Aggregate Implications of Occupational Inheritance in China and India

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Abstract

This paper documents occupational inheritance–interpreted as children inheriting their parents' occupations–in China, India, and other countries. We categorize potential reasons of the prevalence of occupational inheritance in China and India into two main groups: (1) labor market frictions, e.g., household registration system ("hukou"), which ties rural families to agriculture in China, and the caste system, which restricts young workers' occupation choices in India, and (2) barriers to acquiring human capital, e.g., low availability of school education and workplace training. Based on a tractable occupation choice model, counterfactual experiments suggest that if the impediments mentioned above could be reduced to the US level, labor productivity would grow by 62 to 78% in China and over fourfold in India. In addition, China has realized 56 to 68% of this growth potential from the 1980s to 2009.

JEL: D60, D61, E20, O40

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1 Introduction

Occupational inheritance–children inheriting their parents' occupations and more broadly, their occupation status, is very common in many developing countries such as China and India. Sociologists and applied microeconomists have already carried out comparative research on intergenerational occupational transition patterns[1]. However, the existing literature focuses more on establishing facts and examining their implications on inequality, and usually pay more attention to developed countries[2]. In this paper, we want to discuss the implications on efficiency, i.e. productivity, on the macroeconomic level for developing countries. we first systematically document the empirical evidence of occupational inheritance across countries, and then argue that occupational inheritance is an importance channel in creating cross-country differences in per capita output by quantitative exercises. Occupations are linked with specific skill contents, and therefore it is not surprising that patterns of choosing occupations automatically lead to implications for human capital allocation and thus aggregate productivities.

Our first contribution is that we establish cross-country facts about intergenerational occupational transition, especially we correlate occupational inheritance and income level. We use two measures, both the intergenerational occupational mobility (IOM) rate and the Altham statistic, to depict occupational inheritance. According to our findings, workers in poor countries are less likely to move away from their parents' occupations. However, we also find that the average wage ratio between the high-paid occupations and the low-paid occupations are much larger in China and India than in the US, which suggests that Chinese and Indian workers have an even greater incentive to move into higher paying occupations. Greater incentive to move but lower mobility leads to a puzzling contradiction, which suggests

[1]For example, Breen (2004), Erikson and Goldthorpe (1992), Ganzeboom and Treiman (2007), Grusky and Hauser (1984), Long and Ferrie (2013), Treiman and Ganzeboom (2000), and Treiman and Yip (1989). A section in Blanden (2009) provides a short survey on this particular topic.

[2]Two exceptions are Behrman et al. (2001) and Reddy (2015). The former takes care of intergenerational occupational mobility facts in Latin American countries but only classify occupations into the white collar and blue collar due to data limitation, while the latter covers the Indian case.

that in order to start a career in an occupation in which no senior family members have any experience or influence, young workers in developing countries must overcome obstacles much larger than those faced by their counterparts in developed countries. There obstacles may come from different sources, and we classify them into two main categories based on how they would affect the macroeconomy: labor market frictions and barriers to acquiring human capital.

Labor market frictions result in inefficient allocation of human talents. For example in China, household registration ("hukou") ties rural families to agricultural work. In India's case, the caste system groups people into different occupations in specific castes and limits occupation choices, again perpetuating occupational inheritance.

Chinese and Indian workers also face larger barriers to acquire human capital than their US counterparts. China and India lag behind the US in terms of average educational attainment. Meanwhile, poor contract enforcement and binding financial constraints in China and India obstruct workplace training. As a result, workers in China and India are then forced to refer back to senior family members for help, resulting in occupational inheritance.

Except for these two categories of reasons, there is actually another possible channel: structural differences. If occupational inheritance happens more frequently in occupations that are relatively productive and therefore dominant in employment, occupational inheritance would prevail in this economy. One such possibility is that innate talent can be more easily transmitted from parents to children in this economy's dominant occupations. We do not consider such channel to be our target in our quantitative exercises because it roots from the nature of an economy, and we will control for its effects.

In addition, we find that the correlation using IOM rates based on workers' first occupations is much more significant than the correlation using IOM rates based on workers' current occupations. Young workers in poor countries are more likely to start their careers in their parents' occupations than those in rich countries, but this difference gradually fades away when they have more experience. This discovery is novel as far as we know. We do not intend to identify exact reasons behind this phenomenon, but it does shed light on the different situations that young workers face when choosing occupations between developing and developed countries.

The above facts lead to our second contribution. We quantify the aggregate effects of occupational inheritance on per capita output, which provides a new perspective of cross country productivity gap. We use a tractable occupation choice framework from Hsieh, Hurst, Jones, and Klenow (2013, HHJK hereafter), which roots from Roy (1951) and Eaton and Kortum (2002). In this framework, the quality of labor is a product of innate talents and acquired human capital, with human innate talent following an idiosyncratic draw from a Frechet distribution. Heterogeneous individuals choose optimal occupation based on their talent draw and thus determines aggregate productivity.

Our quantitative results suggest that if the barriers to intergenerational occupational mobility could be reduced to the US level, labor productivity would grow by 62 to 78% in China and 456 to 478% in India. In addition, China has realized 56 to 78% of this growth potential from the 1980s to 2009, which indicates that China has made great progress during this period but also imply that it needs to find other sources for sustainable growth going forward.

There is a burgeoning literature using similar framework as in HHJK. The closest research to this paper is Sinha (2014), which also documents high occupational persistence in poor countries but emphasizes the role of financial constraints on inadequate human capital acquiring when discussing the implications on labor productivity.[3] Lagakos and Waugh (2013) use selection as an explanation of enormous cross-country differences in agricultural productivity. Cortes and Gallipoli (2014) evaluate the aggregate costs of occupational mobility in

[3]Both papers are independent research and we know the existence of each other on the job market. Our paper differs from Sinha (2014) in following ways: (1) our paper is about talent misallocation in the generally sense without emphasizing any particular channel such as credit constraints; (2) our quantitative exercises focus on the comparisons between China/India and the US, and especially we compare China before and after the Reform and Opening up policy; (3) the two papers use different datasets, and in this paper we also employ the Altham statistic as a particular measure of intergenerational occupational mobility; (4) the comparison between facts based on the first occupation and the current occupation is unique due to our dataset.

the US, using the Dictionary of Occupational Titles to measure occupation characteristics. Jung (2014) develops a tractable endogenous growth model in which growth comes from better matches between tasks and human talents.

This paper also contributes to the literature on productivity gaps between countries. A strand of existing research focuses on the role of factor input misallocation in creating low TFP, and Restuccia and Rogerson (2013) provide an extensive survey. In a seminal paper of this literature, Hsieh and Klenow (2009) argue that misallocation of capital and labor among different plants leads to TFP loss in China and India. If misallocation at the firm level can be reduced to the level in the US, this would result in a 30 to 50% growth in China's manufacturing TFP and a 40 to 60% growth in India's manufacturing TFP. Our paper indicates that occupational inheritance would lead to an even larger loss in productivity than capital and labor misallocation at the firm level. Acemoglu et al. (2001) and Acemoglu et al. (2012) argue that institutions play a significant role in determining the income across countries. These papers focus on the national and firm/plant level, while our paper targets the most basic unit of production, each individual in the economy. In this sense, our paper is more closely related to Erosa et al. (2010), in which the authors argue that human capital accumulation, typically underprovided in poor countries, significantly magnifies TFP gaps between different countries. These same forces that cause divergence in labor productivity across countries also work through our channel to magnify these effects by influencing individual occupation choice.

The rest of the paper proceeds as follows. We present empirical findings and background information for labor market frictions and human capital accumulation in China and India in Section 2. Section 3 lays out the intergenerational occupation choice model. We discuss data and parameterization procedure in Section 4 and implement quantitative exercises in Section 5. In Section 6, we check robustness, and then conclude in Section 7.

2 Empirical Facts and Background Information

This section presents facts and background information that motivate the paper. First, we present the significant correlation between IOM rates and GDP per capita. We restrict our analysis to the intergenerational occupational transition between fathers and sons for: (1) males are still the majority in the labor force in most countries; (2) limited knowledge about the role of mothers in the process of children's occupation choice; (3) simplicity. Meanwhile, we also investigate whether these results are robust to different specifications and measurements, which in return provides us more information on the process of occupation choice. Second, we report the relationship between Altham statistics and income levels across countries. Lastly, we provide some background information about the labor market frictions and barriers to human capital accumulation in China and India.

2.1 IOM Rates vs. GDP per Capita

In this section, we use the IOM rate as an indicator of intergenerational occupational mobility. Denote by $\pi^L = (\pi_1^L, \pi_2^L, \ldots \pi_M^L)$ the distribution of fathers' occupations. $P = [p_{ij}]_{M\times M}$ denotes the intergenerational occupational transition matrix, where row i corresponds to fathers' occupations and column j corresponds to sons' occupations; p_{ij} is the possibility of a worker choosing occupation j, conditional on the fact that his father workers in occupation i. The IOM rate is defined as:

$$IOM = 1 - \pi^L \cdot diag(P) \tag{1}$$

where $diag(P)$ is the diagonal elements of the transition matrix. By definition, the IOM rate is the proportion of children that choose an occupation different from their fathers. However, It is usually more convenient to think about the percentage of sons that inherit their fathers' occupations, i.e., $(1 - IOM)$, and therefore, equation (1) can be re-written as:

$$1 - IOM = \pi^L \cdot diag(P) \tag{2}$$

We use data from the International Social Survey Programme (ISSP) 2009 (ISSP Research Group 2009)[4] that covers 40 countries and territories in total[5]. We will give more information about the ISSP 2009 in Section 4, but this dataset is especially good for our purposes. First, it uses the International Standard Classification of Occupations 1988 (ISCO88) as the classification system of occupations for all countries, which makes comparisons across countries meaningful. Second, it provides all the necessary information such as the respondent's occupation and the father's occupation. It is worth mentioning that in the ISSP 2009 the question about the respondent's father is "When you were <14-15-16> years old, what kind of work did your father do?" The framing of the survey question, "When you were <14-15-16> years old," is helpful because it restricts the respondent's father's occupation information to a narrowly defined prime age. Third, it provides both the respondent's first occupation and current occupation, which provides interesting comparisons that would be further discussed later. Fourth, as the name suggests, the field work of the ISSP 2009 was carried out around 2009[6] in all participating countries, which removes time variation and makes the data more comparable across countries.

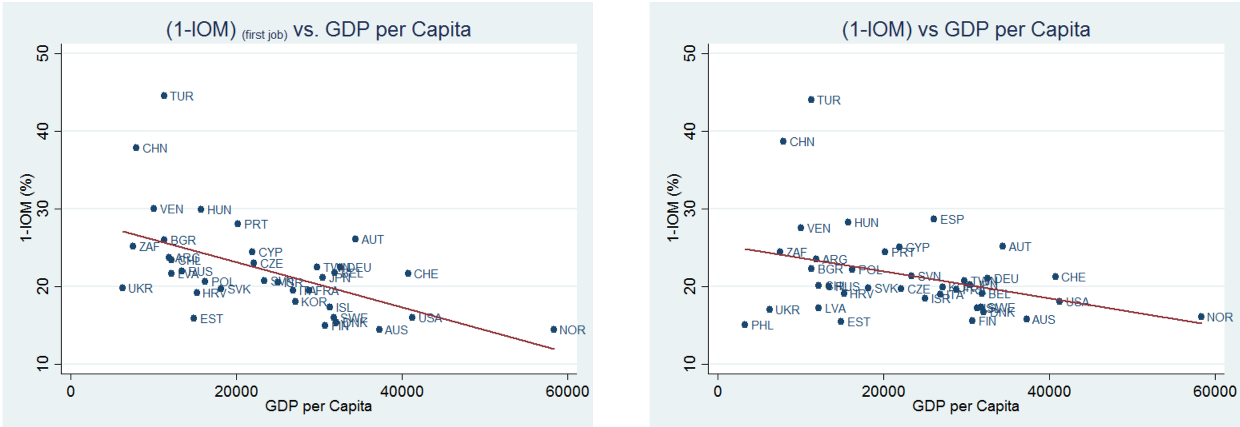
We first calculate $(1-IOM)$ based on the respondent's *first* occupation, and then repeat the same procedures using the respondent's *current* occupation which is our benchmark target. Figure 2.1 present the correlation between $(1-IOM)$ and real GDP per capita based on these two different specifications. Both graphs report a significant correlation between $(1-IOM)$ and GDP per capita; the slopes of the linear fitted line are reported in the first two rows of Table 2.1. According to the first row of this table, the slope for Figure 2.1a is $-2.90 \cdot 10^{-4}$. This implies that if the GDP per capita differs by $40,000 between two countries, we expect the IOM rates to differ by 11.6%.

It is worth mentioning that the GDP per capita correlation for the IOM rate based on the

[4]We sincerely thank Professor Donald Treiman (Department of Sociology, UCLA) for recommending this dataset.

[5]Due to data limitations, we drop to 36 countries and territories in the end.

[6]To be more precise, fieldwork in some countries was carried out in 2008 and 2010. We ignore this small difference in our paper.



(a) First Occupation

(b) Current Occupation

Figure 2.1: $(1 - IOM)$ vs. GDP per Capita

first occupation is much larger than the correlation for the IOM rate based on the current occupation. The implications of the differences between these two graphs is that workers' first occupations, compared with their current occupations, are much more likely to follow their fathers' occupations in poor countries. Potential reasons could be: (1) education in poor countries does not to prepare young workers for occupations different from their fathers well and they have to gain more experience before changing to new occupations, (2) young workers in developing countries face larger barriers when entering new occupations and it takes time to overcome these obstacles, and etc. Identifying the exact reasons is beyond the scope of this paper; however, it is worth emphasizing that even though workers are able to overcome some barriers over time, the negative slope between $(1 - IOM)$ and GDP per capita is still significant and persists. Our quantitative exercises will be based on the current occupation, and therefore our estimates provide a lower bound for the potential gains from removing barriers to intergenerational occupational mobility for China and India.

Unfortunately, the ISSP 2009 data does not include India. In order to include India in our analysis, we use data from the IPUMS International (Minnesota Population Center 2014) dataset, which we will discuss in detail in Section 4. In fact, the IPUMS International data also provides additional data for China as well; however, the IPUMS International data only provides the respondents' current occupations. Therefore, we simply calculate $(1 - IOM)$ from the IPUMS International data and put all the data points on top of Figure 2.1b and produce Figure 7.3 in Appendix C. The IPUMS International data provides five extra data points: China in 1982 and 1990, and India in 1993, 1999, and 2004. It can be seen that these observations all display very high $(1 - IOM)$ rates. This suggests that $(1 - IOM)$ has decreased dramatically for China from the 1980s to 2009. Since these five extra data points are from a different dataset, we do not include them when calculating the correlation between $(1 - IOM)$ and GDP per capita.

		Coefficient	t statistic
IOM Rates	First Occupation	-2.90e-04	-3.75
	Current Occupation	-1.75e-04	-2.21
	First Occupation (w/o Farmers)	-2.53e-04	-3.39
	Current Occupation (w/o Farmers)	-1.27e-04	-1.75
Altham Statistics	First Occupation	-3.13e-04	-1.55
	Current Occupation	-1.95e-04	-0.97

Table 2.1: Regression Results

One might be concerned that sons of farmers are also more likely to be farmers, and the labor force in poor countries usually has a higher proportion of farmers. As a result, the correlation between $(1 - IOM)$ and GDP per capita may simply be a result of a large proportion of farmers in the labor force. It is worth emphasizing that the barriers that impede sons of farmers from moving to new occupations also fits our topic. However, still we would like to know to what extent farmers drive these results. A simple solution is to remove all farmers from the data and reproduce the results. The graphs look the same, with similarly significant and negative slopes, however on a smaller magnitude, which can been seen in Figure 7.1 and 7.2 in Appendix C and in Table 2.1. Farmers do explain part of the occupational inheritance phenomenon, but there is still much to be explained by all the other occupations.

2.2 Altham Statistics vs. GDP per Capita

The $(1 - IOM)$ rate is a product of the distribution of fathers' occupations and the diagonal elements of the intergenerational occupational transition matrix; therefore, it alone cannot disentangle *interaction* from *prevalence* as discussed in Long and Ferrie (2013). Prevalence refers to the difference arising from fathers' occupational distribution, while interaction refers to the conditional probability of sons' switching to new occupations from fathers' occupations. The problem about farmers in the previous subsection is also about excluding the effect of prevalence from interaction. Although both effects fit our topics, we follow Long and Ferrie (2013) to further explore empirical facts.

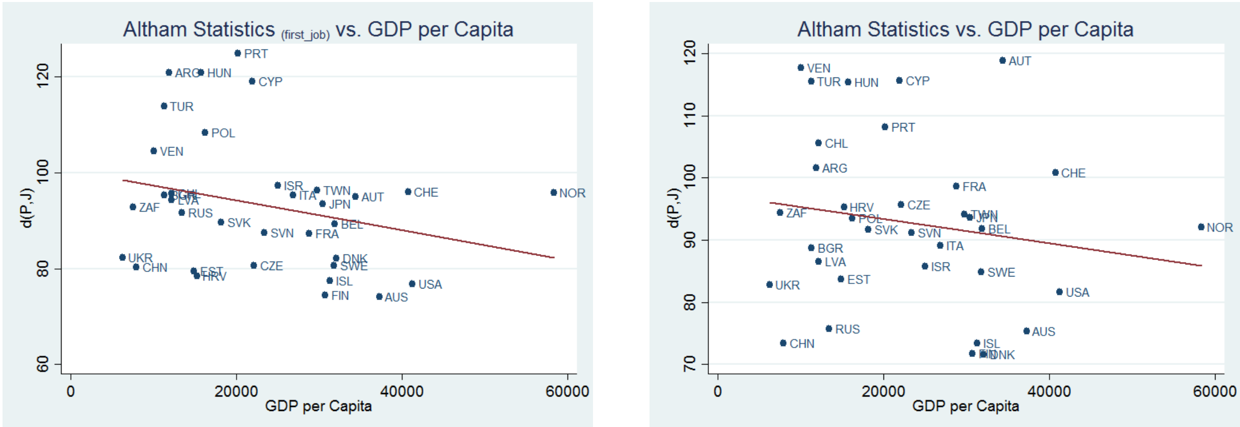
The interaction effect is determined by the intergenerational occupational transition matrix. In order to directly analyze the properties of the transition matrix, Long and Ferrie (2013) propose to use the Altham statistic. For any two matrices $P = \{p_{ij}\}_{r\times s}$ and $Q = \{q_{ij}\}_{r\times s}$, the Altham statistic is defined as:

$$d(P,Q) = [\sum_{i=1}^{r}\sum_{j=1}^{s}\sum_{l=1}^{r}\sum_{m=1}^{s} |log(\frac{p_{ij}p_{lm}q_{im}q_{lj}}{p_{im}p_{lj}q_{ij}q_{lm}})|^2]^{\frac{1}{2}} \tag{3}$$

The Altham statistic $d(P,Q)$ represents the distance between the row-column associations between matrices P and Q. In our case, P is the transition matrix for each country, and Q is the benchmark matrix, i.e., a matrix with all elements to be 1. The economic interpretation of Q is that children from any type of family would have equal opportunity of entering any occupation. In addition, here $r = s$ because the transition matrix is square.

To further understand the mathematical implications of the Altham statistic, we would like to transform equation (3) into a more straightforward form. Define $a_{ij} = log(\frac{p_{ij}}{q_{ij}})$. Following some derivations as in Appendix B, we re-write equation (3) as:

$$d(P,Q)^2 = 4rs \cdot \sum_i \sum_j [a_{ij} - \underbrace{\frac{\sum_m \sum_l a_{ml}}{rs}}_{matrix\,mean} - \underbrace{(\frac{\sum_m a_{mj}}{r} - \frac{\sum_m \sum_l a_{ml}}{rs})}_{column\,deviation} - \underbrace{(\frac{\sum_l a_{il}}{s} - \frac{\sum_m \sum_l a_{ml}}{rs})}_{row\,deviation}]^2 \tag{4}$$



(a) First Occupation

(b) Current Occupation

Figure 2.2: Altham Statistics vs. GDP per Capita

According to equation (4), the items at the core of the equation are: $a_{ij} - matrix\, mean - column\, deviation - row\, deviation = residual$. That is, $d(P, Q)^2$ is a sum of squares of the residual of the matrix $\{a_{ij}\}$. In other words, the Altham statistic $d(P, Q)^2$ is the F test statistic of a two-way analysis of variance (ANOVA) between the transition matrix P and the benchmark matrix Q. The two-way ANOVA F statistic is able to detect the interaction effects between the row variable and the column variable. By calculating $d(P, Q)$, we know to what extent the rows and columns of P are associated. Following a simple calculation, one can find that $d(Q, Q) = 0$. That is, we should find a smaller $d(P, Q)$ for countries where sons are relatively freer to deviate from their fathers' occupation.

We present the relationship between Altham statistics and GDP per capita in Figure 2.2. Again, two subfigures are based on respondents' first occupations and current occupations respectively. As before, we also use data from IPUMS International to calculate Altham statistics for China in 1982/1990 and India in 1993/1999/2004, and they appear in red in Figure 7.4.. The slopes of the regression lines are listed in Table 2.1.

According to Figure 2.2, the correlation between Altham statistics and GDP per capita is negative but on the margin of being significant ($t = -1.55$). This suggests that interaction is not the only determinant of differences in IOM rates between different countries. Moreover, India shows very high Altham statistics in multiple years compared with China. This implies that, regardless of their family background, it is always very difficult for workers in India to transfer from their fathers' occupations to new occupations. This partly explains why in our counterfactual experiment, the effect of reducing barriers in India is much larger than that in China.

2.3 Occupational Wage Ratios

We have established that intergenerational occupational mobility is small in China and India than in the US. However, this could simply be because workers have less incentives to move between occupations in those countries. One such possibility is that occupational wage difference is much smaller in China and India than that in the US.

	India	China	US
Wage Ratios	55.6	12.0	3.9

Table 2.2: Maximum Occupational Wage Ratios

To examine this possibility, we calculate the ratio between the average wages of the highest-paid occupation and the lowest-paid occupation in India, China, and the US, and list them in Table 2.2 (more occupational wage information for these countries can be found in Table 4.3). Contradicting to our hypothesis, the ratio is much higher in India and China than in the US. Thus, we document a puzzling contradiction: on the one hand, greater occupational wage ratios imply an even greater incentive to move into higher paying occupations in China and India, while on the other hand, we observe lower mobility in those countries. This suggests that young workers in China and India must overcome obstacles much larger than those faced by young workers in the US if they want to work in an occupation in which no senior family members have any experience or influence.

2.4 China and India

In this section, we discuss our target countries, China and India, in detail. We first explain why we target China and India, and then introduce some background information on labor market frictions and barriers to human capital accumulation in China and India.

2.4.1 Why China and India?

In this paper, we focus on China and India, although occupational inheritance is a global phenomenon for many developing countries. We choose China and India for several reasons. First, both China and India are large developing countries that are often compared with the US. Thus, we do not need to worry about problems such as economy of scales and extreme occupation distributions. Second, both China and India are populous countries, such that a low productivity problem in these countries has great implications for global poverty. Third, the comparison between China and India is very interesting in itself. Both countries have a very long history and have developed very unique socioeconomic conventions that have important implications for occupational inheritance. As discussed in Section 2.1, India shows very high Altham statistics, while the overall IOM rate in China is slightly higher. In fact, India also suffers from a large difference in wages between high-paid occupations and low-paid occupations. All of these elements in the occupational inheritance phenomenon lead to a much larger productivity loss in India than in China. Lastly, we intend to focus on China and India to make our results comparable to Hsieh and Klenow (2009). Our results suggest that occupational inheritance is an even greater problem for China and India than factor input misallocation at the firm level.

2.4.2 Labor Market Frictions in China and India

Labor market frictions result in inefficient allocation of human talents, which hurt aggregate productivity. In China, major sources of labor market frictions are "hukou" and "guanxi," while in India the caste system restricts occupation choices.

The "hukou" system officially registers each individual's information, such as name, parents, spouse, date of birth, and residence. However, what is most important is that the "hukou" system also provides dual classification of Chinese people (Chan and Zhang 1999). The first classification is the unique permanent residence of an individual and the second is the rural/urban or agricultural/nonagricultural classification. The first classification hinders workers' migration, and workers working in an area different from their permanent residence could be subject to repatriation. The second classification ties rural families to agricultural work. The "hukou" system limits farmers' choices to move to new areas with different jobs; as a result, rural families are forced to work in agriculture generation after generation.

"Guanxi", which translates to social networks or social connections, plays a role almost everywhere in China (See Gold et al. 2002 for a comprehensive introduction), and it is not surprising that it is important in the job search process. According to Bian and Zhang (2001), 75% of new entrants and 80% of current employees that changed jobs relied on "guanxi" in the 1990s Chinese labor market. Bian (2002) argues that, "Indeed, guanxi networks were found to promote job and career opportunities for guanxi users, while constraining those who are poorly positioned in the networks of social relationships." This description from the perspective of sociologists clearly echoes the idea of economists that "guanxi" leads to the inefficient allocation of talent.

The Reform and Opening-up policy has relaxed the enforcement of the "hukou" system. In fact, hundreds of millions of Chinese farmers migrate from inland to coastal areas, where the quickly growing industry needs new labor. In addition, the fast growing market economy on the coastal region in China has mitigated the "guanxi" problem. Private firms facing fierce international competition are usually unwilling to accept unqualified workers simply due to "guanxi." These are all underlying reasons for China's improved intergenerational occupational mobility since the 1980s.

For the Indian case, the caste system began as a classification of occupations around 3000 years ago (Deshpande 2000). It categorizes people into four varnas (ranks or castes), i.e., Brahmins, Kshatriyas, Vaishyas and Shudras, and the untouchable group. Each caste consists of many subcastes. Castes are highly related to occupations. Working in certain occupations is directly correlated with membership of certain castes, and many castes work mainly in one specific occupation (Mayer 2013). The definition of the caste system is well known for limiting occupation choices. It is therefore not surprising that we find unusually high IOM rates and Altham statistics for India in the previous section.

There are other forms of labor market frictions that can lead to inefficient allocation of talent, such as non-monetary payoffs to different occupations. The Chinese have traditionally placed blue collar jobs beneath white collar jobs, such that being a blue collar worker is a significantly negative signal on the marriage market. The effects of this type of discrimination can be conceptualized as labor market frictions in our model, although it is difficult to measure in the quantitative exercise. Another potential labor market friction is incomplete information. Provided with only partial information, agents on the labor market are not able to optimally choose their occupations as in the complete information case. A particular example fitting this paper is that children may grow up with relatively more information about their parents' occupations but have less information about other occupations, which their talents may better fit. In the end, these children choose their parents' occupations as their own instead of choosing the best occupations to fit their talents. If information in developed countries is more easily available than that in developing countries, this also leads to a positive correlation between occupational inheritance and GDP per capita.

2.4.3 Human Capital Accumulation in China and India

For the purpose of our discussion, we further decompose the process of acquiring human capital into two parts: general academic schooling and occupation-specific training, e.g. vocational education in upper secondary schools and workplace apprenticeship.

The quantity of education received by an average individual in developing countries is usually smaller than that in developed countries. We produce Table 2.3 based on data from

Barro and Lee (2013). The average educational attainment for the population aged 25 and older in 2000 is 12.93 years in the US, 6.47 years in China, and 4.41 years in India. The difference in college education which is especially important in deciding occupations, would be even larger between these countries. The average years of tertiary schooling attained for populations aged 25 and older in 2000 is 1.57 in the US, 0.14 in China, and 0.26 in India. However, it is worth mentioning that the quantity of education received for an average individual in both China and India has been increasing over time. Average years of schooling has increased by 2.6 years for China and by 2.53 years for India since 1980.

	India	China	US
Average years of schooling	4.41	6.47	12.93
Average years of tertiary education	0.26	0.14	1.57

Table 2.3: Educational Attainment in 2000 (Source: Barro and Lee 2013)

In terms of vocational school education, China has improved dramatically during past decades, while India still falls behind. OECD (Kuczera et al. 2010) reports that in 2009, China had about 20 million students in vocational schools, which is about half of the total enrollment in upper secondary education. The Chinese government has recently introduced policies to boost upper secondary vocational education, including financial aid to students in vocational schools. However, it is worth mentioning that China made these achievements only in the past few years, and the total admissions of upper secondary vocational school were still less than 4 million in 2001. Considering the fact that vocational school usually takes 2 to 3 years in China, this would mean the total number of students in vocational schools was around 10 million in 2001, which is only half of the number in 2009. However, the quality of vocational schools is questionable in China. Dou (2014) claims that: "In the vast majority of vocational education schools in China, kids are not learning anything...we found dropout rates of 50% in the first two years of these programs." Part of the reason for the low quality of vocational schools in China, especially in poor areas, is that the funding of vocational education partly comes from provincial and city governments whose financial abilities vary according to local economic conditions. Moreover, vocational education in

China also suffers from a lack of quality evaluations and a shortage of teachers.

Regarding India, The World Bank (2007) reports that vocational schools enroll less than 3% of the potential secondary enrollment population, which is far from adequate.

Data on workplace training is limited for both China and India. The Chinese government actively encourages workplace training, but there are few quality standards. There are no formal regulations that regulate workplace training that have been well enforced. Similarly, India also has a "weak non-public training market" except in the ICT sector (The World Bank 2007). Workplace training inevitably involves investments from employers to employees and contracts between trainers and trainees. However, a poor judiciary system and binding financial constraints in developing countries will always work against a socially efficient level of workplace training.

3 Model

There is a continuum of individuals in each generation, and each of them has one offspring. Each individual is born with innate talent $\epsilon = (\epsilon_1, \epsilon_2, \ldots, \epsilon_i, \ldots, \epsilon_M)$ across occupations that is determined by an idiosyncratic draw, and chooses his occupation $j \in J$, where $J = \{1, 2, \ldots, M\}$. Each individual lives one period, but we further decompose it into two sub-periods to distinguish between the period of accumulating human capital ("childhood") and the period of work ("adulthood"). Accumulating human capital in childhood costs time and resources, but also leads to a higher output in adulthood. We denote by s the schooling time and therefore $(1-s)$ is the leisure time, and we denote by e the expenditure of acquiring human capital. Each individual chooses his occupation and decides the amount of time and resources for accumulating human capital in order to maximize his own welfare. Father's occupation (denoted by i) matters in the human capital accumulation process and we group different workers based on i. We also consider the friction (denoted by τ) in the labor market. Consumption is denoted by c, and w is the wage per unit of efficiency labor.

In this model, innate talent ϵ is public information and determines an individual's state jointly with i, i.e., the group. Acquired human capital h is produced using schooling time input s and resource input e with a Cobb-Douglas production function $h = \delta_{ij} s^{\phi} e^{\eta}$. The coefficient of human capital acquirement δ_{ij} depends on the individual's group i, i.e., father's occupation, and his own occupation j.

The individual maximization problem can be written as:

$$\max_{j \in J, c_{ij}, s_{ij}, e_{ij}} \quad U_{(\epsilon,i)}(j) = log(1 - s_{ij}) + \beta log(c_{ij}) \tag{5}$$

$$s.t.\ c_{ij} = (1 - \tau_{ij}) \cdot w\epsilon_j h_{ij} - e_{ij} \tag{6}$$

$$h_{ij} = \delta_{ij} s_{ij}^{\phi_j} e_{ij}^{\eta} \tag{7}$$

Innate talents are drawn from a Frechet distribution as in Eaton and Kortum (2002):

$$\Lambda_i(\epsilon) = exp\{-[\sum_{j=1}^{N} (T_{ij} \epsilon_j^{-\theta})]^{1-\rho}\} \tag{8}$$

The parameter T_{ij} governs the location of the distribution: a larger T_{ij} implies a larger probability of high talent in occupation j for group i. The parameter ρ governs the correlation between talents across different occupations for an individual.

The total amount of efficient labor supply in occupation j thus can be written as:

$$H_j = \sum_{i=1}^{M} \pi_i^L p_{ij} \cdot E_i[h_{ij}\epsilon_{ij}|j] \tag{9}$$

There is a representative firm that hires all occupations of workers and produces final goods according to the CES production function:

$$\max_{j,c,s} \quad Y - \sum_{j=1}^{M} w_j H_j \tag{10}$$

$$s.t.\ Y = \{\sum_{j=1}^{M} (A_j H_j)^{\frac{\sigma-1}{\sigma}}\}^{\frac{\sigma}{\sigma-1}} \tag{11}$$

where A_j is the occupation-specific productivity.

Definition of Competitive Equilibrium:

Given productivity A_j, human capital accumulation coefficient h_{ij}, and labor market friction τ_{ij}, the competitive equilibrium is a set $\{c_{ij}, s_{ij}, p_{ij,} w_j, H_j\}$ such that:

(1) Given innate talent draw ϵ, father's occupation i, and market wage w_j, each individual chooses the optimal occupation i, optimal consumption c_{ij}, and optimal schooling s_{ij} for the individual maximization problem.

(2) Given productivity A_j and market wage w_j, H_j solves the representative firm's maximization problem.

(3) Labor market clears in each occupation.

(4) Goods market clears.

Model Solution

Due to the properties of the Frechet distribution, this model has an analytical solution. We present key equations here and further details can be found in Appendix A.

Based on the individual maximization problem, we can solve for each element in the transition matrix P:

$$p_{ij} = \frac{\psi_{ij}^{\theta}}{\sum_k \psi_{ik}^{\theta}} \tag{12}$$

$$\psi_{ij} = \delta_{ij}(1-\tau_{ij}) T_{ij}^{1/\theta} w_j s_j^{\phi_j} (1-s_j)^{\frac{1-\eta}{\beta}} \tag{13}$$

The average quality and average wage of workers from group i in any occupation is therefore:

$$E_i[h_{ij}\epsilon_{ij}|j] = \frac{1}{w_j(1-\tau_{ij})} \eta^{\frac{1}{1-\eta}} (1-s_j)^{-\frac{1}{\beta}} (\sum_k \psi_{ik}^{\theta})^{\frac{1}{\theta}} \cdot \Gamma(1 - \frac{1}{\theta(1-\rho)(1-\eta)}) \tag{14}$$

From equation (14), we can solve for the average wage for each occupation and each group:

$$\begin{aligned} INC_{ij} &= (1-\tau_{ij})w_j E_i[h_{ij}\epsilon_j|j] \\ &= \eta^{\frac{1}{1-\eta}}(1-s_j)^{-\frac{1}{\beta}}(\sum_k \psi_{ik}^{\theta})^{\frac{1}{\theta}} \cdot \Gamma(1-\frac{1}{\theta(1-\rho)(1-\eta)}) \end{aligned} \tag{15}$$

Note that equation (15) has important implications for the inter-occupation wage ratios and the inter-group wage ratios. Holding group i constant, we reach equation (16) by comparing average sons' income for different occupations. Holding sons' occupations j constant, we reach equation (17) by comparing average income of workers from different groups.

$$\frac{INC_{ig}}{INC_{ih}} = \frac{(\sum_k \psi_{kg}^{\theta})^{\frac{1}{\theta}}}{(\sum_k \psi_{kh}^{\theta})^{\frac{1}{\theta}}} \tag{16}$$

$$\frac{INC_{kj}}{INC_{fj}} = (\frac{1-s_k}{1-s_f})^{-\frac{1}{\beta}} \tag{17}$$

Equation (16) suggests that the wage ratios of different occupations inside a group are constant across all groups; equation (17) suggests that the wage ratios across different groups are constant across all occupations.

Combining equations (12) and (16) and define $\kappa_{ij} = [\delta_{ij}(1-\tau_{ij})]^{-1}$, we reach a key equation:

$$\frac{\kappa_{hj}}{\kappa_{ij}} = \frac{\delta_{ij}(1-\tau_{ij})}{\delta_{hj}(1-\tau_{hj})} = (\frac{T_{hj}}{T_{ij}})^{-\frac{1}{\theta}} \cdot (\frac{INC_{hj}}{INC_{ij}})^{-(1-\eta)} \cdot (\frac{p_{hj}}{p_{ij}})^{-\frac{1}{\theta}} \tag{18}$$

κ is an aggregate measure of labor market friction and human capital barriers. It will determine the intergenerational occupational transition matrix and therefore the next generation's distribution of occupations. Observed data cannot distinguish the difference between δ_{ij} and $(1-\tau_{ij})$. Therefore, our quantitative exercises will continue by assuming two polar cases, that is, the case that $\tau_{ij} = 0$ and the case that $\delta_{ij} = 1$.

4 Data and Parameterization

We feed two sets of data into the model to perform quantitative exercises. The first comes from China and US Censuses and the Indian Employment Survey from the IPUMS International. This data includes China's 1982 and 1990 Censuses, the Indian Employment Survey for 1993, 1999, and 2004, and US Census data from 1990, 2000, 2005, and 2010. The second dataset comes from the ISSP 2009.

Both Chinese Censuses in 1982 and 1990 interviewed 1% of the population, which includes 10,039,191 observations in 1982 and 11,835,947 observations in 1990. The Indian Employment Surveys include 564,740 observations in 1993, 596,688 observations in 1999, and 602,833 observations in 2004. The US Census data includes 5% percent of the population for 1990 and 2000 and 1% for 2005 and 2010. That is, we have 12,501,046 observations in 1990, 14,081,466 observations in 2000, 2,878,380 observations in 2005, and 3,061,692 observations in 2010, respectively. We need such large data to estimate the intergenerational occupational transition matrix. There are M^2 elements in the transition matrix, and therefore, on average, we have only $1/M^2$ of the total number of observations to estimate each cell. It could be a potential problem because the occupation distribution is not evenly distributed.

The variables of interest are: respondent's occupation, occupation of respondent's father, and respondent's income. The India and US data provide all of the information needed for our purpose. However, the Chinese Census data does not provide any income information. As a result, we refer to the ISSP 2009 for more information.

ISSP is an annual program of cross-country surveys on various topics of social science research. The topic of the ISSP 2009 was social inequality, which fits our interests in this paper. There are 40 countries and territories in this data (including China and the US, but not India) and the total sample size is 54,733. The size of the ISSP data is relatively small, and therefore we choose the IPUMS International data as our benchmark. However, the ISSP data is still very useful to us for two reasons: (1) we can find the income information for China in the ISSP 2009; (2) we will use the ISSP 2009 to calculate the productivity gain for China from the 1980s to 2009.

The occupation classification follows ISCO88. ISCO88 has a hierarchical structure with 10 major groups (1-digit level), 28 sub-major groups (2-digit level), 116 minor groups (3-digit level), and 390 unit groups (4-digit level). For all data, we use the ISCO88 1-digit occupation classification. There are 10 occupations at this level, but we drop "Armed Force" because it is difficult to measure its output and in many countries, being a soldier is only a temporary occupation. The detailed 1-digit ISCO88 is listed in Table 7.1 of Appendix C.

We use four sets of data to parameterize the whole model: (1) intergenerational occupational transition matrix $P = \{p_{ij}\}$; (2) average occupation wage $\{INC_i\}$; (3) average wage ratios across all groups $\frac{INC_{kj}}{INC_{fj}}$; and (4) average schooling in one particular group (i.e. farmers). These four sets of data include $M(M-1)$, M , $M-1$, and 1 moments, respectively. In total, we use $M(M+1)$ moments for the estimation process.

		Son's Occupation								
		1	2	3	4	5	6	7	8	9
Father's Occupation	1	0.0074	0.0493	0.1265	0.0740	0.0985	0.2345	0.2658	0.0868	0.0571
	2	0.0057	0.1062	0.1275	0.0573	0.0777	0.2245	0.2738	0.0734	0.0538
	3	0.0047	0.0266	0.0886	0.0352	0.0695	0.4206	0.2466	0.0652	0.0431
	4	0.0075	0.0376	0.1101	0.0905	0.1198	0.1259	0.3337	0.1035	0.0713
	5	0.0058	0.0110	0.0400	0.0184	0.1871	0.3944	0.2412	0.0583	0.0438
	6	0.0012	0.0019	0.0086	0.0014	0.0053	0.9074	0.0599	0.0091	0.0052
	7	0.0022	0.0097	0.0345	0.0146	0.0553	0.3480	0.4086	0.0687	0.0584
	8	0.0019	0.0131	0.0427	0.0183	0.0733	0.2973	0.3139	0.1619	0.0777
	9	0.0092	0.0177	0.0512	0.0246	0.0847	0.2213	0.3771	0.1007	0.1133

Table 4.1: China: Intergenerational Occupational Transition Matrix

We pool data from the 1982 and 1990 Chinese Censuses to generate Table 4.1 and we pool the 1993, 1999, and 2004 Indian Employment Survey data to generate Table 4.2. We pool this data to eliminate short term fluctuations and because there is no significant difference between datasets. It is worth mentioning that the transition from farmer to farmer (cell (6,6)) is very high in both China and India. We also report the intergenerational occupational transition matrix for the US in Table 7.2 in Appendix C.

We also need the average wages for each occupation in China, India, and the US. As

		Son's Occupation								
		1	2	3	4	5	6	7	8	9
Father's Occupation	1	0.5959	0.0444	0.0152	0.0248	0.0687	0.0815	0.0861	0.0283	0.0550
	2	0.1432	0.2654	0.0409	0.0588	0.0479	0.2996	0.0751	0.0335	0.0358
	3	0.1232	0.0905	0.2685	0.0606	0.0934	0.1424	0.1184	0.0481	0.0549
	4	0.1368	0.1251	0.0463	0.1570	0.0717	0.2410	0.1283	0.0430	0.0508
	5	0.0605	0.0413	0.0159	0.0337	0.3976	0.1389	0.1456	0.0589	0.1075
	6	0.0417	0.0272	0.0077	0.0102	0.0154	0.7381	0.0564	0.0228	0.0806
	7	0.0335	0.0246	0.0109	0.0185	0.0481	0.0998	0.6135	0.0489	0.1023
	8	0.0531	0.0347	0.0163	0.0375	0.0881	0.1108	0.1996	0.3143	0.1455
	9	0.0221	0.0085	0.0041	0.0075	0.0385	0.1195	0.1045	0.0329	0.6623

Table 4.2: India: Intergenerational Occupational Transition Matrix

Occupation	1	2	3	4	5	6	7	8	9
China	47143	23433	20955	16649	14506	3932	13369	15664	14821
India	50	495	505	715	236	12.87	170	263	173
US	20844	20135	14874	8142	6105	5301	14203	11925	6197

Table 4.3: Average Wages across Occupations

mentioned earlier, IPUMS data provides wage information for India and the US, while ISSP provides wage information for China. Average occupational wages are listed in the following table. For China, data is reported as the annual occupational income in CNY; for India, it is reported as the weekly wage and salary income in INR; for the US, it is reported as the yearly wage and salary income in USD.

We also need average income based on fathers' occupations, or groups. Based on equation (15), we know that the model implies that the income ratio between different groups is constant across occupations. We denote the average group wage factor by $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_M)$. We normalize $\lambda_6 = \lambda_{farmer} = 1$, that is, we choose workers with fathers who are farmers as the base group.

$$\begin{aligned} \frac{INC_g}{INC_h} &= \frac{\sum_j p_{gj} w_j \lambda_g}{\sum_j p_{hj} w_j \lambda_h} = \frac{\lambda_g}{\lambda_h} \frac{\sum_j p_{gj} wage_j}{\sum_j p_{hj} wage_j} \\ \Rightarrow \frac{\lambda_g}{\lambda_h} &= \frac{INC_g}{INC_h} \frac{\sum_j p_{hj} wage_j}{\sum_j p_{gj} wage_j} \end{aligned} \tag{19}$$

The symbol $wage_j$ is simply the average income for occupation j, while INC_g is the average income for group g. According to equation (19), the average group wage ratios observed in the data are weighted averages of occupational wages multiplied by occupation-specific λ. We can solve for all λ using equation (19), given that the base group $\lambda_6 = \lambda_{farmer} = 1$.

Parameterization

Our calibration process largely follows HHJK. We need $\{\theta, \rho, \eta\}$ to govern the distribution of talents, since the distribution of human talents is not observable and any calibration or estimation process inevitably involves some arbitrary choices. To maintain comparability across papers using this framework, we simply borrow parameters from HHJK, that is, $\theta = 4.5867$, $\rho = 0.0930$, $\eta = 0.25$. According to equation (17), β determines the Mincerian return. A survey of the Mincerian return in China suggests estimation results starting from 3.29%[7] in Johnson and Chow (1997), 10.24% in Zhang (2011), and 17.26% in Awaworyi and Mishra (2014). We choose the level $\beta = 0.693$ to match the Mincerian return 12.7% in the US as the benchmark. We will implement further robustness checks on β in Section 6. We assume the distribution of talents are constant across both generations' occupations, that is, $T_{ij} = 1$ for now, and will relax this assumption in Section 5.3. We choose $\sigma = 3$ as a benchmark.

We want to infer the aggregate measure of the previously discussed impediments, matrix $\{\kappa_{ij}\}_{M\times M}$, for China, India, and the US. We consider these $\{\kappa_{ij}\}_{M\times M}$ as the deep parameters that distinguish developed countries from developing countries. The estimation of $\{\kappa_{ij}\}_{M\times M}$ involves equation (18), which uses elements in the intergenerational occupational transition matrix and wage information as inputs. We calculate average years of schooling in China and India using IPUMS data for farmers, which leads to 4.8 years and 5.2 years respectively. We then solve for all s using equation (17) and for all ϕ using equation (20) in Appendix A. Finally, we pin down occupation-specific A_j to clear all occupation-specific labor markets.

[7] To be precise, 3.29% in urban area and 4.02% in rural area.

5 Quantitative Exercises

Our counterfactual experiment is intended to check to what extent the impediments to intergenerational occupational mobility hurt efficiency. In the benchmark case, we aim to measure the gains of labor productivity in China and India if these impediments could be reduced to the US level. In the implementation, we keep China and India's calibrated values for $\{A, T, s, \phi\}$ fixed, but we replace aggregate measures of impediments, i.e., κ_{CN} and κ_{IN}, by the US value κ_{US}. It is worth emphasizing that we do not directly replace China or India's IOM rates by the US counterpart, because doing this would ignore the fundamental structrual differences between economies.

In total, we complete three sets of quantitative exercises. In Section 5.1, we carry out the benchmark case. In Section 5.2, we calculate the labor productivity gain for China by reducing the impediments to intergenerational occupational mobility from the 1980s to 2009. So far we have been assuming that $T_{ij} = 1$ for our quantitative exercises throughout the paper, i.e., we assume sons' innate talents are ex ante the same across groups and occupations. We relax this assumption in Section 5.3 to see to what extent our results depend on this assumption. Recall that $\kappa = [\delta \cdot (1 - \tau)]^{-1}$ and we cannot discriminate between δ and $(1 - \tau)$ in the data using this framework; thus, we examine two polar cases, $\tau_{ij} = 0$ and $\delta_{ij} = 1$. Therefore, for each set of quantitative exercises, we have two groups of results corresponding to the two polar cases.

5.1 Counterfactual Experiments

We normalize $\kappa_{ii} = 1$ for all i, i.e., we assume when sons inherit their fathers' occupations, the impediments they face are normalized to 1. We want to check the total output of the economy under the new parameters and calculate the gains from this experiment. To achieve this goal, we have to solve for $\{w_c, P_c\}$ where subscript c means "counterfactual."

The results of the counterfactual experiments are listed in Table 5.1. These results indi-

	$\tau_{ij} = 0$	$\delta_{ij} = 1$
China	61.61%	78.40%
India	456.12%	478.81%

Table 5.1: Benchmark: Productivity Gains

cate that both China and India can gain by a large magnitude by reducing the impediments to intergenerational occupational mobility. Comparing these two countries, we find that the gain for India is especially large. According to our previous empirical results, we can attribute this gain to the following reasons: (1) India's very high Altham statistics, i.e., it is very unlikely for Indian workers to move to a new occupation, regardless of their fathers' occupations; and (2) the wage ratios between high-paid occupations and low-paid occupations are much larger in India.

5.2 Accounting for China: the 1980s - 2009

As discussed in previous sections, China has made significant improvements in several dimensions over the past decades. First, China's Reform and Opening-up policy has relaxed constraints such as "hukou" (household registration) that tied farmers to field work and restricted internal migration, and as a result, many young farmers move to coastal cities to work in new occupations. Second, the quick expansion of the market economy on the coastal region gradually mitigated the "guanxi" problem. Compared with state-owned enterprises, private firms facing intense international competition are less willing to hire simply because of "guanxi". Due to the expansion of the market economy, the relative proportion of state-owned enterprises has decreased dramatically since the 1980s. Third, China has improved general academic and vocational school education as discussed in Section 2.2.3.

In order to examine to what extent China has gained through reductions in occupational inheritance, we again use data from the ISSP 2009 and calculate the intergenerational occupational transition matrix as in Table 5.2. We follow the same steps as in Section 5.1. We keep the calibrated values $\{A, T, s, \phi\}$ fixed for China in the 1980s, but we feed in the

		Son's Occupation								
		1	2	3	4	5	6	7	8	9
Father's Occupation	1	0.1250	0.2083	0.0952	0.0476	0.2083	0.0774	0.0893	0.0595	0.0893
	2	0.0424	0.1780	0.0847	0.0254	0.1864	0.1441	0.0932	0.1186	0.1271
	3	0.1077	0.2154	0.1385	0.1077	0.1231	0.0615	0.0615	0.1077	0.0769
	4	0.0010	0.2495	0.0832	0.0010	0.0832	0.1663	0.1663	0.0832	0.1663
	5	0.0570	0.1329	0.1013	0.0127	0.2785	0.1076	0.0949	0.0886	0.1266
	6	0.0387	0.0490	0.0329	0.0161	0.1075	0.5300	0.0716	0.0497	0.1045
	7	0.0895	0.0789	0.0842	0.0368	0.1842	0.0842	0.2000	0.1263	0.1158
	8	0.0522	0.1478	0.0696	0.1043	0.1391	0.0783	0.1304	0.1130	0.1652
	9	0.0531	0.0885	0.1062	0.0177	0.2655	0.0619	0.0885	0.1062	0.2124

Table 5.2: China in 2009: Intergeneration Occupational Transition Matrix

coefficients in 2009, κ_{CN2009}.

	$\tau_{ij} = 0$	$\delta_{ij} = 1$
Benchmark	61.61%	78.40%
2009	42.19%	44.13%
2009/Benchmark	68.48%	56.29%

Table 5.3: China: Productivity Gains from the 1980s to 2009

The results are listed in the second row in the Table 5.3. We also list the results from the benchmark counterfactual from Section 5.1 in the first row for comparison. In the third row, we list the realized growth potential for China from the 1980s to 2009. Our results suggest that China has realized 56 to 68% of the growth potential from the US counterfactual experiment during the past decades. These results indicate that China has made great progress towards reducing occupational inheritance; however, China also needs to find other sources to continue sustainable growth in the future.

5.3 Experiment: Relaxing Equal Innate Talent Assumption

So far we have assumed that the parameters of innate talent distribution is constant regardless of group and occupation, i.e., $T_{ij} = 1$. However, it may be true that fathers working in some occupations may give birth to kids with high innate talent to work in the same occupation. For example, one may argue that sons of athletes, on average, are born stronger

	China		India	
	$\tau_{ij}=0$	$\delta_{ij}=1$	$\tau_{ij}=0$	$\delta_{ij}=1$
Benchmark	61.61%	78.40%	456.12%	478.81%
$T_{ii}=1.5^{\theta}$	69.44%	76.47%	435.88%	482.79%
$T_{ii}=2^{\theta}$	83.06%	86.33%	412.73%	484.04%
$T_{ii}=(skill\,level)^{\theta}$	129.96%	127.96%	361.19%	442.28%

Table 5.4: Relaxing Equal Innate Talent Assumption

and faster than the sons of non-athletes, providing a natural advantage to be athletes. In this case, we would expect T_{ij} to vary across i and j. However, it is unlikely that we can correctly parameterize the exact value of T_{ij}, that is, we will never know to what extent sons of athletes are naturally more suitable to be athletes in the future. Instead of attempting to find correct numbers for T_{ij}, we simply assign values to T_{ij} with some arbitrariness and check to what extent our results are sensitive to this assumption.

On top of the benchmark counterfactual experiment, we impose three different sets of T_{ij} and reproduce the results in order to see how our results rely on the assumption. Since this paper is about occupational inheritance, we will only change the values of T_{ii}, but keep the assumption that $T_{ij}=1, \forall i \neq j$.

The three sets of values that we choose for this experiment are (1) $T_{ii}=2^{\theta}$; (2) $T_{ii}=3^{\theta}$; (3) $T_{ii}=(skill\,level)^{\theta}$. The skill level in case (3) is introduced by International Labour Office (1990) to measure the degree of complexity and skill requirement for occupations in ISCO88. There are four skill levels, from 1 to 4, and details can be found in Table 7.1. For the third set of values of T_{ii}, we simply assign values of each occupation's skill level.

How large are our values of T_{ii} in these experiments? Here we want to provide some straightforward intuition. Innate talent follows a Frechet distribution as in equation (8). For simplicity, we assume that for each individual, his innate talent for all occupations is not correlated, i.e., $\rho=1$. According to the property of the Frechet distribution, it follows that $E_i(\epsilon_j) \propto T_{ij}^{\frac{1}{\theta}}$. In other words, when we impose $T_{ii}=2^{\theta}$, a worker working in the same occupation as his father would, on average, be twice as efficient as working in other occupations. Therefore, we consider the three sets of values are large enough to detect problems in our results if the equal innate talent assumption is violated. The results for this experiment are listed in Table 5.3. According to this table, relaxing the equal innate talent assumption does not fundamentally change our conclusion.

6 Robustness Check

As discussed earlier, there is some controversy about the correct values for β for China and India, which determines the Mincerian return to education. Meanwhile, parameters $\{\eta, \theta\}$, which determine the distribution of talent, are also difficult to correctly calibrate. In this section, we execute robustness checks to test whether our results are sensitive to different parameter specifications. In all the tables in this section, each cell reports a certain productivity gain.

		$\tau_{ij} = 0$	$\delta_{ij} = 1$
$\beta = 0.5$	China	61.62%	78.36%
	India	456.12%	478.81%
$\beta = 0.8$	China	61.61%	78.38%
	India	456.12%	478.81%
$\beta = 8$	China	61.60%	78.38%
	India	456.18%	478.89%

Table 6.1: Robustness Check: β

The robustness check results for parameter β are listed in Table 6.1. It turns out that this model is insensitive to the specification of this parameter β. We also list the robustness check results for parameters $\{\eta, \theta\}$ in Table 6.2. Both parameters $\{\eta, \theta\}$ can change our results to some extent; however, they do not fundamentally change the intuition of our results. Overall, our results are robust to different specifications of parameters.

		$\tau_{ij}=0$	$\delta_{ij}=1$
$\eta=0.1$	China	67.44%	83.64%
	India	494.01%	446.13%
$\eta=0.5$	China	50.26%	63.14%
	India	384.85%	436.92%

(a) η

		$\tau_{ij}=0$	$\delta_{ij}=1$
$\theta=2$	China	69.80%	71.85%
	India	513.06%	270.76%
$\theta=5$	China	61.34%	78.57%
	India	455.77%	499.16%

(b) θ

Table 6.2: Robustness Check

7 Conclusion

There has been a large literature intending to explain the productivity gap between developed countries and developing countries. Traditionally, researchers have targeted barriers to acquiring human capital as one of the possible explanations for the divergence in developing countries. However, past studies on this topic only focus on the mechanisms behind low educational attainment in developing countries, e.g., financial constraints, while ignoring the fact that there are still many other determinants of occupation choice during the transition from school to the workplace. For a young worker, this transition is shaped not only by the quality and quantity of education received, but also by how the economy allocates workers to jobs. This paper provides a more comprehensive explanation by using a new occupation choice framework. We estimate deep parameters, i.e., coefficients of labor market frictions and coefficients of barriers to accumulating human capital, and investigate the aggregate implications of this particular sociological phenomena, occupational inheritance.

This paper first contributes to the empirical literature on intergenerational occupational mobility. We document the significant correlation between IOM rates and GDP per capita. Moreover, we find that the correlation using IOM rates based on workers' first occupations is much more significant than the correlation using IOM rates based on workers' current occupations. This fact is documented for the first time and sheds light on the differences in how young workers choose occupations between developing and developed countries when they look for their very first jobs. We also contribute by systematically calculating the Altham statistics for intergenerational occupational transition matrices across countries, which distinguishes the interaction effect from the prevalence effect. We also observe higher occupational wage ratios in China and India compared with the US, despite lower intergenerational occupational mobility in the developing countries. This suggests that the aforementioned impediments dominate the income incentives to move to other occupations.

In our quantitative exercises, we first estimate the coefficients of labor market frictions and the coefficients of barriers to accumulating human capital for China, India, and the US. In a counterfactual experiment, we calibrate an economy according to China and India, then feed in the coefficients from the US. We calculate to what extent China and India could improve in terms of labor productivity from reducing the aforementioned impediments to the levels observed in the US. Our counterfactuals suggest that the productivity gain is large for China and enormous for India. The findings in this paper suggest that removing impediments to occupation choice would lead to significant productivity gains for developing countries.

In addition, by comparing China in the 1980s and 2009, we find that China has made significant progress in reducing the barriers to accumulating human capital and labor market frictions, which leads to labor productivity growth. This is both good and bad news for China: on the one hand, it indicates China's success in the past two decades in reducing these impediments, while on the other hand, China must now look for other sources of potential growth moving forward.

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APPENDIX A: Solve the Model

The individual maximization problem (equation 5-7) can be solved explicitly:

$$s_j = \frac{1}{1+\frac{1-\eta}{\beta\phi_j}} \tag{20}$$

$$e_{ij} = [\delta_{ij}(1-\tau_{ij})w_j\epsilon_j\eta s_j^{\phi_j}]^{\frac{1}{1-\eta}} \tag{21}$$

$$U_{ij} = [\delta_{ij}(1-\tau_{ij})w_j\epsilon_j\eta^{\eta}(1-\eta)^{1-\eta}s_j^{\phi}(1-s_j)^{\frac{1-\eta}{\beta}}]^{\frac{\beta}{1-\eta}} \tag{22}$$

Based on the solution to the individual maximization problem, we can solve for each element in the transition matrix:

$$p_{ij} = \frac{\psi_{ij}^{\theta}}{\sum_k \psi_{ik}^{\theta}} \tag{23}$$

$$\psi_{ij} = \delta_{ij}(1-\tau_{ij})T_{ij}^{1/\theta}w_j s_j^{\phi_j}(1-s_j)^{\frac{1-\eta}{\beta}} \tag{24}$$

Given the occupation distribution of the last generation, we are able to calculate the occupation distribution of the next generation:

$$\pi_j = \sum_i \pi_i^L p_{ij} = \sum_i \pi_i^L \cdot \frac{\psi_{ij}^{\theta}}{\sum_k \psi_{ik}^{\theta}} \tag{25}$$

We also can derive the average quality and average wage of workers in each occupation:

$$E_i[h_{ij}\epsilon_{ij}|j] = \delta_{ij}^{\frac{1}{1-\eta}}(1-\tau_{ij})^{\frac{\eta}{1-\eta}}(s_j^{\phi_j}\eta^{\eta})^{\frac{1}{1-\eta}}w_j^{\frac{\eta}{1-\eta}}(\frac{T_{ij}}{p_{ij}})^{\frac{1}{\theta(1-\eta)}} \cdot \Gamma(1-\frac{1}{\theta(1-\rho)(1-\eta)}) \tag{26}$$

Combined with equation (23), we re-write equation (26) as:

$$E_i[h_{ij}\epsilon_j|j] = \frac{1}{w_j(1-\tau_{ij})}\eta^{\frac{1}{1-\eta}}(1-s_j)^{-\frac{1}{\beta}}(\sum_k \psi_{ik}^{\theta})^{\frac{1}{\theta}} \cdot \Gamma(1-\frac{1}{\theta(1-\rho)(1-\eta)}) \tag{27}$$

The total amount of the supply of efficiency labor in occupation j thus can be written as:

$$H_j = \sum_{i=1}^{M} \pi_i^L p_{ij} \cdot E_i[h_{ij}\epsilon_{ij}|j] \tag{28}$$

Plugging equation (26) into equation (28):

$$H_j = (\eta^\eta s_j^\phi w_j^\eta)^{\frac{1}{1-\eta}} \cdot \{\sum_i [\pi_i^L p_{ij}^{1-\frac{1}{\theta(1-\eta)}} \cdot T_{ij}^{\frac{1}{\theta}\frac{1}{1-\eta}} \cdot (\delta_{ik}(1-\tau_{ik})^\eta)^{\frac{1}{1-\eta}}]\} \cdot \Gamma(1 - \frac{1}{\theta(1-\rho)(1-\eta)}) \tag{29}$$

Define Φ_j:

$$\Phi_j = (\eta^\eta s_j^\phi)^{\frac{1}{1-\eta}} \cdot \{\sum_i [\pi_i^L p_{ij}^{1-\frac{1}{\theta(1-\eta)}} \cdot T_{ij}^{\frac{1}{\theta}\frac{1}{1-\eta}} \cdot (\delta_{ik}(1-\tau_{ik})^\eta)^{\frac{1}{1-\eta}}]\} \cdot \Gamma(1 - \frac{1}{\theta(1-\rho)(1-\eta)}). \tag{30}$$

As a result, equation (29) can be simplified as:

$$H_i = \Phi_i \cdot w_i^{\frac{\eta}{1-\eta}} \tag{31}$$

From the maximization problem of the representative firm (equation 10-11), we can solve for wage per unit of efficiency labor:

$$w_j = Y^{\frac{1}{\sigma}} A_j^{\frac{\sigma-1}{\sigma}} H_j^{-\frac{1}{\sigma}} \tag{32}$$

Combining equations (11), (31) and (32) and denoting $\zeta = 1 + \frac{1}{\sigma}\frac{\eta}{1-\eta}$, we can solve for H_j and w_j:

$$H_j = \Phi_j^{\frac{1}{\zeta}} A_j^{\frac{\sigma-1}{\sigma}\frac{\eta}{1-\eta}\frac{1}{\zeta}} Y^{\frac{\eta}{\sigma\zeta(1-\eta)}} \tag{33}$$

$$w_j = \Phi_j^{\frac{1-\zeta}{\zeta}\frac{1-\eta}{\eta}} A_j^{\frac{\sigma-1}{\sigma}\frac{1}{\zeta}} Y^{\frac{1}{\sigma\zeta}} \tag{34}$$

We also can solve for aggregate output Y:

$$Y = \{\sum_j (A_j^{1+\frac{\sigma-1}{\sigma}\frac{\eta}{1-\eta}\frac{1}{\zeta}} \Phi_j^{\frac{1}{\zeta}})^{\frac{\sigma-1}{\sigma}}\}^{\frac{\sigma}{\sigma-1}\cdot\frac{1}{1-\frac{1}{\sigma}\frac{1}{\zeta}\frac{\eta}{1-\eta}}} \tag{35}$$

APPENDIX B: Altham Statistics

By definition, the Altham statistic $d(P,Q)$ measures the distance between matrices P and Q:

$$d(P,Q) = [\sum_{i=1}^{r}\sum_{j=1}^{s}\sum_{l=1}^{r}\sum_{m=1}^{s} |log(\frac{p_{ij}p_{lm}q_{im}q_{lj}}{p_{im}p_{lj}q_{ij}q_{lm}})|^2]^{\frac{1}{2}}$$

Define $a_{ij} = log(\frac{p_{ij}}{q_{ij}})$. It follows that:

$$\begin{aligned} d(P,Q)^2 =& [\sum_i\sum_j\sum_l\sum_m |log(\frac{p_{ij}p_{lm}q_{im}q_{lj}}{p_{im}p_{lj}q_{ij}q_{lm}})|^2] \\ =& \sum_i\sum_j\sum_l\sum_m (a_{ij} + a_{lm} - a_{im} - a_{lj})^2 \\ =& 4rs\sum_i\sum_j a_{ij}^2 + 4(\sum_i\sum_j a_{ij})^2 - 4r\sum_i(\sum_j a_{ij})^2 - 4s\sum_j(\sum_i a_{ij})^2 \end{aligned}$$

On the other hand, we know:

$$\begin{aligned} & 4rs\cdot\sum_i\sum_j[a_{ij} - \underbrace{\frac{\sum_m\sum_l a_{ml}}{rs}}_{matrix\,mean} - \underbrace{(\frac{\sum_m a_{mj}}{r} - \frac{\sum_m\sum_l a_{ml}}{rs})}_{column\,deviation} - \underbrace{(\frac{\sum_l a_{il}}{s} - \frac{\sum_m\sum_l a_{ml}}{rs})}_{row\,deviation}]^2 \\ =& 4rs\cdot\sum_i\sum_j(a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s} + \frac{\sum_m\sum_l a_{ml}}{rs})^2 \\ =& 4rs\cdot\sum_i\sum_j[\underbrace{(a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s})^2}_{term\,1} + \underbrace{(\frac{\sum_m\sum_l a_{ml}}{rs})^2}_{term\,2} + \underbrace{2\cdot(a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s})\cdot\frac{\sum_m\sum_l a_{ml}}{rs}}_{term\,3}] \end{aligned} \tag{36}$$

We can further simplify the three terms in equation (37) as follows:

$$\begin{aligned}
term\,1 &= \sum_i \sum_j (a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s})^2 \\
&= \sum_i \sum_j (a_{ij}^2 + \frac{(\sum_m a_{mj})^2}{r^2} + \frac{(\sum_l a_{il})^2}{s^2} - 2a_{ij} \cdot \frac{\sum_m a_{mj}}{r} - 2a_{ij} \cdot \frac{\sum_l a_{il}}{s} + 2\frac{\sum_m a_{mj}}{r} \cdot \frac{\sum_l a_{il}}{s})^2 \\
&= \sum_i \sum_j a_{ij}^2 + \frac{1}{r} \sum_j (\sum_i a_{ij})^2 + \frac{1}{s} \sum_i (\sum_j a_{ij})^2 - 2\frac{1}{r} \sum_j (\sum_i a_{ij})^2 - 2\frac{1}{s} \sum_i (\sum_j a_{ij})^2 + 2\frac{1}{rs} (\sum_i \sum_j a_{ij})^2 \\
&= \sum_i \sum_j a_{ij}^2 - \frac{1}{r} \sum_j (\sum_i a_{ij})^2 - \frac{1}{s} \sum_i (\sum_j a_{ij})^2 + 2\frac{1}{rs} (\sum_i \sum_j a_{ij})^2 \qquad (37) \\
term\,2 &= \sum_i \sum_j (\frac{\sum_m \sum_l a_{ml}}{rs})^2 = \frac{1}{rs} (\sum_i \sum_j a_{ij})^2 \qquad (38) \\
term\,3 &= \sum_i \sum_j 2 \cdot (a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s}) \cdot \frac{\sum_m \sum_l a_{ml}}{rs} \\
&= \frac{2}{rs} \cdot [(\sum_i \sum_j a_{ij})^2 - (\sum_i \sum_j a_{ij})^2 - (\sum_i \sum_j a_{ij})^2] \\
&= -\frac{2}{rs} (\sum_i \sum_j a_{ij})^2 \qquad (39)
\end{aligned}$$

Plugging equations (37)-(39) back into equation (37):

$$\begin{aligned}
&4rs \cdot \sum_i \sum_j [\underbrace{(a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s})^2}_{term\,1} + \underbrace{(\frac{\sum_m \sum_l a_{ml}}{rs})^2}_{term\,2} + \underbrace{2 \cdot (a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s}) \cdot \frac{\sum_m \sum_l a_{ml}}{rs}}_{term\,3}] \\
=&4rs \cdot [\sum_i \sum_j a_{ij}^2 - \frac{1}{r} \sum_j (\sum_i a_{ij})^2 - \frac{1}{s} \sum_i (\sum_j a_{ij})^2 + 2\frac{1}{rs} (\sum_i \sum_j a_{ij})^2 + \frac{1}{rs} (\sum_i \sum_j a_{ij})^2 - \frac{2}{rs} (\sum_i \sum_j a_{ij})^2] \\
=&4rs \cdot [\sum_i \sum_j a_{ij}^2 - \frac{1}{r} \sum_j (\sum_i a_{ij})^2 - \frac{1}{s} \sum_i (\sum_j a_{ij})^2 + \frac{1}{rs} (\sum_i \sum_j a_{ij})^2] \\
=&4rs \sum_i \sum_j a_{ij}^2 + 4(\sum_i \sum_j a_{ij})^2 - 4r \sum_i (\sum_j a_{ij})^2 - 4s \sum_j (\sum_i a_{ij})^2 \qquad (40)
\end{aligned}$$

Comparing equations (35) and (40), we have reached the conclusion that:

$$\begin{aligned}
&d(P, Q)^2 = \\
&\qquad 4rs \cdot \sum \sum_j [a_{ij} - \underbrace{\frac{\sum_m \sum_l a_{ml}}{rs}}_{matrix\,mean} - \underbrace{(\frac{\sum_m a_{mj}}{r} - \frac{\sum_m \sum_l a_{ml}}{rs})}_{column\,deviation} - \underbrace{(\frac{\sum_l a_{il}}{s} - \frac{\sum_m \sum_l a_{ml}}{rs})}_{row\,deviation}]^2
\end{aligned}$$

APPENDIX C

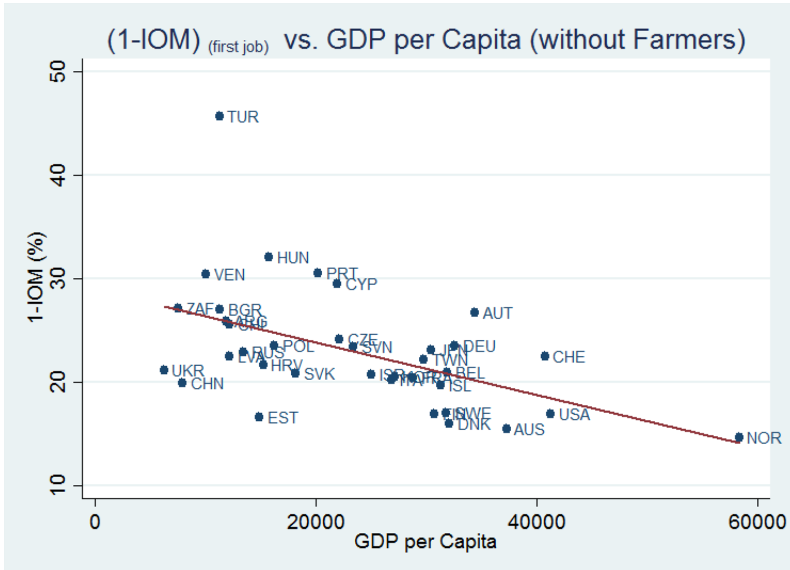

Figure 7.1: $(1 - IOM)_{(first\,job)}$ vs. GDP per Capita (without Farmers)

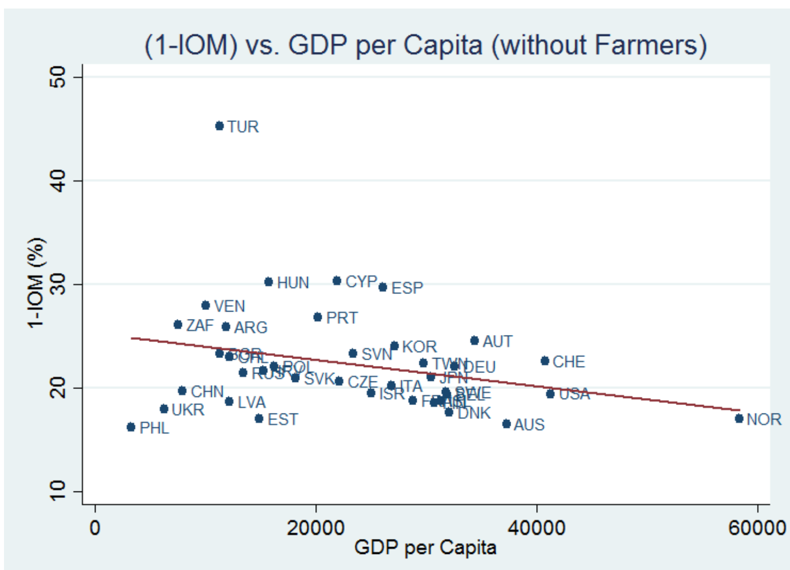

Figure 7.2: $(1 - IOM)$ vs. GDP per Capita (without Farmers)

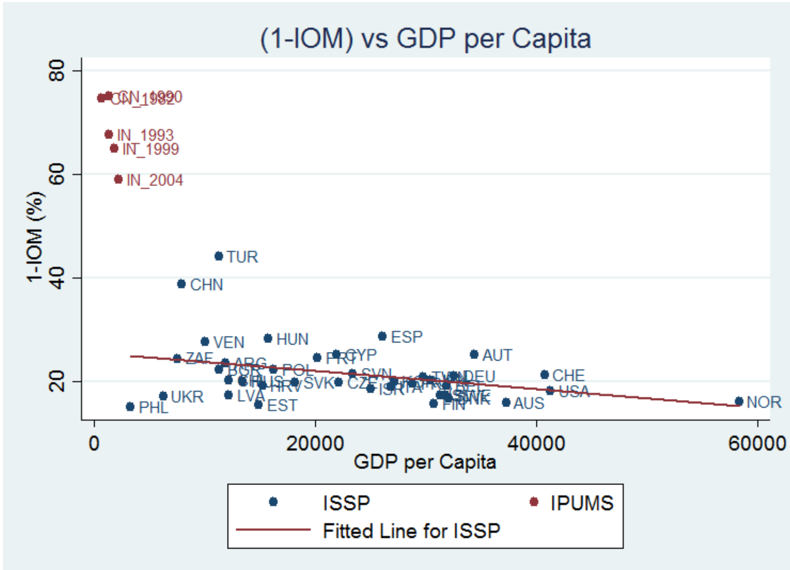

Figure 7.3: ISSP and IPUMS: (1-IOM) vs. GDP per Capita

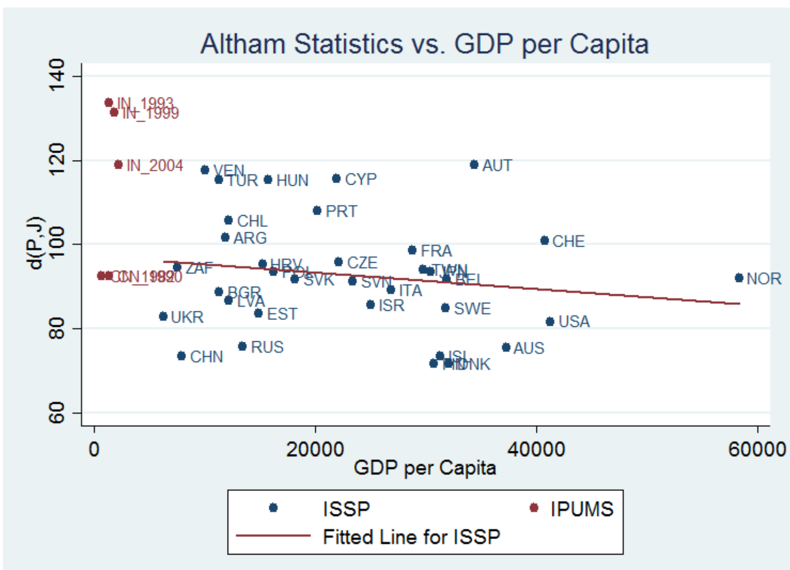

Figure 7.4: ISSP and IPUMS: Altham Statistics vs. GDP per Capita

1-digit Code	Occupation	Skill Level
1	Legislators, senior officials and managers	3
2	Professionals	4
3	Technicians and associate professionals	3
4	Clerks	2
5	Service workers and shop and market sales workers	2
6	Skilled agricultural and fishery workers	2
7	Craft and related trades workers	2
8	Plant and machine operators and assemblers	2
9	Elementary occupations	1

Table 7.1: ISCO88 1-digit Occupations

* The skill level for occupation 1 is not listed on ISCO official documents. We assign this number based on the skill level for occupations 2 and 3.

		Son's Occupation								
		1	2	3	4	5	6	7	8	9
Father's Occupation	1	0.0517	0.0546	0.0600	0.2556	0.3202	0.0180	0.0629	0.0643	0.1128
	2	0.0402	0.0871	0.0780	0.2457	0.3304	0.0210	0.0464	0.0542	0.0972
	3	0.0396	0.0608	0.0803	0.2585	0.3322	0.0189	0.0537	0.0612	0.0948
	4	0.0410	0.0543	0.0546	0.2855	0.2977	0.0160	0.0639	0.0798	0.1072
	5	0.0403	0.0492	0.0518	0.2525	0.3345	0.0172	0.0653	0.0833	0.1058
	6	0.0248	0.0365	0.0332	0.1670	0.2172	0.1145	0.0729	0.0954	0.2385
	7	0.0321	0.0373	0.0431	0.2441	0.2966	0.0185	0.1067	0.0969	0.1247
	8	0.0314	0.0338	0.0390	0.2425	0.2883	0.0179	0.0789	0.1362	0.1318
	9	0.0301	0.0328	0.0348	0.2209	0.2704	0.0259	0.0760	0.1124	0.1968

Table 7.2: US: Intergenerational Occupational Transition Matrix