates that high-wage industries obtain some rent from non-competitiveness. Katz and Summers (1989) also believe that workers get rent in high-wage industries.

What kind of labor can enter high-income industries, and where does the labor market “rent” come from? This double question has two implications. First, after controlling for personal characteristics related to productivity, if there are other characteristics that significantly influence industry entry, then we can be sure that inter-industry wage inequality is not entirely caused by differences in productivity. Second, the current literature concerning

China's labor market segmentation puts more emphases on ownership (Chen *et al.*, 2005; Démurger *et al.*, 2006). If some non-productivity characteristics are found to influence industry entry, then we can identify the labor market segmentation by industry. This judgment is important for future improvement of the urban labor market. As is well known, there is no research relating an individual's non-productivity characteristics to labor market entry. More and more people who lack urban household registration status (*hukou* identity), a nice family background, and urban social networks are entering the urban labor market. If non-market factors indeed become entry barriers , then these workers cannot enter high-wage industries. This result will aggravate the rising urban income gap. Therefore, breaking industrial entry barriers in the urban labor market is an essential policy for reducing China's urban wage inequality.

Will the process of marketization (often taken to be synonymous with economic development) weaken the effect of non-market forces as labor market entry barriers? This question is very important for predicting trends in China's labor market. However, there is very little research on this topic. Our study separates samples of coastal cities from those of inland cities in order to contrast them. In particular, we compare the two regions in terms of the influence of social networks and urban *hukou* identity on industry entry. The changing impact of social capital (especially social networks, a kind of informal institution) is attracting the attention of economists in regard to the process of marketization. Stiglitz (2000) suggests that social networks may have enduring impact. However, the development of markets and formal institutions such as laws and regulations eventually replaces networks based on social groups, leading to a decline in the value of social networks and related social capital . A similar view is that the division of labor is simple during the early stage of economic development, and thus governance based on social networks (relational contracts) is better than that based on regulations (laws and democracy). With the development of the economy and labor division, the marginal transaction costs of regulation governance become lower and lower, and thus formal contracts gradually replace relational contacts (Dixit, 2003; Li, 2003; Krishna and Matsusaka, 2009). However, empirical research in China does not yield a consistent conclusion. In that country, if existing social networks are embedded into the market mechanism, their returns increase with the development of market mechanisms (Li, Lu and Sato, 2009). Our paper provides further evidence of the changing influence of social networks during the process of economic development and marketization.

3. Data and Model

The data used in our research comes from the 2002 Chinese Household Income Project Survey (CHIPS2002) collected by the Chinese Academy of Social Sciences, which is a sub-sample of the yearly household survey made by the National Bureau of Statistics. The urban survey data covers 12 provinces and municipalities, including Beijing, Shanxi, Liaoning, Jiangsu, Anhui, Henan, Hubei, Guangdong, Yunnan, Gansu, Sichuan, and Chongqing. As in the previous two rounds of the survey (1988 and 1995), the 2002 survey also samples from the yearly household survey performed by the National Bureau of Statistics. When choosing urban samples, a two-stage random sampling method is followed. In the first stage, cities, counties, and towns are chosen; in the second stage, families are chosen from these regions.

As part of the first stage, cities, counties, and towns are classified into five categories according to population: megalopolis, metropolis, medium city, small city, and town. Within each category, cities are sorted into six regions: northeast, north, east, middle, northwest and southwest. Within each region, cities are ranked by their urban employees' average wages. The last part of the first stage involves tallying the number of urban employees, and then sampling the cities and counties at the 1-million employee intervals. In the second stage, sample families are selected using a multi-stage random sampling method: districts are chosen, then neighborhood committees (*juweihui*), and finally families from each neighborhood committee. In medium and small cities, sampling starts with neighborhood committees, then moves directly to families. In 2002, there were 45,000 sample families in the yearly household survey made by the National Bureau of Statistics. These samples represent about 450 million urban residents. Sample families are required to keep income and expenditure journals for three consecutive years and are interviewed every month.

We also need to categorize industries according to whether they enjoy excess profits. We regress an income equation, controlling for the variables denoting productivity. Then we control industry dummies and identify each industry's character by the sign and significance of industry coefficients. In previous research, we estimated a semi-logarithmic personal income equation, where income is the sum of wages, bonuses, price supports, income in kind, and secondary job income. Explanatory variables include secondary job, full/partial employment, gender, age and its square, Communist Party member, minority ethnic identity, level of education, and type of occupation. All these variables influence productivity. We also control for unit ownership and urban dummy. Our results show that in 2002 there were 6 industries with significant wage differentials, taking the manufacturing sector as a reference group. From 1988 to 1995, the coefficients of two large industries ("transportation, storage and posts and telecommunication" and "finance and insurance") changed from insignificant to significantly positive and their coefficients become larger. From 1995 to 2002, the coefficients of these two industries remained positive and become even larger. In 2002, wages in these two industries were 16.3% and 21.0%, respectively, higher than the average wage in manufacturing[1].

The dependent variable of our model in this paper is an industry ranking variable. If the average wage in an industry is significantly lower than that of manufacturing in our income equation, then we define it as -1; if the difference is not significant, it is 0. If the coefficient of the industry dummy in the income equation is significantly positive, we define the ranking variable as 1. According to our estimation results for the income equation: low-wage industries include social service; five industries ("electric, gas and water production supply," architecture, "transportation, storage and posts and telecommunication," "finance and insurance," and real estate) are high-wage industries; and the other industries (including the benchmark manufacturing) are medium-wage industries. According to this definition, we adopt an ordered probit model. In such models, the direction of the marginal effect is not always the same as the coefficient's sign. Therefore, for simplicity of interpretation and feasibility of the following instrumental variable estimation, we report the OLS results instead, because their coefficients have almost the same signs and significance levels as seen with the ordered probit model.

In the model, we also control for personal socioeconomic characteristics including gender, marital status, age, education, experience, health, *hukou* status,[2] minority group, and Communist Party standing. Because industry entry might be related to a worker's past experience and performance, we control for the dummy variable of "has ever changed jobs." In order to reflect personal desire to enter a high-wage industry we also control for the

[1] These results can be found in Chen, Wan, and Lu (2008).
[2] In our urban sample, 0.9% of the respondents report their *hukou* identity as rural, because they lack an urban *hukou*. During the urbanization process, many rural people have begun working and living in cities, but their *hukou* identity often remains unchanged.

dependency ratio, which is measured by the number of non-working members in a household divided by the number of working members. Results are reflected in equation (1). As the primary non-productivity factor, social networks are controlled for in equation (2) and measured by "how many people could help you during job hunting." Simple comparison of the means between groups shows that people in high-wage industries have more people to ask for help when seeking work (see Appendix 2). Social networks might have some relationship with some unobserved factors; therefore, in order to reduce possible missing variable bias, we add controls for family background: father's education, his party membership, and whether he operated a business before 1960. Results are shown in Table 1.

Comparing equations (1), (2), and (3), we find that most variables' signs and significance levels do not substantially change. Only education's coefficient decreases when more variables are controlled for. This implies that some of education's influence on industry entry is through social networks and family background. Before discussing the results, we need to explain the measurement of Communist Party standing. We tried using the absolute value of party standing as an explanatory variable, but its coefficient was significantly negative and hard to explain. The effect of party membership is not only related to one's seniority (number of years as a member, which is equivalent to party standing), but also to one's age which correlates with party standing. Therefore, we use the ratio of party standing to age in order to measure political status rather than the party standing itself. The implication of this modification is: when age is controlled for, people who have greater political status (i.e., greater relative party standing) are those who joined the party at younger ages, and they have an advantage in the labor market. Because the influence of relative party standing might be non-linear, we also control for its quadratic term.

In Table 1, the coefficient of social networks, which is our main focus, is significantly positive. This means social networks are helpful for individuals to enter high-wage industries. With social networks included in the regression, education's coefficient decreases a little while the coefficients of the other variables do not change. When family background is added, the coefficient of social networks does not change significantly. Higher levels of father's education and father's party membership are also helpful for someone trying to enter high-wage industries. It is worth mentioning that the coefficient of father's party membership is almost ten times that of his education. This means becoming a party member is equivalent to an additional 10 years of education in terms of being able to help a child enter a high-wage industry. We also find that *hukou* is a very significant factor influencing industry entry. This means the income differential of people who have different *hukou* identities, as described in previous literature (Meng and Zhang, 2001), partly comes from entry barriers in the labor market. All these results mean that non-productivity factors affect fair competition in the labor market. They transfer the excess profits of monopoly industries into personal monopoly gains through social networks, family background, and *hukou*.

However, these results confirming entry barriers do not mean productivity factors are unimportant for industry entry. Years of education and experience each raise the possibility of entering high-wage industries. After controlling for experience (years of earning income), the coefficient of age is negative. This might mean that age induces unemployability in other aspects. Comparing the values of the coefficients, we can see that the coefficients of education, experience, and age are approximately that of social networks, but much lower than that of father's party membership and personal *hukou* identity. Comparing the models' goodness of fit, the adjusted R^2 decreases to 0.0477 when personal education, experience, age, and health are discarded as per equation (3). If social networks, family background, and *hukou* identity are not included, the adjusted R^2 decreases to 0.0496. This means non-productivity and productivity factors are approximately equal in regard to explaining industry entry in the labor market.

Other variables' coefficients are also interesting. It is not easy for individuals who have changed jobs to enter high-wage industries. This might be because changing jobs reflects (or is assumed to reflect) poor performance at previous jobs or discloses information about personal disregard for job stability. Further studies of this variable are needed. Compared to women, it is easier for men to enter high-wage industries. After controlling for other variables, gender affects industry entry so significantly and so strongly that we are compelled to attribute this result to gender discrimination. Relative party standing is significantly negative and its square is also significant in the model described by equation (3). After simple calculation, we find that the turning point of relative party standing is about 0.4315. When someone's relative party standing is greater than the turning point, party membership is helpful for entering high-wage industries. For example, the critical point of relative party standing is 17.26 for a 40-year-old. That is, someone of that age must have joined the party before age 23 in order to get a benefit for entering high-wage industries. For someone who is 50 years old, having joined the party before age 29 is the turning point.

In these models, there might be a measurement error in regard to the value of social networks for job hunting. For example, people may not utilize their networks as resources. In CHIPS 2002, respondents were asked how they find jobs, such as government arrangement (ordinary job re-assignment), getting a job at one's parent's place of work when the parent retires or dies, scoring well on a public exam, introduction from an employment agency, newspaper recruitment, private introduction, searching on one's own initiative, and self-employment or private business (other answers were acceptable, including do not work at present). On the basis of equation (3), we classify two of the aforementioned methods as finding a job "through social networks": getting a job at one's parent's place of work when the parent retires or dies; and private introduction. We define other ways of finding a job as being "through the market." We take the latter category as a reference group and find that the former category raises the possibility of entering high-wage industries[1]. These results are reported in model (4). Results in models (1) – (4) are based on the OLS estimation, where the signs of the coefficients and their significance levels are almost the same as those in the ordered probit model. Model (5) uses an ordered probit estimation, where all the control variables are the same as in model (3).

4. Endogeneity of Social Networks and Instrumental Variable Estimation

Although we try to avoid measurement error by changing measurements of social network and we reduce possible missing variable bias by including family background in regressions, nevertheless there might be estimation biases induced by other missing variables. In particular, simultaneous endogeneity bias is a serious concern, because lower income individuals can take more advantage of their social networks to find jobs. In order to reduce estimation biases induced by the endogeneity of social networks further, we use the instrumental variable method. The instrumental variable we use here is father-in-law's political identity during the land reform of the 1950s. This use of people related by marriage means we must drop

[1] If we regard government arrangement (ordinary job transfer) and employment agency introduction as "finding a job through social networks," the conclusion does not change. If we use "do it oneself" (own initiative) as a reference group and control for various ways of finding jobs by using different dummy variables, we still find that the possibility of entering high-wage industries is higher for those who utilize a personal relationship (private introduction).

unmarried samples. Because it is difficult to use instrumental variables for ordered probit models, we use the OLS method in the following estimations. Models (3) and (6) are OLS estimations for the entire sample and the sample-minus-unmarried, respectively. Comparison reveals that dropping unmarried samples only has a large influence on the coefficients of relative party standing and health. Other coefficients and significance levels do not change much.

It is necessary to explain our choice of the instrumental variable. In the early days of the People's Republic of China (late 1940s to early 1950s), Chairman Mao Zedong initiated the Movement of Land Reform to strengthen the power of the state and eliminate the counter-revolutionary forces hidden in rural areas. Families were labeled according to categories of political identities ("poor peasant or landless," "lower-middle peasant," "rich-middle peasant," "rich peasant," and "landlord"), based on their economic status and the acreage the family owned. The "excess" land and property of the "rich peasants" and "landlords" were redistributed to the "lower-middle peasants" and "poor peasants or landless" who had owned little or no land. As a result, the "lower-middle peasants" and "poor peasants or landless" who had been at the bottom of rural society jumped to the top in a sudden reversal of political status, while the "landlords" and "rich peasants" were deprived of their political and economic power, becoming a class of untouchables ("black class"). The lifelong political identity was an important criterion for judging someone's worth in regard to employment, marriage, and many aspects of social life. In fact, political status was not identified strictly by property ownership. In places that lacked wealthy families, the local criteria for fulfilling the political task of redistribution were modified so that families which had enjoyed relations with the Kuomintang were labeled "rich peasant" or "landlord" and thereby suffered loss and humiliation (Huang, 1995).

In our research, we generate a dummy variable for the father-in-law's political identity during the period of land reform. The value of the dummy for "rich-middle peasant," "rich peasant," "landlord," or "business owner" is 1; for other labels, it is 0. In politics, "rich-middle peasant" was combined with "lower-middle peasant" and "poor peasant or landless," but "rich-middle peasant" category were treated almost as "black class." in practice. Sato and Li (2007) reviewed the role of political identities in intergenerational educational attainment. Although their study distinguished "rich-middle peasants" from "rich peasants" and “landlords,” and used two dummies to control them separately, they found that the interaction terms of these political identities during the Maoist era are significantly negative. In other words, during Mao’s time both dummy variables had a negative effect, so we are justified in classifying “rich-middle peasants” in the same group as “landlords” and “rich peasants” when we generate our dummy variable. Although people who had undesirable political identities were repressed by the reversal of status, these families were restored to their prior status after Deng Xiaoping started the “Socialism with Chinese Characteristics” economic reforms in 1978 (Sato and Li, 2007; 2008). In the cities, most families that had suffered loss regained their previous high social status, so we can hypothesize that if the father-in-law had undesirable political identity in the past, the two families joined by marriage might have resumed higher social status by the time CHIPS began in 1988. This would endow them with richer social networks and the father-in-law’s former political identity (basically, an inverse of his present socioeconomic status) would reflect the full extent of personal social networks.

In order to verify the effectiveness of the instrumental variable, we take “how many people could help you during job hunting” as a dependent variable on the basis of equation (3), and take other explanatory variables and the father-in-law’s political identity as control variables. After the estimation of equation (8), we found that undesirable political identity can significantly increase the number of people who could help someone find a job. Its t-value is 2.44 and its p-value is 0.015. If we perform an F-test on this single variable, its test value is 5.98 which confirms it as a reasonably good instrumental variable. We surmise that the father-in-law’s political identity in the past will not influence someone’s industry entry in the labor market. Although this assumption cannot be tested directly, we can acquire indirect information in support of it. First, we put the father-in-law’s political identity in the industry entry model; the results show this variable to be insignificant. Then, according to each individual’s father-in-law’s political identity, we calculate the percentage of different groups in industries that have different wage levels; again the result shows that there is no significant difference. In low-wage industries, the percentage of individuals whose father-in-law had undesirable political identity is lower, but the high- and medium-wage industries had roughly equal percentages of individuals whose father-in-law had such identity. If we merge the low- and medium-wage industries, the combined group’s percentage of individuals whose father-in-law had undesirable political identity is a little higher than the percentage in high-wage industries, but the difference is not significant. (See Appendix Table 2.)

We also use the father-in-law's political identity as an instrumental variable in a two-stage least squares estimation of model (6), with the result shown in equation (7). If we focus on the coefficient of social networks in the two estimations, we find that its value is 0.103 in the IV estimation, but only 0.00656 in the OLS estimation. This result implies that people in low-wage industries depend more on social networks to find a job, and consequently the coefficient of social networks in the OLS regression was greatly underestimated. Of course, there might be some unobserved factors, such as work ability, which would generate estimation biases in the OLS regression. If it is harder for people with less ability or skill to enter high-wage industries, and if these people depend more on social networks to find a job, then the coefficient of social networks in the OLS regression might have been underestimated.

5. Model Extension: Regional Comparison of the Impact of Social Network

After identifying the influence of non-market factors on entry barriers in the labor market, we can ask whether the influence varies across regions that have different levels of marketization and economic development. In order to make regional comparisons, we divide our sample into two parts: the coastal part includes Beijing, Jiangsu, Liaoning, and Guangdong; and the inland part contains Shanxi, Anhui, Henan, Hubei, Yunnan, Gansu, Sichuan, and Chongqing. As shown via models (9) and (10), the coefficient of social networks is slightly larger in the coastal region than in the inland region, but the difference is insignificant. Considering the possible endogeneity of social networks, we again use the IV method. Remember that the previous instrumental variable forces us to drop unmarried samples; however, the results of the OLS regressions are basically unchanged, except that relative party standing is insignificant. Similarly, for both the coastal and inland regions, the coefficient of social networks is much higher in IV-OLS than that in OLS. This implies an underestimation of the effect of social networks in the OLS regression. Comparing the OLS and IV-OLS regression results, we find that the coefficient of the instrumental variable increases from 0.00831 to 0.173 in the coastal region and from 0.00517 to 0.0345 in the inland region. This means the estimation bias caused by social networks' endogeneity is larger in the coastal region. After considering the endogenous factors, we conclude that social networks' influence on entry into high-wage industries in the coastal region is about five times larger than its influence in the inland region. Actually, even if we do not use instrumental variable estimation, the coefficient of social network in the coastal region is higher. In other words, we do not find evidence supporting the claim that marketization and economic development have a reducing effect on social networks' influence.

Comparisons of other coefficients across regions are also very interesting. In the coastal region, education and experience each greatly increase the possibility of entering high-wage industries but these two productivity variables have much smaller (though still significant) values in the inland region. This is consistent with the fact that the market is more developed in the coastal region. It is worth noting that the coefficient of urban *hukou* in the coastal region is three times that in the inland region. This means *hukou* identity's influence on industry entry is stronger in the coastal region, which is an unwelcome phenomenon in the process of marketization. It is also interesting that father's education is not significant in the coastal region, but father's party membership is significantly positive there. The situation is just the opposite in the inland region, where father's education is significantly positive but his political status (party membership) is not significant. (See Table 3.)

6. Concluding Remarks and Policy Implications

Recognizing that industry monopoly profits and entry barriers in the labor market are two necessary conditions for inter-industrial wage inequality, we explored the determinants of labor market entry barriers empirically. Even when factors that might influence productivity (e.g., education, age, gender) are controlled for, we found that social networks, father's education and political status (i.e., Communist Party membership), and an individual's urban *hukou* identity are helpful factors for gaining entrance to high-wage industries. After addressing the endogeneity of social networks by using the father-in-law's political identity (determined during the Mao era land reform) as an instrumental variable, we found that the importance of social networks for entering high-wage industries became greater. These findings show that inter-industry wage differentials are at least partly a result of labor market entry barriers due to non-market factors. When we estimated models for the coastal and inland regions separately and controlled for endogeneity by using the IV estimation, we found that social networks as well as education and experience are more important in the coastal region than the inland region. We also noticed that the effects of urban *hukou* identity on industry entry mainly occur in the coastal region. This regional variation shows that non-market factors are distorting the labor market mechanism in the coastal region, probably due to the fast pace of marketization there.

The main policy implication of this paper is: in order to establish fair competition, China should break industry entry barriers in the urban labor market and thereby improve inter-industry wage equalization. Based on our analysis of the CHIPS data of 2002, we conclude that the realization of inter-industry wage equalization would reduce urban income inequality by 5–10%. If non-market entry barriers in the labor market of several monopoly industries can be removed, the type of industry would no longer be an important factor inducing wage differentials (Chen, Wan, and Lu, 2008). After all, it is salutary to implement fair competition policies in the labor market.

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Table 1: Social networks and industry entries in the labor market

	(1) Networks Uncontrolled (OLS)	(2) Networks Controlled (OLS)	(3) Family Background Controlled (OLS)	(4) Ways of Finding Jobs Controlled (OLS)	(5) Family Background Controlled (ordered probit)
Social networks		0.00625^{**}	0.00609^{**}		0.0143^{**}
		(0.00264)	(0.00264)		(0.00618)
Uses social networks during job hunting				0.0381^{**}	
				(0.0155)	
Has local urban *hukou*	0.262^{***}	0.261^{***}	0.260^{***}	0.261^{***}	0.601^{***}
	(0.0556)	(0.0555)	(0.0555)	(0.0555)	(0.129)
Years of education	0.00712^{***}	0.00682^{***}	0.00574^{***}	0.00668^{***}	0.0142^{***}
	(0.00193)	(0.00193)	(0.00197)	(0.00198)	(0.00461)
Years of experience	0.00724^{***}	0.00726^{***}	0.00718^{***}	0.00724^{***}	0.0170^{***}
	(0.00109)	(0.00109)	(0.00110)	(0.00110)	(0.00257)
Age	-0.00660^{***}	-0.00657^{***}	-0.00628^{***}	-0.00623^{***}	-0.0147^{***}
	(0.00117)	(0.00117)	(0.00117)	(0.00117)	(0.00274)
Relative party standing	-0.158^{**}	-0.162^{**}	-0.170^{**}	-0.161^{**}	-0.404^{**}
	(0.0714)	(0.0714)	(0.0715)	(0.0715)	(0.182)
Relative party standing squared	0.179	0.181	0.197^{*}	0.194^{*}	0.483
	(0.117)	(0.117)	(0.117)	(0.117)	(0.309)
Healthy	0.0162^{**}	0.0157^{**}	0.0155^{**}	0.0165^{**}	0.0365^{**}
	(0.00674)	(0.00674)	(0.00674)	(0.00674)	(0.0158)
Single	0.0516	0.0504	0.0600	0.0650	0.133
	(0.0451)	(0.0451)	(0.0452)	(0.0452)	(0.106)
Married	0.0465	0.0454	0.0435	0.0456	0.0957
	(0.0400)	(0.0400)	(0.0400)	(0.0400)	(0.0935)
Male	0.141^{***}	0.141^{***}	0.141^{***}	0.142^{***}	0.333^{***}
	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0259)
Belongs to a minority group	0.0359	0.0350	0.0345	0.0350	0.0793
	(0.0295)	(0.0295)	(0.0295)	(0.0295)	(0.0694)
Father's education (years)			0.00253^{*}	0.00270^{*}	0.00595^{*}
			(0.00143)	(0.00143)	(0.00334)
Father's party membership (Yes=1)			0.0234^{*}	0.0238^{**}	0.0558^{**}
			(0.0120)	(0.0120)	(0.0280)
Father operated a business (Yes=1)			–0.00496	–0.00598	–0.0110
			(0.0199)	(0.0199)	(0.0465)
Ever changed jobs (Yes=1)	-0.104^{***}	-0.106^{***}	-0.106^{***}	-0.111^{***}	-0.247^{***}
	(0.0182)	(0.0182)	(0.0182)	(0.0183)	(0.0422)
Dependency ratio	0.0308	0.0327	0.0381	0.0351	0.0876
	(0.0275)	(0.0276)	(0.0276)	(0.0276)	(0.0645)
Constant	-0.438^{***}	-0.441^{***}	-0.457^{***}	-0.475^{***}	
	(0.106)	(0.106)	(0.108)	(0.108)	
No. of Obs.	9957	9957	9955	9951	9955
Adusted R^2 or pseudo R^2	0.052	0.052	0.053	0.053	0.0406

Note: *, **, *** mean the coefficients are significant at <.10, <.05, and <.01, respectively.

Table 2: Social networks and industry entries in the labor market (IV estimation)

	(3) OLS whole samples	(6) OLS	(7) IV-OLS	(8) First stage
Social networks	0.00609**	0.00650**	0.103	
	(0.00263)	(0.00280)	(0.114)	
Father-in-law's political identity				0.157**
				(0.0648)
Has local urban *hukou*	0.260***	0.278***	0.264***	0.148
	(0.0555)	(0.0571)	(0.0632)	(0.221)
Years of education	.00574***	0.00458**	0.000385	0.0430***
	(0.00197)	(0.00206)	(0.00542)	(0.00795)
Years of experience	0.00718***	0.00752***	0.00769***	–0.00184
	(0.00110)	(0.00113)	(0.00122)	(0.00435)
Age	–0.00628***	–0.00632***	–0.00574***	–0.00638
	(0.00117)	(0.00121)	(0.00146)	(0.00469)
Relative party standing	–0.170**	–0.0931	–0.168	0.751*
	(0.0715)	(0.0995)	(0.138)	(0.384)
Relative party standing squared	0.197*	0.0640	0.130	–0.625
	(0.117)	(0.180)	(0.207)	(0.696)
Healthy	0.00117**	0.0186***	0.0120	0.0687**
	(0.00674)	(0.00704)	(0.0108)	(0.0272)
Single	0.0600			
	(0.0452)			
Married	0.0435	0.0627	0.0486	0.159
	(0.0400)	(0.0730)	(0.0797)	(0.282)
Male	0.141***	0.141***	0.138***	0.0371
	(0.0110)	(0.0116)	(0.0131)	(0.0449)
Belongs to a minority group	0.0345	0.0398	0.0196	0.206*
	(0.0295)	(0.0320)	(0.0417)	(0.124)
Father's education (years)	0.00253*	0.00258*	0.000973	0.0162***
	(0.00143)	(0.00151)	(0.00249)	(0.00583)
Father's party membership (Yes=1)	0.0234*	0.0259**	0.0241*	0.0169
	(0.0120)	(0.0124)	(0.0134)	(0.0481)
Father operated a business (Yes=1)	–0.00496	–0.0105	–0.00469	–0.0536
	(0.0199)	(0.0214)	(0.0238)	(0.0826)
Ever changed jobs (Yes=1)	–0.106***	–0.114***	–0.139***	0.264***
	(0.0182)	(0.0197)	(0.0365)	(0.0760)
Dependency ratio	0.0381	0.0623**	0.0885**	–0.273**
	(0.0276)	(0.0304)	(0.0448)	(0.117)
Constant	–0.457***	–0.562***	–0.592***	0.315
	(0.108)	(0.128)	(0.141)	(0.493)
No. of Obs.	9955	8617	8617	8617
Adjusted R^2	0.053	0.059		0.064

Note: *, **, *** mean the coefficients are significant at <.10, <.05, and <.01, respectively.

Table 3: Regional Comparison of social networks and industry entry in the labor market

	(9) Coastal	(10) Inland	(11) Coastal (OLS, married)	(12) Inland (OLS, married)	(13) Coastal (IV-OLS)	(14) Inland (IV-OLS)
Social networks	0.00677	0.00543*	0.00831*	0.00517	0.173	0.0345
	(0.00458)	(0.00318)	(0.00505)	(0.00332)	(0.151)	(0.171)
Has local urban *hukou*	0.460***	0.0832	0.440***	0.138*	0.404***	0.135*
	(0.0898)	(0.0708)	(0.0924)	(0.0733)	(0.112)	(0.0755)
Years of education	0.0106***	0.00336	0.0102**	0.00203	0.00158	0.000882
	(0.00377)	(0.00224)	(0.00410)	(0.00232)	(0.00922)	(0.00707)
Years of experience	0.0103***	0.00649***	0.0117***	0.00652***	0.0108***	0.00664***
	(0.00237)	(0.00120)	(0.00254)	(0.00122)	(0.00307)	(0.00142)
Age	–0.00976***	–0.00552***	–0.0115***	–0.00508**	–0.00967**	–0.00492**
	(0.00260)	(0.00127)	(0.00279)	(0.00130)	(0.00365)	(0.00161)
Relative party standing	–0.342*	–0.120	–0.316	0.0225	–0.395*	–0.00499
	(0.191)	(0.0766)	(0.197)	(0.112)	(0.240)	(0.196)
Relative party standing squared	0.466	0.151	0.416	–0.108	0.416	–0.0765
	(0.347)	(0.118)	(0.357)	(0.203)	(0.413)	(0.275)
Healthy	0.00448	0.0218***	0.0128	0.0220***	0.00541	0.0195
	(0.0121)	(0.00796)	(0.0129)	(0.00826)	(0.0164)	(0.0163)
Single	0.0237	0.0607				
	(0.0864)	(0.0520)				
Married	–0.0133	0.0731	0.0393	0.0767	0.0103	0.0723
	(0.0782)	(0.0452)	(0.156)	(0.0800)	(0.182)	(0.0846)
Male	0.178***	0.118***	0.189***	0.112***	0.180***	0.111***
	(0.0193)	(0.0131)	(0.0211)	(0.0137)	(0.0257)	(0.0147)
Belongs to a minority group	0.0716	0.0106	0.0827	0.0172	0.00357	0.0150
	(0.0554)	(0.0341)	(0.0619)	(0.0366)	(0.102)	(0.0391)
Father's education (years)	–0.00145	0.00468***	–0.00232	0.00490***	–0.00386	0.00429
	(0.00262)	(0.00167)	(0.00286)	(0.00174)	(0.00360)	(0.00395)
Father's party membership (Yes=1)	0.0399*	0.0125	0.0406*	0.0162	0.0509*	0.0144
	(0.0219)	(0.0140)	(0.0233)	(0.0144)	(0.0286)	(0.0179)
Father operated a business (Yes=1)	0.0179	–0.0176	–0.00608	–0.0119	–0.0195	–0.00761
	(0.0352)	(0.0238)	(0.0393)	(0.0250)	(0.0472)	(0.0356)
Ever changed jobs (Yes=1)	–0.143***	–0.0810***	–0.163***	–0.0846***	–0.233***	–0.0894**
	(0.0314)	(0.0220)	(0.0354)	(0.0233)	(0.0762)	(0.0364)
Dependency ratio	0.0529	0.0304	0.0799	0.0533	0.141*	0.0598
	(0.0483)	(0.0332)	(0.0554)	(0.0358)	(0.0852)	(0.0524)
Constant	–0.599***	–0.151	–0.663***	–0.202	–0.652**	–0.345
	(0.177)	(0.128)	(0.230)	(0.145)	(0.266)	(0.250)
No. of Obs.	3798	6157	3160	5457	3160	5457
Adjusted R^2	0.063	0.048	0.075	0.049	.	0.035

Note: *, **, *** mean the coefficients are significant at < .10, < .05, and < .01, respectively.

Appendix Table 1: Statistical Descriptions of Variables

Variable	No. of Obs.	Mean	S. D.	Minimum	Maximum
Industrial_ranking	9957	0.080	0.529	-1	1
Ever changed jobs	9957	0.093	0.291	0	1
Has local urban *hukou*	9957	0.991	0.095	0	1
Gender (male=1)	9957	1.443	0.497	1	2
Marriage (married=1)	9957	1.916	0.334	1	3
Age	9957	40.550	9.256	1	77
Healthy	9957	3.891	0.822	1	5
Relative party standing	9957	0.096	0.181	0	2.115
Belongs to a minority group	9957	1.040	0.197	1	2
Years of education	9957	11.429	2.986	0	23
Years of experience	9957	20.212	9.680	0	43
Social networks	9957	1.238	2.035	0	24
Uses social networks during job hunting	9957	0.144	0.390	0	9
Father's education (years)	9957	5.549	3.973	0	17
Father's party membership (Yes=1)	9955	1.675	0.468	1	2
Father's party membership (Yes=1)	9955	1.923	0.266	1	2
Dependency ratio	9957	0.374	0.195	0	1

Appendix Table 2: Group Comparison of Social Networks and Father-in-Law's Political Identity

Industry type	Number of people who could help find a job		Father-in-law has undesirable political identity	
Low income	1.104 (0.062)	1.204 (0.024)	0.097 (0.010)	0.124 (0.004)
Medium income	1.218 (0.025)		0.128 (0.004)	
High income	1.262 (0.055)		0.122 (0.008)	

Note: Standard deviation in parenthesis.