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Essays on Macroeconomics

A dissertation submitted in partial satisfaction
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by

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Abstract of the Dissertation

Essays on Macroeconomics

by

Ting Ji

Doctor of Philosophy in Economics

University of California, Los Angeles, 2015

Professor Lee Ohanian, Chair

In these essays, I examine the role of allocating human capital and labor in an economy. I target the phenomenon of "occupational inheritance" in developing countries and investigate its role on labor productivity in the first chapter; in the second chapter, I explain increasing low-skill service workers with increasing female labor force participation in the US labor market; the third chapter is a simple theory about how to allocate human talents into different processes of innovation to achieve efficiency. I provide further details in the following paragraphs.

The first chapter documents occupational inheritance–interpreted as children inheriting their parents' occupations–in China, India, and the US. I argue that the prevalence of occupational inheritance in China and India, usually presented as low intergenerational occupational mobility rates, is largely due to two categories of impediments: (1) labor market frictions, e.g., parents' social networks ("guanxi") giving unfair advantages to their children and household registration ("hukou"), which ties rural families to agriculture in China, and the caste system, which restricts young workers' occupational choices in India, and (2) barriers to acquiring human capital, i.e., it is much easier for the young in the US to accumulate human capital from sources other than senior family members compared with the young in China and India. Based on a new tractable occupational choice model using techniques from Eaton and Kortum (2002), this chapter quantitatively evaluates the aggregate implications of occupational inheritance. Counterfactual experiments suggest that if the impediments

mentioned above could be reduced to the US level, labor productivity would grow 57 to 73% in China and over fourfold in India. In addition, China has realized 60 to 74% of this growth potential from the 1980s to 2009.

The second chapter builds on three empirical facts in the US labor market: from 1980 to 2005, there was (1) about 30% growth in low-skill service jobs, (2) about 9% increase in female labor force participation, and (3) almost constant average home production hours conditional on employment status and gender. Linking all three facts, I propose a hypothesis for the growth in low-skill service jobs: the increase in female labor force participation decreases economy-wide home production and leads households to purchase substitutable goods from the market. I present a simple accounting framework and produce a benchmark quantitative exercise using this framework to show that this theory can explain about 50% of the increase in low-skill service jobs.

In the third chapter, I develop a simple theory of efficient innovation. Individuals are heterogeneous in innovation ability and the allocation of innovative agents into two different types of innovation, i.e. process innovation and product innovation, determines the level of innovation efficiency and economy-wide growth rate. I investigate a competitive economy version of the model and also solve for a closed-form social planner's balanced growth path. By comparing these two different versions of the problem, I identify several sources of inefficiency of the competitive economy, notably the frictions in the innovator market.

The dissertation of Ting Ji is approved.

Hugo Hopenhayn

Pablo Fajgelbaum

Antonio Bernardo

Lee Ohanian, Committee Chair

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2015

To my parents and my wife

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CHAPTER 1

Aggregate Implications of Occupational Inheritance in China and India

1.1 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. As a measure of occupational inheritance, the intergenerational occupational mobility (IOM) rate has been studied by sociologists for decades as a subtopic of social stratification (for example, Ganzeboom and Treiman 2007, Treiman and Ganzeboom 2000, and Treiman and Yip 1989) and by economists as a subtopic of intergenerational income elasticity (see Blanden 2009 for a review). A recent paper by Long and Ferrie (2013) has piqued renewed interest on this topic by introducing a new measure, the Altham statistic (Altham 1970 and Altham and Ferrie 2007), to investigate the properties of the intergenerational occupation transition matrix. However, as far as we know, macroeconomists have been largely silent on this important topic. If we define an "occupation" as a skillset, then patterns of choosing occupations automatically lead to implications for aggregate human capital and thus, aggregate productivities.

In this paper, we first document one important pattern of occupational choice across countries, i.e., the statistically significant correlation between IOM rates and GDP per capita. That is, 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. This contradiction suggests 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. We classify these impediments into two categories: labor market frictions and barriers to acquiring human capital.

Labor market frictions result in the inefficient allocation of human talents, which hurt aggregate productivity. If the price of labor, i.e. wage, does not fully reflect the marginal product of labor, this creates a wedge that may assign workers to the wrong occupations. Both China and India have a very long history developing unique cultral and socioeconomic conventions. This brings national pride but may also burden economic development. For example in China, parents often abuse their social networks ("guanxi") in order to gain an unfair advantage for their children, especially in the same occupation, in the labor market, leading to occupational inheritance. In addition, household registration ("hukou"), which originates from the "baojia" system established in the 11th century (Cheng and Selden 1994), ties rural families to agricultural work. In India's case, the caste system groups people into different occupations in specific castes and limits occupational choices, again perpetuating the occupational inheritance phenomenon.

Meanwhile, acquiring human capital as a preparation for jobs involves two types of training: general academic schooling and occupation-specific training (e.g. vocational education and workplace apprenticeship). China and India lag behind the US in terms of average educational attainment, especially at the college level. In addition, the quality and quantity of vocational school education in China and India have historically been unsatisfactory, due to problems such as limited funding, limited enrollment, poor management of educational content, shortage of teachers, etc. Moreover, a relatively poor judiciary system and binding financial constraints in China and India also create huge barriers to accumulating human capital through workplace training, which usually involves contracts between trainers and trainees and investments from employers to employees. In general, it is reasonable to argue that China and India significantly diverge from the US in terms of acquiring human capital, through both formal schooling and the workplace. When it is difficult to accumulate human capital from sources outside of their families, young workers in China and India are then forced to refer back to senior family members for help, resulting in occupational inheritance.

In this paper, we first present facts correlating occupational inheritance and GDP per capita. We use both the traditional IOM measure and the new Altham statistic. We then use a new occupational choice framework from Hsieh, Hurst, Jones, and Klenow (2013, HHJK hereafter) to quantitatively evaluate the aggregate implications of the impediments mentioned above. The HHJK framework is a general equilibrium Roy's model (Roy 1951) with occupational choice. HHJK assumes that 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. In this model, heterogeneous individuals choose optimal consumption and schooling time for any given occupation and optimal occupation based on their talent draw. The properties of Frechet distributions guarantee the tractability of the model, just as in Eaton and Kortum (2002). Applying this framework to US Census data, HHJK argues that convergence in the occupational distribution between white men, women, and blacks implies 15 to 20% of the productivity growth for the US in the past 50 years.

Our quantitative results suggest that if the barriers to intergenerational occupational mobility could be reduced to the US level, labor productivity would grow 57 to 73% in China and 441 to 465% in India. In addition, China has realized 60 to 74% of this growth potential from the 1980s to 2009. The former result, i.e. the difference in labor productivity gains between China, India, and the US, can be traced back to the differences in socioeconomic conventions between these countries, which we will discuss further in Section II. The latter result indicates that China has made great economic progress due to a reduction in these barriers; however, China still needs to find other sources for sustainable growth going forward.

There is a burgeoning literature using similar framework as HHJK. Cortes and Gallipoli (2014) evaluate the aggregate costs of occupational mobility in 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. Lagakos and Waugh (2013) use selection as an explanation of enormous cross-country differences in agricultural productivity.

This paper also contributes to the large literature on productivity gaps between countries. In a seminal paper, 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 40 to 50% growth in China's manufacturing TFP and a 40 to 60% growth in India's manufacturing TFP. However, 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 occupational choice.

This paper also contributes to the literature discussing intergenerational occupational mobility. Traditionally, sociologists use IOM rates as their measure of social mobility and we systematically document the correlation between IOM rates and GDP per capita. 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. This fact has not yet been documented as far as we know, but it sheds light on the differences in how young workers choose occupations between developing and developed countries. In addition, we document the Altham statistics systematically across countries for the first time.

The rest of the paper proceeds as follows. We present some facts on IOM rates and background information for labor market frictions and human capital accumulation in China and India in Section II. We then present the occupational choice model in Section III and solve it explicitly. We talk about data and parameterization procedure in Section IV. In

Section V, we carry out various quantitative exercises and discuss the results. In Section VI, we implement robustness checks. We conclude in Section VII.

1.2 Empirical Facts and Background Information

This section presents some facts and background information that motivate the paper. First, we present the statistically significant correlation between IOM rates and GDP per capita. Because China and India (and most developing countries) are still largely patriarchal societies, with females only playing a supporting role in production, we restrict our analysis to the intergenerational occupation transition between fathers and sons. We also investigate whether these results are robust to different specifications and measurements, providing us more information on the process of occupational choice. We also report the relationship between the Altham statistics and GDP per capita across countries. We then discuss the labor market frictions and barriers to human capital accumulation in China and India.

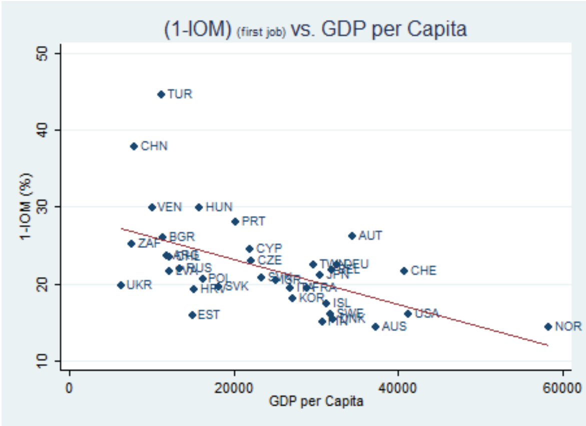
1.2.1 IOM Rate vs. GDP per Capita

In this section, we use the IOM rate as an indicator of intergenerational occupational mobility. Denote $\pi^L = (\pi_1^L, \pi_2^L, \ldots \pi_M^L)$ as the distribution of occupations for the fathers' generation. Denote $P = [p_{ij}]_{M \times M}$ as the intergenerational occupation transition matrix, where the row i corresponds to fathers' occupations and the column j corresponds to sons' occupations. The IOM rate is defined as:

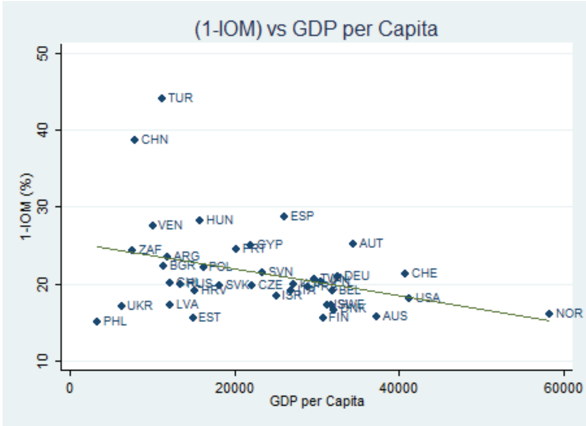
$$IOM = 1 - \pi^L \cdot diag(P) \tag{1.1}$$

where $diag(P)$ is the diagonal elements of the transition matrix. It is usually more convenient to think about the percentage of sons that inherit their fathers' occupations and therefore, Equation (1) can be re-written as:

$$1 - IOM = \pi^L \cdot diag(P) \tag{1.2}$$



(a) First Occupation



(b) Current Occupation

Figure 1.2.1: $(1 - IOM)$ vs. GDP per Capita

We use data from the International Social Survey Programme (ISSP) 2009 (ISSP Research Group 2009)[1] which covers 41 countries and territories in total[2]. We will give more information about the ISSP 2009 in Section IV, but it is especially good for our purposes for several reasons. 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 reasonable and reliable. Second, it provides all the information on the respondent's first occupation, current occupation, and father's occupation. It is worth mentioning that the ISSP 2009 asks for the occupation of the respondent's father by asking, "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, as the name suggests, the field work of the ISSP 2009 was carried out around 2009[3] in all participating countries, which removes time variation and makes the data more comparable across countries.

We first calculate $(1-IOM)$ based on father's occupation and respondent's *first* occupa-

[1]We sincerely thank Professor Donald Treiman at Department of Sociology UCLA for recommending this dataset.

[2]Due to data limitations, we drop to 35 countries and territories in the end.

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

tion. We then proceed and present $(1-IOM)$ based on father's occupation and respondent's *current* occupation. We present the correlation between $(1-IOM)$ and real GDP per capita based on the two different definitions in Figure 1.2.1. 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 1.2.1. According to the first row of this table, the slope for Figure 1.2.1a 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 $2.90 \cdot 10^{-4} \times 40000 = 11.6\%$.

It is worth mentioning that the GDP per capita correlation for the IOM rate based on the 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 are that workers' first occupations, compared with their current occupations, are much more likely to follow their fathers' occupations in poor countries. Education in poor countries does not seem to prepare young workers for occupations different from their fathers' as much as it does in rich countries. However, after gaining years of work experience, some young workers are able to gradually overcome these barriers to occupational transition and deviate from their fathers' occupations. However, 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 occupation 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 International IPUMS (Minnesota Population Center 2014) dataset, which we will discuss in detail in section IV. In fact, the International IPUMS also provides additional data for China as well; however, the International IPUMS data only provides the respondents' current occupations. Therefore, we simply calculate $(1 - IOM)$ from the International IPUMS data and put all the data points on top of Figure 1.2.1b and produce Figure 1.10.3 in Appendix C. The International IPUMS 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, which has great implications for our quantitative exercises. 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 Rate	First Occupation	-2.90e-04	-3.75
	Current Occupation	-1.75e-04	-2.21
	First Occupation (No Farmers)	-2.53e-04	-3.39
	Current Occupation (No Farmers)	-1.27e-04	-1.75
Altham Statistics	First Occupation	-3.13e-04	-1.55
	Current Occupation	-1.95e-04	-0.97

Table 1.2.1: Regression Results

The $(1-IOM)$ rate is a product of the distribution of fathers' occupations and the diagonal elements of the intergenerational occupation transition matrix; therefore, it alone cannot disentangle *interaction* from *prevalence*. Following 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. In this paper, 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, i.e., prevalence.

Although the barriers that impede sons of farmers from moving to new occupations also fit our topic, we would like to know to what extent farmers drive these results. There are two ways to solve this problem. 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 1.10.1 and 1.10.2 in Appendix C and in Table 1.2.1. Farmers do explain part of the occupational inheritance phenomenon, but there is still much to be explained by all the other occupations. We introduce the second solution in the next section.

1.2.2 Altham Statistics vs. GDP per Capita

The interaction effect is determined by the intergenerational occupation 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:

$$d(P,Q) = [\sum_{i=1}^{r}\sum_{j=1}^{s}\sum_{l=1}^{r}\sum_{m=1}^{s} |log(\frac{p_{ij}p_{lm}q_{im}q_{lj}}{p_{im}p_{lj}q_{ij}q_{lm}})|^2]^{\frac{1}{2}} \tag{1.3}$$

The Altham statistic $d(P,Q)$ shows us the distance between the row-column associations and between matrices P and Q. We choose P as the transition matrix for each country, and Q is a matrix in which all elements are ones. In this particular case, $r = s$.

To further understand the mathematical implications of the Altham statistic, we would like to transform Equation (3) into a more straightforward form. Denote $a_{ij} = log(\frac{p_{ij}}{q_{ij}})$. After some derivation, which can be found in Appendix B, Equation (3) can be written as:

$$d(P,Q)^2 =$$

$$4rs \cdot \sum_i\sum_j[a_{ij} - \underbrace{\frac{\sum_m\sum_l a_{ml}}{rs}}_{matrix\,mean} - \underbrace{(\frac{\sum_m a_{mj}}{r} - \frac{\sum_m\sum_l a_{ml}}{rs})}_{column\,deviation} - \underbrace{(\frac{\sum_l a_{il}}{s} - \frac{\sum_m\sum_l a_{ml}}{rs})}_{row\,deviation}]^2 \tag{1.4}$$

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 transition matrix P and 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 the Altham statistics and GDP per capita in Figure

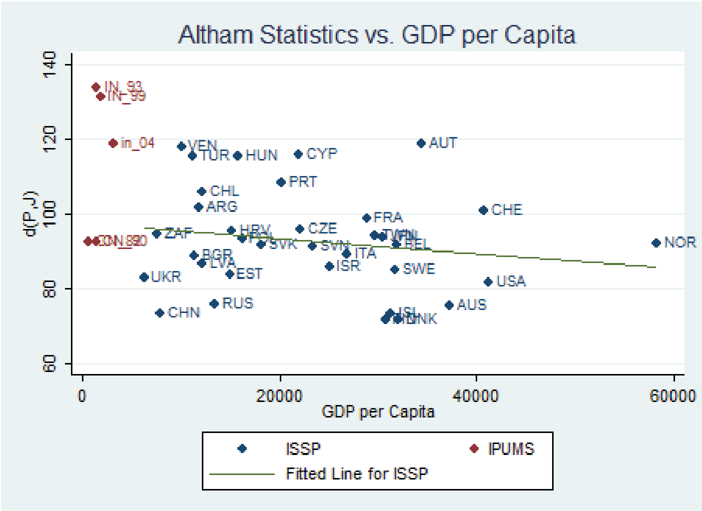


Figure 1.2.2: Altham Statistic vs. GDP per Capita

1.2.2. This graph is calculated based on respondents' current occupations, and we present a similar graph for the Altham statistics based on respondents' first occupations in Figure 1.10.4 in Appendix C. As before, we also use data from International IPUMS to calculate the Altham statistics for China in 1982/1990 and India in 1993/1999/2004, and they appear in red in Figure 1.2.2. The slopes of the regression lines are listed in Table 1.2.1.

According to Figure 1.2.2, the correlation between Altham statistics and GDP per capita is negative but not 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 it is 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.

1.2.3 Occupational Wage Ratios

We have established that intergenerational occupation mobility is less likely in China and India than in the US. However, this could simply be due to the fact that workers have less incentives to move in those countries. Suppose all occupations pay similar wages; then workers are not encouraged to move to new occupations, because this costs effort but does

	India	China	US
Wage Ratios	55.6	12.0	3.9

Table 1.2.2: Occupational Wage Ratios

not bring much benefit.

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 1.2.2 (more occupational wage information for these countries can be found in Table 1.4.3). Surprisingly, 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.

1.2.4 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.

1.2.4.1 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 scale and resource curse/abundance. 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 capital and labor misallocation at the firm level.

1.2.4.2 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 "guanxi" and "hukou," while in India, the caste system restricts occupational choices.

"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. Granovetter (1973) and Bian (1997) complete a comparison between Western countries and China on how social connections are used when searching for a job. When searching for a job, Western people use "weak ties of infrequent interaction and low intimacy" to gather information; however, in China, people use "strong ties" such as "relatives and friends of high intimacy" not only to gather information, but also to secure the job. From the perspective of economics, spreading information is beneficial to efficiency, but assigning jobs simply based on “guanxi” is harmful for efficiency.

Fathers are the main source of “guanxi” in China. In recent years, the phrase “pindie” has become increasingly popular on Chinese social media. The literal translation of “pindie” is to compare fathers or to compete with fathers. An idiomatic translation would be father privilege competition. In China, fathers are notorious for abusing “guanxi” to gain unfair advantages for their children, and thus “pindie” has become one of the defining keywords for social interactions in China.

The “hukou” system officially registers each individual’s information, such as name, parents, spouse, and date of birth. However, what is most important to us 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.

However, it is worth mentioning that 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.” In addition, the Reform and Opening-up policy has also relaxed the enforcement of the “hukou” system. In fact, hundreds of millions of Chinese farmers migrate from inland to coastal areas, where the fastly growing industry needs new labor. These are all underlying reasons for China’s improved intergenerational occupational mobility since the 1980s.

On the other hand, the caste system in India 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 varna of Brahmins are traditionally priests and the learned class; the varna of Kshatriyas are the ruler, warrior, and landowner class; the varna of Vaishyas are commercial livelihoods; the varna of Shudras are the servile laborers; and the untouchables work in jobs such as toilet cleaning and garbage removal. The definition of the caste system is well known for limiting occupational choices. It is therefore not surprising that we find unusually high IOM rates and the 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.

1.2.4.3 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 never on par with that in developed countries. We produce Table 1.2.3 based on data from

	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 1.2.3: Educational Attainment in 2000

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. College education is especially important in deciding occupations and the difference would be even larger between China, India and the US. 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 .26 in India. However, it is worth mentioning that the quantity of education received by 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 2.53 years for India since 1980.

In terms of the quality of education, China has performed relatively well in pre-college education, while India still lags behind. The OECD Programme for International Student Assessment (PISA) studies 15-year-old school pupils' scholastic performance in mathematics, science, and reading (OECD 2014). Shanghai has the top performance for both the 2009 and 2012 PISA, while the performance of Tamil Nadu and Himachal Pradesh of India is unsatisfactory. However, PISA results in Shanghai are not entirely representative of China, as it is one of the richest regions, while the educational quality is much lower in the poorer inland regions. Furthermore, universities in China and India are unsatisfactory. According to the Academic Ranking of World Universities 2014 from Shanghai Jiaotong Universitity, the best universities in China and India are still ranked outside the top 100 in the world.

In terms of vocational school education, China has improved dramatically, 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. Official statistics reported 29 million students in vocational schools in 2013. 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.

According to a World Bank report on the vocational education and training system in India (The World Bank 2007), vocational schools enroll less than 3% of the potential secondary enrollment population, a number that is essentially negligible for further discussion in this paper.

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.

1.3 Model

There is a continuum of individuals in each generation, and each of them has one offspring. There are M occupations in this economy and each individual chooses his occupation $j \in J$, where $J = \{1, 2, \ldots, M\}$. Each individual is born with innate talent

$\epsilon = (\epsilon_1, \epsilon_2, \ldots, \epsilon_i, \ldots, \epsilon_M)$ across occupations and the value of ϵ is determined by an idiosyncratic draw. Each individual lives one period, but we further decompose this 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 s as the schooling time and therefore $(1-s)$ is the leisure time, and we denote e as 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. We assume that father's occupation (denoted by i) matters in the human capital accumulation process and we group different workers based on father's occupation 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 father's occupation i. 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:

$$\max_{j \in J, c_{ij}, s_{ij}, e_{ij}} \quad U_{(\epsilon,i)}(j) = log(1 - s_{ij}) + \beta log(c_{ij}) \tag{1.5}$$

$$s.t.\ c_{ij} = (1 - \tau_{ij}) \cdot w \epsilon_j h_{ij} - e_{ij} \tag{1.6}$$

$$h_{ij} = \delta_{ij} s_{ij}^{\phi_j} e_{ij}^{\eta} \tag{1.7}$$

Using the technique as in Eaton and Kortum (2002), innate talents are drawn from a Frechet distribution:

$$\Lambda_i(\epsilon) = exp\{-[\sum_{j=1}^{N} (T_{ij} \epsilon_j^{-\theta})]^{1-\rho}\} \tag{1.8}$$

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

The individual maximization problem implicitly defines an intergenerational occupation transition matrix , where p_{ij} is the probability of a son choosing occupation i conditional on the fact that his father works in occupation j.

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

$$H_j = \sum_{i=1}^{M} \pi_i^L p_{ij} \cdot E_i[h_{ij}\epsilon_{ij}|j] \tag{1.9}$$

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

$$\max_{j,c,s} \quad Y - \sum_{j=1}^{M} w_j H_j \tag{1.10}$$

$$s.t.\ Y = \{\sum_{j=1}^{M}(A_j H_j)^{\frac{\sigma-1}{\sigma}}\}^{\frac{\sigma}{\sigma-1}} \tag{1.11}$$

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.

Solve the model

Due to the properties of the Frechet distribution, this model has an analytical solution. Here, we simply present equations with key implications; further details can be found in Appendix A.

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

$$p_{ij} = \frac{\psi_{ij}^{\theta}}{\sum_k \psi_{ik}^{\theta}} \tag{1.12}$$

$$\psi_{ij} = \delta_{ij}(1-\tau_{ij})T_{ij}^{1/\theta} w_j s_j^{\phi_j}(1-s_j)^{\frac{1-\eta}{\beta}} \tag{1.13}$$

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

$$E_i[h_{ij}\epsilon_{ij}|j] = \frac{1}{w_j(1-\tau_{ij})}\eta^{\frac{1}{1-\eta}}(1-s_j)^{-\frac{1}{\beta}}(\sum_k \psi_{ik}^{\theta})^{\frac{1}{\theta}} \cdot \Gamma(1-\frac{1}{\theta(1-\rho)(1-\eta)}) \tag{1.14}$$

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

$$\begin{aligned} INC_{ij} &= (1-\tau_{ij})w_j E_i[h_{ij}\epsilon_j|j] \\ &= \eta^{\frac{1}{1-\eta}}(1-s_j)^{-\frac{1}{\beta}}(\sum_k \psi_{ik}^{\theta})^{\frac{1}{\theta}} \cdot \Gamma(1-\frac{1}{\theta(1-\rho)(1-\eta)}) \end{aligned} \tag{1.15}$$

Note that equation (15) has important implications for the inter-occupational wage ratios and the inter-group wage ratios. Holding fathers's occupation 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.

$$\frac{INC_{ig}}{INC_{ih}} = \frac{(\sum_k \psi_{kg}^{\theta})^{\frac{1}{\theta}}}{(\sum_k \psi_{kh}^{\theta})^{\frac{1}{\theta}}} \tag{1.16}$$

$$\frac{INC_{kj}}{INC_{fj}} = (\frac{1-s_k}{1-s_f})^{-\frac{1}{\beta}} \tag{1.17}$$

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 denoting $\kappa_{ij} = [\delta_{ij}(1-\tau_{ij})]^{-1}$, we reach a key equation:

$$\frac{\kappa_{hj}}{\kappa_{ij}} = \frac{\delta_{ij}(1-\tau_{ij})}{\delta_{hj}(1-\tau_{hj})} = (\frac{T_{hj}}{T_{ij}})^{-\frac{1}{\theta}} \cdot (\frac{INC_{hj}}{INC_{ij}})^{-(1-\eta)} \cdot (\frac{p_{hj}}{p_{ij}})^{-\frac{1}{\theta}} \tag{1.18}$$

κ is an aggregate measure of labor market friction and human capital barriers. It will determine the intergenerational occupation 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 $\delta_{ij} = 1$.

1.4 Data and Parameterization

We use two sets of data. The first comes from China and US Censuses, and the Indian Employment Survey from the International IPUMS. 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 we use 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. The large size of the data is important because we want to estimate the intergenerational occupation transition matrix. The size of the transition matrix is M^2 if we denote the number of occupations to be M. On average, there are only $\frac{1}{M^2}$ of the total number of observations for each cell. Considering that the occupation distribution is not evenly distributed, some cells may have less than $\frac{1}{M^2}$ of the total number of observations to be estimated.

The variables of interest are: respondent's occupation, respondent's father's occupation, 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 41 countries and territories in this data (including China and the US, but not India) and the total sample size is 54,733. In fact, ISSP provides all the information we need: respondent's occupation, respondent's father's occupation, and respondent's income. However, the size of the ISSP data is relatively small, and therefore we choose the International IPUMS 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 ten occupations at this level, but we drop the "Armed Force" occupation 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 1.10.1 in Appendix C.

We use four sets of data to parameterize the whole model: (1) intergenerational occupation 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 1.4.1: China: Intergenerational Occupation Transition Matrix

		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 1.4.2: India: Intergenerational Occupation Transition Matrix

We pool data from the 1982 and 1990 Chinese Censuses to generate Table 1.4.1 and we pool the 1993, 1999, and 2004 Indian Employment Survey data to generate Table 1.4.2. 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 occupation transition matrix for the US in Table 1.10.2 in Appendix C.

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 1.4.3: Average Wages across Occupation

We also need the average wages for each occupation in China, India, and the US. As 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 Table 1.4.3. 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 to be $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_M)$. We normalize $\lambda_{farmer} = \lambda_6 = 1$, that is, we choose people with fathers who are farmers as the base group.

$$\begin{aligned}\frac{INC_g}{INC_h} &= \frac{\sum_j p_{gj} w_j \lambda_g}{\sum_j p_{hj} w_j \lambda_h} = \frac{\lambda_g}{\lambda_j} \frac{\sum_j p_{gj} wage_j}{\sum_j p_{hj} wage_j} \\ \Rightarrow \frac{\lambda_g}{\lambda_h} &= \frac{INC_g}{INC_h} \frac{\sum_j p_{hj} wage_j}{\sum_j p_{gj} wage_j} \end{aligned} \tag{1.19}$$

The symbol $wage_j$ is simply the average income for occupation j, while INC_g is the average income for group i. We intentionally use different symbols to avoid potential confusion. According to Equation (19), the average group wage ratios for groups that are observed in the data are weighted averages of occupational wage multiplied by λ. We can solve for λ using Equation (19).

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, $\theta = 4.5867$, $\rho = .0930$, $\eta = .25$. From Equation (17), we know that β determines the Mincerian return. A survey of the Mincerian return in China suggests estimation results starting from 3.29%[4] in Johnson and Chow (1997), 10.24% in Zhang (2011), and 17.26% in Awaworyi and Mishra (2014). We choose the level $\beta = .693$ to match the Mincerian return 12.7% in the US as the benchmark. We will do further robustness checks on the parameter β. We assume the distributions of talents are constant across both generations' occupations, that is, $T(i, j) = 1$. We also use $\sigma = 3$ for a benchmark.

We want to estimate the aggregate measure of the previously discussed impediments $\{\kappa_{ij}\}$ for China, India, and the US. We consider these $\{\kappa_{ij}\}$ as the deep parameters that distinguish developed countries from developing countries. The estimation of $\{\kappa_{ij}\}$ involves Equation (18), which uses elements in the intergenerational occupation transition matrix and wage information as inputs, conditional on the assumption that the distribution of talents is even, i.e., $T(i, j) = 1$. 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. In the last step, we pin down occupation-specific A_j to clear all labor markets.

1.5 Quantitative Exercises

We complete three sets of quantitative exercises. In Section 5.1, we implement counterfactual experiments to check the labor productivity gain for China and India if the impediments to intergenerational occupational mobility are reduced to the US level. 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 equal across groups and occupations. We relax this assumption in Section 5.3 to see to what

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

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.

1.5.1 Counterfactual Experiments

We start by assuming $\kappa_{ii} = 1$, for all i. That is, we assume when sons inherit their fathers' occupations, they face no labor market frictions and their coefficients of human capital accumulation are normalized to 1. In our counterfactual experiment, we keep China and India's calibrated values for $\{A, T, s, \phi\}$, but feed in the coefficients from the US, κ_{US}. 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."

	$\tau_{ij} = 0$	$\delta_{ij} = 1$
China	56.95%	73.05%
India	440.94%	464.83%

Table 1.5.1: Productivity Gains in Counterfactuals

The results of the counterfactual experiments are listed in Table 1.5.1. These results indicate 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.

1.5.2 Accounting for China: the 1980s - 2009

As discussed in previous sections, China has made improvements in several dimensions over the past decades. First, the quick expansion of the market economy on the coastal region gradually mitigated the "guanxi" problem. Private firms facing intense international competition are less willing to hire simply because of "guanxi" than state-owned enterprises, where rent seeking is more common. Due to the expansion of the market economy, the relative proportion of state-owned enterprises has decreased dramatically since the 1980s. Second, the Chinese economic reform 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. Third, China has improved general academic and vocational school education as discussed in Section 2.2.3.

		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 1.5.2: China in 2009: Intergeneration Occupation Transition Matrix

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 occupation transition matrix as in Table 1.5.2. We follow the same steps as in Section 5.1. We keep the calibrated values $\{A, T, s, \phi\}$ for China in the 1980s, but feed in the coefficients from 2009, κ_{CN2009}.

The results are listed in the second row in the Table 1.5.3. We also list the results from the benchmark counterfactual from Section 5.1 in the first row for comparason. In the third row, we list the realized growth potential for China from the 1980s to 2009. Our results

	$\tau_{ij} = 0$	$\delta_{ij} = 1$
Benchmark	56.95%	73.05%
2009	42.19%	44.13%
2009/Benchmark	74.08%	60.41%

Table 1.5.3: Productivity Gains of China from the 1980s to 2009

suggest that China has realized 60 to 74% of the growth potential from the US counterfactual experiment during the past two 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.

1.5.3 Experiment: Relaxing Equal Innate Talent Assumption

So far we have assumed that the parameter 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 could reasonably argue that sons of athletes, on average, are born stronger and faster than sons of non-athletes, providing a natural advantage for fathers' occupation. In this case, we would expect T_{ij} to vary across i and j. However, the problem is that 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.

We use the experiment that reduces the impediments of intergenerational occupational mobility in China and India in the 1980s to the US level in Section 5.1 as the benchmark. We will impose three different sets of T_{ij} and reproduce the results in order to see to what extent our results rely on the assumption. Since this paper is about occupational inheritance, we will 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) $T_{ii} = (skill\,level)^{\theta}$. International Labour Office (1990) introduces skill level to measure the degree of complexity and skill requirement for occupations in ISCO88. There are four

	China		India	
	$\tau_{ij} = 0$	$\delta_{ij} = 1$	$\tau_{ij} = 0$	$\delta_{ij} = 1$
Benchmark	56.95%	73.05%	440.94%	464.83%
$T_{ii} = 2^{\theta}$	83.06%	86.33%	412.73%	484.04%
$T_{ii} = 3^{\theta}$	129.96%	133.69%	361.19%	445.79%
$T_{ii} = (skill\, level)^{\theta}$	129.96%	127.96%	361.19%	442.28%

Table 1.5.4: Relaxing the Assumption on T

skill levels that can be found in Table 1.10.1. For the third set of values of T_{ii}, we simply assign the skill level from ISCO88.

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 1.5.3. According to this table, relaxing the equal innate talent assumption does not fundamentaly change our conclusion.

1.6 Robustness Check

As we discussed earlier, there is some controversy about the correct parameters for β for China and India. β determines the Mincerian return to education. 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.

The robustness check results for parameter β are listed in Table 1.6.1. 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 1.6.2. Both parameters $\{\eta, \theta\}$ can change our

		$\tau_{ij} = 0$	$\delta_{ij} = 1$
$\beta = .5$	China	61.62%	78.36%
	India	456.12%	478.81%
$\beta = .8$	China	61.61%	78.38%
	India	456.12%	478.81%
$\beta = 8$	China	61.60%	78.38%
	India	456.18%	478.89%

Table 1.6.1: Robustness Check: β

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.

		$\tau_{ij} = 0$	$\delta_{ij} = 1$
$\eta = .1$	China	67.44%	83.64%
	India	494.01%	446.13%
$\eta = .5$	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 1.6.2: Robustness Check

1.7 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 occupational 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 occupational 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 statistically 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. We document this fact for the first time, shedding light on the differences in how young workers choose occupations between developing and developed countries. On the other hand, in order to clarify the concerns that one single occupation, farmers, dominates the results, we exclude all farmers and reproduce the former results. We find that without farmers, the correlation between IOM rates and GDP per capita is weakened but still statistically significant. We also contribute by systematically calculating the Altham statistics for intergenerational occupation transition matrices across countries, which distinguishes the interaction effect from the prevalence effect. We find that the correlation between the Altham statistics and GDP per capita still exists, however weaker than that between IOM rates and GDP per capita. 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 aformentioned 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 occupational 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.

1.8 Appendix A: Model Solution

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

$$s_j = \frac{1}{1 + \frac{1-\eta}{\beta\phi_j}} \tag{1.20}$$

$$e_{ij} = [\delta_{ij}(1-\tau_{ij})w_j\epsilon_j\eta s_j^{\phi_j}]^{\frac{1}{1-\eta}} \tag{1.21}$$

$$U_{ij} = [\delta_{ij}(1-\tau_{ij})w_j\epsilon_j\eta^{\eta}(1-\eta)^{1-\eta}s_j^{\phi}(1-s_j)^{\frac{1-\eta}{\beta}}]^{\frac{\beta}{1-\eta}} \tag{1.22}$$

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

$$p_{ij} = \frac{\psi_{ij}^{\theta}}{\sum_k \psi_{ik}^{\theta}} \tag{1.23}$$

$$\psi_{ij} = \delta_{ij}(1-\tau_{ij})T_{ij}^{1/\theta}w_j s_j^{\phi_j}(1-s_j)^{\frac{1-\eta}{\beta}} \tag{1.24}$$

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

$$\pi_j = \sum_i \pi_i^L p_{ij} = \sum_i \pi_i^L \cdot \frac{\psi_{ij}^{\theta}}{\sum_k \psi_{ik}^{\theta}} \tag{1.25}$$

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

$$E_i[h_{ij}\epsilon_{ij}|j] = \delta_{ij}^{\frac{1}{1-\eta}}(1-\tau_{ij})^{\frac{\eta}{1-\eta}}(s_j^{\phi_j}\eta^{\eta})^{\frac{1}{1-\eta}}w_j^{\frac{\eta}{1-\eta}}(\frac{T_{ij}}{p_{ij}})^{\frac{1}{\theta(1-\eta)}} \cdot \Gamma(1-\frac{1}{\theta(1-\rho)(1-\eta)}) \tag{1.26}$$

Combined with Equation (23), Equation (26) can be rewritten as:

$$E_i[h_{ij}\epsilon_j|j] = \frac{1}{w_j(1-\tau_{ij})}\eta^{\frac{1}{1-\eta}}(1-s_j)^{-\frac{1}{\beta}}(\sum_k \psi_{ik}^{\theta})^{\frac{1}{\theta}} \cdot \Gamma(1-\frac{1}{\theta(1-\rho)(1-\eta)}) \tag{1.27}$$

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

$$H_j = \sum_{i=1}^{M} \pi_i^L p_{ij} \cdot E_i[h_{ij}\epsilon_{ij}|j] \tag{1.28}$$

Plugging Equation (26) into Equation (28):

$$H_j = (\eta^\eta s_j^\phi w_j^\eta)^{\frac{1}{1-\eta}} \cdot \{\sum_i [\pi_i^L p_{ij}^{1-\frac{1}{\theta(1-\eta)}} \cdot T_{ij}^{\frac{1}{\theta}\frac{1}{1-\eta}} \cdot (\delta_{ik}(1-\tau_{ik})^\eta)^{\frac{1}{1-\eta}}]\} \cdot \Gamma(1 - \frac{1}{\theta(1-\rho)(1-\eta)}) \tag{1.29}$$

Denote Φ_j:

$$\Phi_j = (\eta^\eta s_j^\phi)^{\frac{1}{1-\eta}} \cdot \{\sum_i [\pi_i^L p_{ij}^{1-\frac{1}{\theta(1-\eta)}} \cdot T_{ij}^{\frac{1}{\theta}\frac{1}{1-\eta}} \cdot (\delta_{ik}(1-\tau_{ik})^\eta)^{\frac{1}{1-\eta}}]\} \cdot \Gamma(1 - \frac{1}{\theta(1-\rho)(1-\eta)}). \tag{1.30}$$

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

$$H_i = \Phi_i \cdot w_i^{\frac{\eta}{1-\eta}} \tag{1.31}$$

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

$$w_j = Y^{\frac{1}{\sigma}} A_j^{\frac{\sigma-1}{\sigma}} H_j^{-\frac{1}{\sigma}} \tag{1.32}$$

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:

$$H_j = \Phi_j^{\frac{1}{\zeta}} A_j^{\frac{\sigma-1}{\sigma}\frac{\eta}{1-\eta}\frac{1}{\zeta}} Y^{\frac{\eta}{\sigma\zeta(1-\eta)}} \tag{1.33}$$

$$w_j = \Phi_j^{\frac{1-\zeta}{\zeta}\frac{1-\eta}{\eta}} A_j^{\frac{\sigma-1}{\sigma}\frac{1}{\zeta}} Y^{\frac{1}{\sigma\zeta}} \tag{1.34}$$

We also can solve for aggregate output Y:

$$Y = \{\sum_j (A_j^{1+\frac{\sigma-1}{\sigma}\frac{\eta}{1-\eta}\frac{1}{\zeta}} \Phi_j^{\frac{1}{\zeta}})^{\frac{\sigma-1}{\sigma}}\}^{\frac{\sigma}{\sigma-1} \cdot \frac{1}{1-\frac{1}{\sigma}\frac{1}{\zeta}\frac{\eta}{1-\eta}}} \tag{1.35}$$

1.9 Appendix B: Altham Statistics

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

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

Denote $a_{ij} = log(\frac{p_{ij}}{q_{ij}})$. 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:

$$\begin{aligned}
&4rs \cdot \sum_i\sum_j [a_{ij} - \underbrace{\frac{\sum_m\sum_l a_{ml}}{rs}}_{matrix\,mean} - \underbrace{(\frac{\sum_m a_{mj}}{r} - \frac{\sum_m\sum_l a_{ml}}{rs})}_{column\,deviation} - \underbrace{(\frac{\sum_l a_{il}}{s} - \frac{\sum_m\sum_l a_{ml}}{rs})}_{row\,deviation}]^2 \\
=& 4rs \cdot \sum_i\sum_j (a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s} + \frac{\sum_m\sum_l a_{ml}}{rs})^2 \\
=& 4rs \cdot \sum_i\sum_j [\underbrace{(a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s})^2}_{term\,1} + \underbrace{(\frac{\sum_m\sum_l a_{ml}}{rs})^2}_{term\,2} \\
&+ \underbrace{2 \cdot (a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s}) \cdot \frac{\sum_m\sum_l a_{ml}}{rs}}_{term\,3}]
\end{aligned} \tag{1.36}$$

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

$$
\begin{aligned}
term\,1 &= \sum_i \sum_j (a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s})^2 \\
&= \sum_i \sum_j (a_{ij}^2 + \frac{(\sum_m a_{mj})^2}{r^2} + \frac{(\sum_l a_{il})^2}{s^2} - 2a_{ij} \cdot \frac{\sum_m a_{mj}}{r} \dots \\
&\qquad - 2a_{ij} \cdot \frac{\sum_l a_{il}}{s} + 2\frac{\sum_m a_{mj}}{r} \cdot \frac{\sum_l a_{il}}{s})^2 \\
&= \sum_i \sum_j a_{ij}^2 + \frac{1}{r} \sum_j (\sum_i a_{ij})^2 + \frac{1}{s} \sum_i (\sum_j a_{ij})^2 \\
&\qquad - 2\frac{1}{r} \sum_j (\sum_i a_{ij})^2 - 2\frac{1}{s} \sum_i (\sum_j a_{ij})^2 + 2\frac{1}{rs} (\sum_i \sum_j a_{ij})^2 \qquad (1.37) \\
&= \sum_i \sum_j a_{ij}^2 - \frac{1}{r} \sum_j (\sum_i a_{ij})^2 - \frac{1}{s} \sum_i (\sum_j a_{ij})^2 + 2\frac{1}{rs} (\sum_i \sum_j a_{ij})^2 \qquad (1.38) \\
term\,2 &= \sum_i \sum_j (\frac{\sum_m \sum_l a_{ml}}{rs})^2 = \frac{1}{rs} (\sum_i \sum_j a_{ij})^2 \qquad (1.39) \\
term\,3 &= \sum_i \sum_j 2 \cdot (a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s}) \cdot \frac{\sum_m \sum_l a_{ml}}{rs} \\
&= \frac{2}{rs} \cdot [(\sum_i \sum_j a_{ij})^2 - (\sum_i \sum_j a_{ij})^2 - (\sum_i \sum_j a_{ij})^2] \\
&= -\frac{2}{rs} (\sum_i \sum_j a_{ij})^2 \qquad (1.40)
\end{aligned}
$$

Plugging Equations (37)-(39) back into Equation (37):

$$
\begin{aligned}
&4rs \cdot \sum_i \sum_j [\underbrace{(a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s})^2}_{term\,1} + \underbrace{(\frac{\sum_m \sum_l a_{ml}}{rs})^2}_{term\,2} \dots \\
&\qquad + \underbrace{2 \cdot (a_{ij} - \frac{\sum_m a_{mj}}{r} - \frac{\sum_l a_{il}}{s}) \cdot \frac{\sum_m \sum_l a_{ml}}{rs}}_{term\,3}] \\
=&4rs \cdot [\sum_i \sum_j a_{ij}^2 - \frac{1}{r} \sum_j (\sum_i a_{ij})^2 - \frac{1}{s} \sum_i (\sum_j a_{ij})^2 \\
&\qquad + 2\frac{1}{rs} (\sum_i \sum_j a_{ij})^2 + \frac{1}{rs} (\sum_i \sum_j a_{ij})^2 - \frac{2}{rs} (\sum_i \sum_j a_{ij})^2] \\
=&4rs \cdot [\sum_i \sum_j a_{ij}^2 - \frac{1}{r} \sum_j (\sum_i a_{ij})^2 - \frac{1}{s} \sum_i (\sum_j a_{ij})^2 + \frac{1}{rs} (\sum_i \sum_j a_{ij})^2] \\
=&4rs \sum_i \sum_j a_{ij}^2 + 4(\sum_i \sum_j a_{ij})^2 - 4r \sum_i (\sum_j a_{ij})^2 - 4s \sum_j (\sum_i a_{ij})^2 \qquad (1.41)
\end{aligned}
$$

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

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

1.10 Appendix C

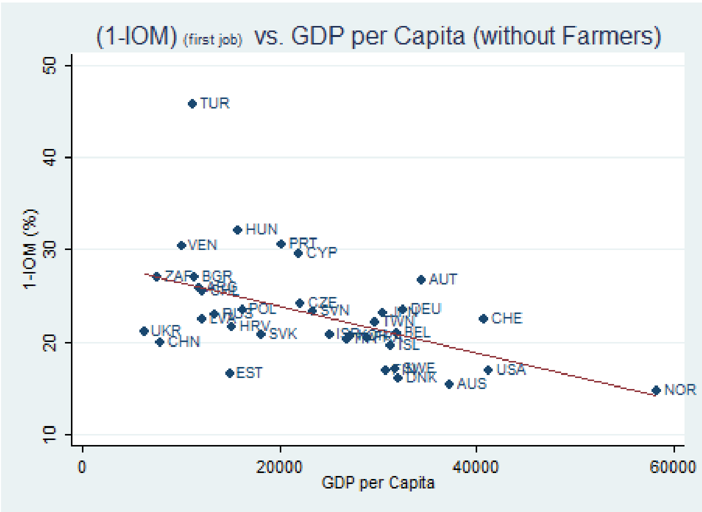


Figure 1.10.1: $(1 - IOM)_{(first\,job)}$ vs. GDP per Capita (without Farmers)

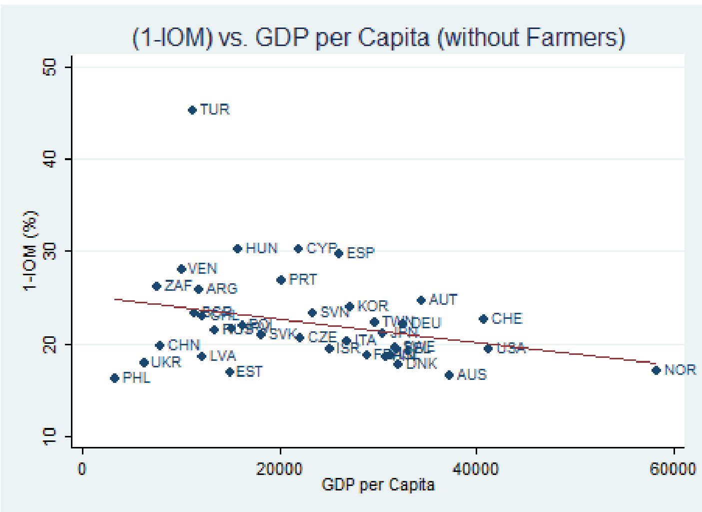


Figure 1.10.2: $(1 - IOM)$ vs. GDP per Capita (without Farmers)

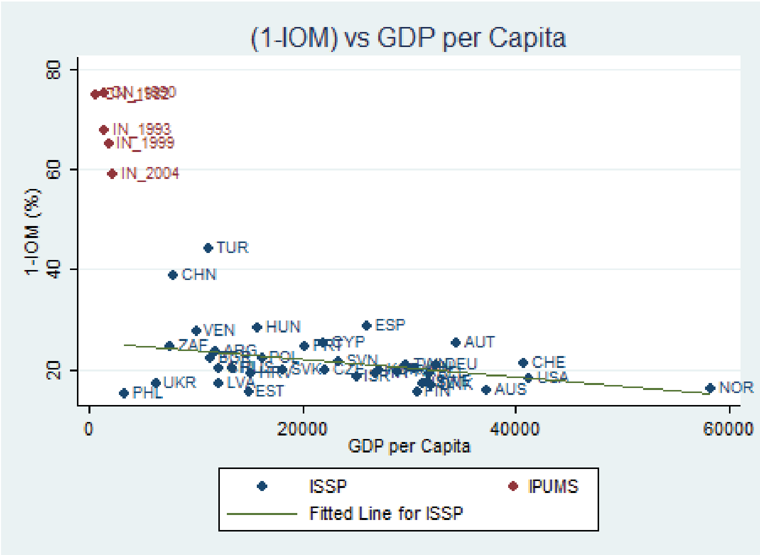


Figure 1.10.3: ISSP and IPUMS: (1-IOM) vs. GDP per Capita

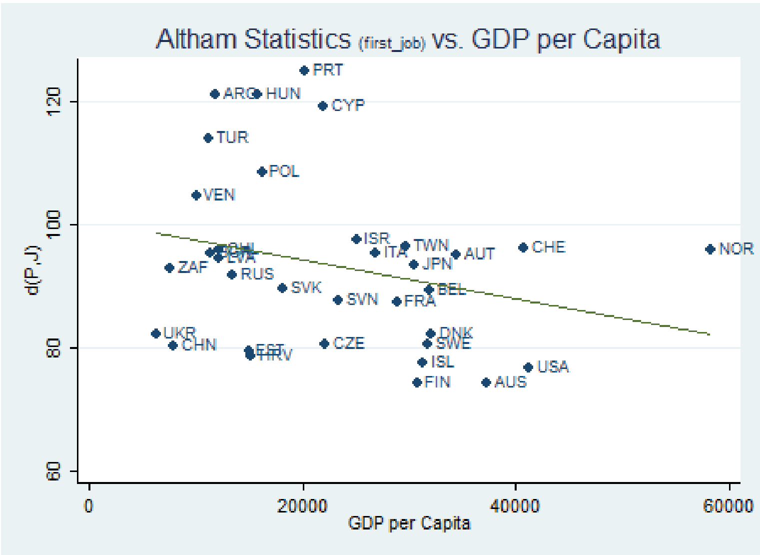


Figure 1.10.4: Altham Statistic vs. GDP per Capita: First Occupation

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 1.10.1: 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 1.10.2: US: Intergenerational Occupation Transition Matrix

CHAPTER 2

Behind Job Polarization: A Quiet Revolution

2.1 Introduction

The end of the 20th century and the beginning of the 21st century witnessed dramatic changes in the US labor market and women's role in the market. For the former, the phenomenon named "job polarization" as in Autor et al. (2006), describes the U-shape change in employment, where employment increase in high-wage and low-wage jobs but shrinks for middle-wage jobs. For the latter, the "Quiet Revolution" in women's economic role, as termed by Goldin (2006), took place as women became more attached to work and enjoyed a better chance of a successful career. There are several interesting empirical facts linking job polarization to the Quiet Revolution. There was about a 30% increase in low-skilled service jobs during this time period; at the same time, there was also approximately 9% increase in female labor force participation in the US. Lying in the intersection of these two important phenomena, this paper intends to connect these empirical facts and attribute the rise of low-skilled service jobs to women's increased attachment to the labor force.

Goos and Manning (2007) coined the term "job polarization" with the finding that the highest and lowest wage occupations have risen in employment shares in the UK since 1975. Goos et al. (2009) and Dustmann et al. (2009) report similar findings among other developed EU countries. Autor et al. (2006) describes the job polarization phenomenon in the US. These empirical findings all suggest that job polarization is a quite robust fact throughout post-industrial economies.

As the name suggests, job polarization means higher employment shares in both the upper-tail and lower-tail of the wage distribution. There are extensive theories explaining the rise in the upper tail, the most important being skill biased technology change (SBTC). In a seminal paper, Krusell et al. (2000) develop a framework for understanding SBTC in which the increasing rate of decline in equipment prices rewards skilled workers, due to capital-skill complementarities, but punishes unskilled workers, by substituting their labor with capital. This ultimately increases the skill premium and contributes to the rise in the upper tail share of employment. Acemoglu and Autor (2011) also have a similar framework, which they call the canonical model. In their model, high-skilled and low-skilled workers are substitutable. If the high-skilled-worker-augmenting technology outpaces the low-skilled-worker-augmenting technology, the demand of high-skilled workers would increase, resulting in both more employment and higher wages for them.

However, existing theories have difficulties in explaining the rise in low-skilled jobs. If SBTC rewards high-skilled workers but punishes low-skilled workers, we expect lower wages and employment for low-skilled jobs. However, empirical results suggest otherwise. In particular, Autor and Dorn (2013) document a relatively large increase in low-skilled service workers in terms of both employment shares and average wages from 1980 to 2005. They explain the growth of low-skilled service jobs as a result of the "interaction of consumer preference and production technology." In their model, there are three types of labor inputs: manual, routine, and abstract. Routine and abstract labor are used to produce goods, and the elasticity of substitution between routine labor and capital is higher than that between abstract labor and capital. Manual labor is used to produce services. Final goods are aggregated with goods and services using a CES function. If the elasticity of substitution in production between (computer) capital and routine labor is high relative to the elasticity of substitution between goods and services in consumption, a quick drop in the price of capital would asymptotically lead to the vanishment of manual labor and all unskilled workers would work in the service sector. This paper is a further extension of the previous SBTC theory.

In this paper, I examine the role of women's increasing attachment to the labor force in explaining the rise of low-skilled service jobs. From 1980 to 2005, the female labor force participation rate rose by about 9%, according to our calculations based on BLS data. Juhn and Potter (2006) report an increasing female labor force participation rate by cohort. In the period that this paper examines, the growth in female labor force participation is significant, especially for prime age females. Women's wages also increased relative to men's over this time period. Blau et al. (2012) report that the US gender earnings ratio rose from around 65% in 1980 to around 80% in 2005. In an earlier paper, Blau and Kahn (2000) conclude that gender-specific factors, including "gender differences in qualifications and discriminations", etc., are the main force behind the decreasing gender gap.

In fact, women's rising attachment to the labor force has a much broader implication besides employment and wages. Goldin (2006) uses the term "Quiet Revolution" to describe the significant change in women's social and economic status. She points out three important aspects in this revolution, i.e., "more predictable attachment to the workplace", "greater identity with career", and "better ability to make joint decisions with their spouses". It can be easily seen that all of these changes are heavily related to their performance in the labor market. In this period, women obtain more education and play an increasing role in professional occupations, such as lawyers, physicians, professors, and managers – all of which have been historically dominated by males. Costa (2000) presents a survey of changes women experienced in the labor force; the title "From Mill Town to Board Room: The Rise of Women's Paid Labor" conveys the core message of the paper.

There is a large literature explaining why women increased their labor force participation during this period. One strand of literature looks into the labor market aspect of this phenomenon, such as narrowing gender earnings gap (Jones et al. 2003; Attanasio et al. 2008), less discrimination, the introduction of household appliances Greenwood et al. (2005), fewer manual labor components among all jobs Galor and Weil (1996), and the rise of IT technology (Krueger 1993; Weinberg 1999). Another strand of literature looks at reasons beyond the labor market, including medical progress such as improved maternal health and infant formula (Albanesi and Olivetti 2009), child care costs (Attanasio et al. 2008; Del Boca and Vuri 2007), cultural change (Fernandez and Fogli 2009; Antecol 2000; Fernandez et al. 2004), and safety nets from divorce.

Another important related fact is the dramatic rise in female college enrollment. Goldin et al. (2006) report the narrowing gender gap and its eventual reversal. They list fertility, changing expectations, and better contraceptive methods as reasons for the catch-up; furthermore, the reversal in this trend can also be explained by greater economic benefit but lower effort cost for women's college attendance. Di Prete and Buchmann (2013) also provide a very detailed discussion on the advantages of girls in schools, starting as early as kindergarten. Bronson (2014) argues that for women, college degrees can offer insurance against low income, especially in the event of divorce.

Although this paper is closely related to women's increasing attachment to the labor force, it is important to note that the reasons behind this increase are not the focus of this paper. It does not matter to us why females increase their labor force participation; we only focus on the result of it. Furthermore, the typical time period for SBTC, such as in Acemoglu and Autor (2011) and Krusell et al. (2000), is from 1980 to 2005, while the Quiet Revolution from Goldin (2006) began in the late 1970s. We could have a greater success if we began our analysis from 1975; however, we do not have data for job polarization from 1975 to 1980, simply because 1975 is not a census year. We constrain ourselves within the limits of existing data and thus our estimates represent a lower bound for the importance of this relationship.

This paper is also related to the literature on home production. Becker (1965) provides a static theory of home production and Gronau (1980) further extends this theory by linking the allocation of time to the allocation of goods and comparing the value of time and the value of home products. These are classical theories about home production. Entering the 1990s, there has been a large literature linking home production and the business cycle, notably Benhabib et al. (1991), Greenwood and Hercowitz (1991), and McGrattan et al. (1997). These papers show that including home production could improve the performance of the real business cycle model; Gronau (1997)provides an excellent survey of this literature.

The importance of home production can be inferred from its size; however, it is impossible to directly measure the value of home production. Kuznets et al. (1946) suggest the size of home production could be 1/3 of GDP and believe this number actually underestimates the size. Folbre and Wagman (1993) estimate that the value of home production was approximately 25% to 50% of GDP in the US from 1800 to 1860, subject to different assumptions.

On the other hand, Gronau (1980) shows that home production by US wives in 1973 was worth more than 60% of the family income before tax.

In recent years, there have been new empirical findings on home production and time use patterns, from which we build this paper for the relevant period. Ramey (2009) reports a variety of results on home production hours for the 20th century. The most important result for this paper is the finding that there is no significant trend in home production after 1980, conditional on employment status and gender. This finding is similar to Aguiar and Hurst (2007) for the same period; however, they also find a large drop in home production hours from 1965 to 1980. Aguiar et al. (2013) find that during the Great Recession (2007-2010), roughly 45% of foregone market hours are reallocated to non-market work and child care combined. Their results are supportive of the conjecture that the elasticity of substitution between home production and market production is high. Baxter and Rotz (2009) provide some other interesting empirical results using CEX data to "detect household production." For example, they find one-worker families spend a higher share of their expenditure on high-time-input goods, but a lower share on low-time-input goods, relative to two-worker families. Typical high-time-input goods include flour and eggs, while typical low-time-input goods include biscuits and cakes.

This paper is also related to the literature linking structural change and female labor force participation. However, it is important to emphasize that our paper focuses on low-skilled services, not services in general as in related literature. The large increase in high-skilled services has been widely documented (for example, Akbulut 2011, Rendall 2010, Buera and Kaboski 2012, and Ngai and Petrongolo 2013). These papers focus on the rise of high-skilled services, such as law services, financial services, and etc. The mechanism behind this increase is that high-skilled services grow fast and are more favorable to women, compared with traditional jobs. This would endogenously create a gender-based demand shift that increases female employment and narrows the gender gap. However, in this paper, we focus instead on low-skilled service jobs, common occupations for women who leave home production to work in the formal labor force. Increasing female attachment in this labor market would lead to a higher share of low-skilled services in consumption and shift demand, leading to a growth in low-skilled service jobs.

It is interesting to note that both job polarization and the increase in female labor force participation have not only been documented in the US, but also in most western EU countries. As mentioned earlier, Goos et al. (2010) andAdermon and Gustavsson (2015) report and analyze facts about job polarization in European countries; Jaumotte (2003) reports that female labor force participation rates have increased in most OECD countries except Turkey, Hungary, Poland, and the Czech Republic, which are relatively less developed countries. Thus, jobless recovery and women's rising role in the labor market seem to be universal phenomena among post-industrial countries.

This paper contributes to the existing literature for the following reasons. First, as far as we know, it is the first to link job polarization with the Quiet Revolution. Existing theories attempt to explain the rise of low-skilled service jobs using the SBTC mechanism. However, we show that a conventional story of women going to work would also explain this aspect of job polarization. Second, it presents a simple but convenient accounting framework that can easily show the effects of labor force participation on structural transformation. By taking advantage of the properties of an individual maximization problem, we obtain an optimal solution that is invariant over time for individuals and families, conditional on employment status. The invariant allocation of time is consistent with the data from Ramey (2009), and we use the consumption decision to back out the proportion of structural change that could be explained by increasing female labor force participation.

This paper is organized as follows. Section 1 gives a general introduction; Section 2 presents all related empirical facts; Section 3 presents a simple model and shows several important and useful properties of the model; Section 4 calibrates the model to the data; Section 5 presents the results of the quantitative exercise; and Section 6 concludes.

2.2 Facts

This section documents the key empirical facts motivating this paper. First, we present the rapid growth in low-skilled service jobs, which is an important component of the job polarization phenomenon. Second, we look into the details of low-skilled service jobs and present their growth by occupation. Third, we present the historical home production hours conditional on employment status and gender in the time period of interest. Fourth, we document the increase in labor force participation for women. Fifth, we present the difference in the consumption pattern between families with different composition of workers in the labor market.

2.2.1 Growth of Low-Skilled Service Jobs

A typical graph of employment polarization shows mean wage of occupations on the horizontal axis and change in employment share of occupations on the vertical axis. The polarization phenomon is then simply the positive change in employment share for the upper- and lower-tails and the negative change in employment share for the middle of the distribution. We defer further discussion to the literature on job polarization, e.g. Acemoglu and Autor (2011).

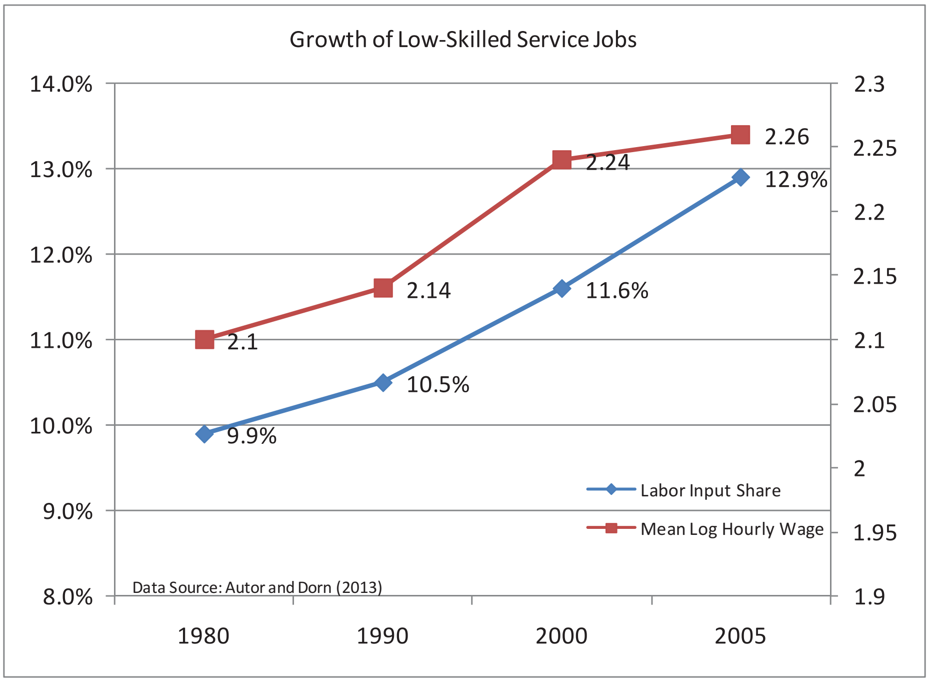


Figure 2.2.1: Growth of Low-Skilled Service Jobs

In Figure 2.2.1, we focus on low-skilled service jobs (Data source: Autor and Dorn

2013). Our targeted service occupations are: food preparation and service occupations, child care workers, personal appearance occupations, miscellaneous personal care and service occupations, housekeeping and cleaning occupations, building/grounds cleaning/maintenance occupations, healthcare support occupations (including dental services), recreation and hospitality occupations, and protective services. From 1980 to 2005, the employment share of these low-skilled service jobs has increased from 9.9% to 12.9%. For the same time, the mean log hourly wage of low-skilled service jobs has risen from 2.1 to 2.26. Both the employment share and wage increase suggest an increasing demand for low-skilled service workers.

2.2.2 Labor Input by Occupation

In Figure 2.2.2, we present the change in employment share by occupation from 1980 to 2005 (Data source: Autor and Dorn 2013). Food preparation and service occupations represent the largest share and growth. Other occupations such as child care workers, personal appearance occupations, and miscellaneous personal care and service occupations are strongly substitutable goods with home products.

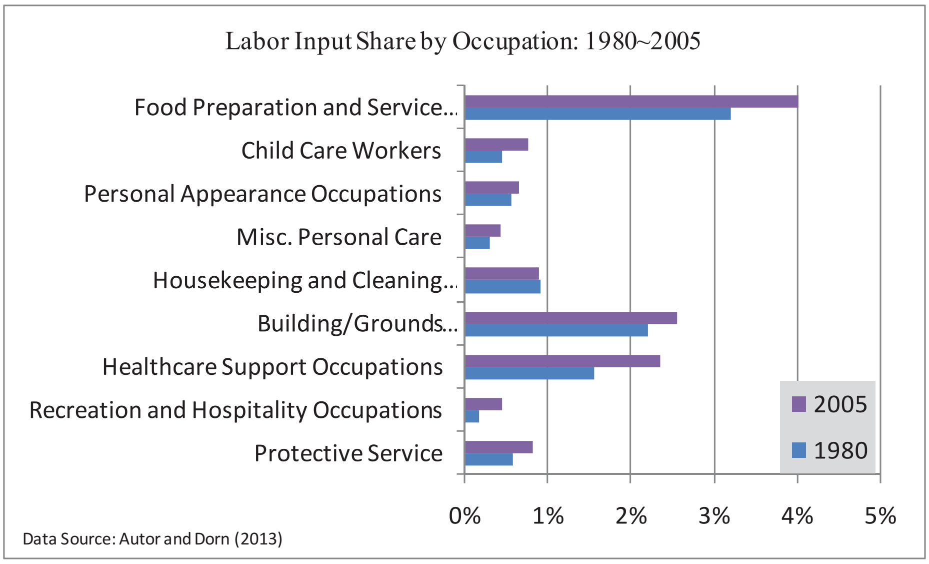


Figure 2.2.2: Labor Input by Occupation

2.2.3 Home Production Hours

Figure 2.2.3 presents home production hours for individuals conditional on gender and employment status (Data source: Ramey 2009). There are several interesting patterns in this graph. First, there is no significant trend of home production conditional on gender and employment status. Second, women always work more than men at home, regardless of employment status. Third, the difference between employed and unemployed women is about 14 hours per week, while this number is about 4 to 5 hours per week for men. This means that even if we control for the total number of workers in an economy, women's entry and men's exit would still result in a decrease in home production.

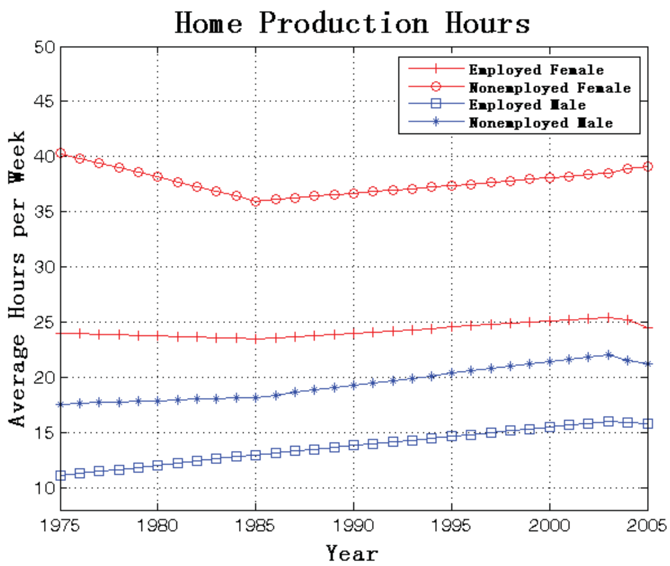


Figure 2.2.3: Home Production Hours

2.2.4 Labor Force Participation Rate

Figure 2.2.4 depicts the labor force participation rates by gender and for the general population (Data source: BLS). There is a dramatic increase in the labor force participation rate, mostly as a result of increased female labor force participation. In fact, from 1980 to 2005, there was a 4% decrease in the male labor force participation rate, while the female labor force participation rate increased by about 9%. One potential problem is that labor force participation is different from employment. However, since we are studying a long term trend here, as long as there is no significant trend in the unemployment rate, the difference between labor force participation and employment should not be a valid concern.

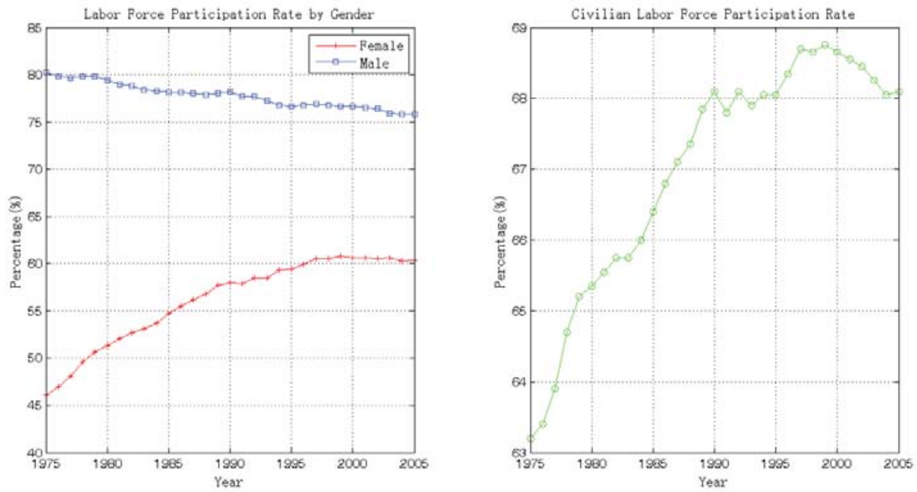


Figure 2.2.4: Labor Force Participation Rate

2.2.5 Consumption Pattern

I use Consumer Expenditure Survey (CEX) to study the consumption patterns of different families. However, the original CEX contains information that is not necessary for our purposes. Instead, I use the Consumer Expenditure Survey Family-Level Extracts (1980:1 - 2003:2) from NBER, which is provided by John Sabelhaus and Ed Harris[1]. This data combines all 5 quarterly interview surveys for the same family and provides the consumption, income, and demographic information at the family level, which fits perfectly for the objective of this paper. I combined all the available data from 1980 to 2003 and checked the correlation between family consumption patterns and employment status of family members.

The variable *ser_share* is the low-skilled services' share[2] of total family consumption

[1] Available from http://www.nber.org/data/ces_cbo.html

[2] Here I define the following expenditure categories as low-skilled services: 024. Food On-Premise; 025. Food Furnished Employees; 028. Alcohol On-Premise; 030. Clothing Services; 033. Barbershops, Beauty Parlors, Health Clubs; 040. Water and Other Sanitary Services; 043. Domestic Service, Other Household Operation; 047. Hospitals; 048. Nursing Homes; 054. Repair, Greasing, Washing, Parking, Storage, Rental;

VARIABLES	(1) ser_share	(2) ser_share	(3) ser_share	(4) ser_share
worker_share	0.0296***	0.0186***	0.0285***	0.0233***
	(0.00104)	(0.00152)	(0.00104)	(0.00168)
fe_share			-0.0132***	-0.00959***
			(0.00118)	(0.00149)
f_fe_nonworkershare		-0.0180***		-0.00898***
		(0.00182)		(0.00230)
Constant	0.133***	0.144***	0.141***	0.144***
	(0.000705)	(0.00133)	(0.000986)	(0.00133)
Observations	51,380	51,380	51,380	51,380
R-squared	0.016	0.018	0.018	0.018

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.2.1: Consumption Patterns

expenditure; *worker_share* is the share of workers among adults in the family; *fe_share* is the share of females among adults in the family; *f_fe_share* is the share of nonworking females among all adults in the family. The regressions are consistent with the hypothesis in our paper. For an average family, more workers among family members lead to a larger share of consumpion of low-skilled services. More females in the family is associated with a smaller share of low-skilled services in the consumption bundle; however, more working females in a family is associated with more consumption of low-skilled services. All of these correlations are statistically signicant. I also add real total per capita income as a control and all regression results hold.

2.3 Model

Time is infinite and discrete with t={0,1,2,...}. There are two types of labor: m (male) and f (female). Each type is of measure 1. There are two market sectors in the economy: sector 1 produces goods and sector 2 produces services. Labor is assumed to be indivisible and all

058. Mass Transit Systems; 059. Taxicab, Railway, Bus, and Other Travel Expenses; 064. Other Recreation Services. The numbers before the categories are the codes in the original data.

workers spend time $\bar{h}$ in working. The numbers of males and females working in the goods sector are denoted n_M and n_F, and correspondingly, s_M and s_F are the numbers of male and female workers in the service sector. Home production hours are denoted by $h_{i,j}$, where $i \in \{m,\ f\}$ indicates gender and $j \in \{e, u\}$ indicates employment status. The remainder of time is leisure $l_{i,j}$.

The production function for the goods sector is

$$Y_{g,t} = A_{g,t}[\alpha_t(n_{m,t}\bar{h})^{\rho_1} + (1-\alpha_t)(n_{f,t}\bar{h})^{\rho_1}]^{\frac{1}{\rho_1}} \tag{2.1}$$

where α_t indicates the change in technology and $\frac{a_t}{(1-a_t)}$ determines the relative productivity of males and females. This production function is similar to Ngai and Petrongolo (2013).

Denote the total employment in goods sector $N_t = n_{m,t} + n_{f,t}$, and denote shares of males and females to be $\varphi_{m,t} = \frac{n_{m,t}}{N_t}$ and $\varphi_{f,t} = \frac{n_{f,t}}{N_t}$. Equation (1) is then rewritten as:

$$Y_{g,t} = A_{g,t} \cdot N_t \cdot \bar{h} \cdot [\alpha_t \cdot (\frac{\varphi_{m,t}}{\varphi_{m,t} + \varphi_{f,t}})^{\rho_1} + (1-\alpha_t)(\frac{\varphi_{f,t}}{\varphi_{m,t} + \varphi_{f,t}})^{\rho_1}]^{\frac{1}{\rho_1}} \tag{2.2}$$

That is, the production of goods is linear in the employment of sector N_t.

Given the production function, we can calculate wage as:

$$w_{m,t} = \alpha_t \cdot A_{g,t}[\alpha_t(n_{m,t}\bar{h})^{\rho_1} + (1-\alpha_t)(n_{f,t}\bar{h})^{\rho_1}]^{\frac{1-\rho_1}{\rho_1}} \cdot (n_{m,t}\bar{h})^{\rho_1 - 1} \cdot \bar{h} \tag{2.3}$$

$$w_{f,t} = (1-\alpha_t) \cdot A_{g,t}[\alpha_t(n_{m,t}\bar{h})^{\rho_1} + (1-\alpha_t)(n_{f,t}\bar{h})^{\rho_1}]^{\frac{1-\rho_1}{\rho_1}} \cdot (n_{f,t}\bar{h})^{\rho_1 - 1} \cdot \bar{h} \tag{2.4}$$

Similarly, the production function for the services sector is:

$$Y_{s,t} = A_{s,t}[\beta_t(s_{m,t}\bar{h})^{\rho_2} + (1-\beta_t)(s_{f,t}\bar{h})^{\rho_2}]^{\frac{1}{\rho_2}} \tag{2.5}$$

and following the same strategy as in the goods sector, denote the total employment in the service sector $S_t = s_{m,t} + s_{f,t}$ and denote shares of males and females in this sector to be

$\phi_{m,t} = \frac{s_{m,t}}{S_{g,t}}$ and $\phi_{f,t} = \frac{s_{f,t}}{S_{g,t}}$. Equation (3) could be rewritten as:

$$Y_{s,t} = A_{s,t} \cdot S_t \cdot \bar{h} \cdot [\beta_t \cdot (\frac{\phi_{m,t}}{\phi_{m,t} + \phi_{f,t}})^{\rho_2} + (1 - \beta_t)(\frac{\phi_{f,t}}{\phi_{m,t} + \phi_{f,t}})^{\rho_2}]^{\frac{1}{\rho_2}} \tag{2.6}$$

That is, the production of market services is also linear in the employment of sector S_t.

The male and female labor force participation is denoted:

$$\begin{aligned} p_m &= n_m + s_m \\ p_f &= n_f + s_f \end{aligned}$$

Home production is given by the function:

$$y_{h,t} = A_{h,t} \cdot h_t$$

Individual Problem

For each individual, the final good is:

$$c_t = y_t = \{\theta y_{g,t}^{\epsilon_1} + (1 - \theta)[\mu y_{s,t}^{\epsilon_2} + (1 - \mu) y_{h,t}^{\epsilon_2}]^{\frac{\epsilon_1}{\epsilon_2}}\}^{\frac{1}{\epsilon_1}} \tag{2.7}$$

The utility function is assumed to be separable in consumption and leisure: $u_i(c_t, l_t) = log(c_t) + G_i(l)$, where $i \in \{M, F\}$.

The maximization problem for an individual (i, j) is as follows:

$$\max_{c_{g,t}, c_{s,t}, c_{h,t}, l_t} \sum_{t=0}^{\infty} \{log(c_t) + G_i(l)\} \tag{2.8}$$

$$s.t. \;\; c_t = \{\theta c_{g,t}^{\epsilon_1} + (1 - \theta)[\mu c_{s,t}^{\epsilon_2} + (1 - \mu) c_{h,t}^{\epsilon_2}]^{\frac{\epsilon_1}{\epsilon_2}}\}^{\frac{1}{\epsilon_1}}$$

$$a_t = c_{g,t} + P_t \cdot c_{s,t}$$

$$c_{h,t} = A_{h,t} \cdot h$$

$$\bar{h} \cdot \Pi_t + h_t + l_t = 1$$

where Π is an indicator function such that:

$$\Pi_t \begin{cases} = 1, & if\ employed \\ = 0, & if\ unemployed \end{cases}$$

and a_t is the income of the individual:

$$a_t \begin{cases} = (1-\tau)\cdot w_t, & if\ \Pi_t = 1 \\ = b_t, & if\ \Pi_t = 0 \end{cases}$$

where w_t is the income after tax in the labor market and b_t is the government transfer.

In the end, this maximization problem can be reduced to two first order conditions: one describing the allocation of consumption between goods and services (Equation 9), and the other describing the work-leisure tradeoff (Equation 10).

$$\begin{aligned} p \cdot \frac{\partial c}{\partial c_g} &= \frac{\partial c}{\partial c_s} \\ \Rightarrow p \cdot \theta c_g^{\epsilon_1 - 1} &= (1-\theta)\Phi^{\epsilon_1-\epsilon_2}\mu c_s^{\epsilon_2-1} \end{aligned} \tag{2.9}$$

where $\Phi = [\mu c_s^{\epsilon_2} + (1-\mu)c_h^{\epsilon_2}]^{\frac{1}{\epsilon_2}}$.

$$\frac{1}{c}\frac{\partial c}{\partial h} = G_i^i(l) \tag{2.10}$$

Matching data to the model, the solution to equation (10) should be equal to home production hours. To avoid further complication of assuming the functional form of $G_i(l)$, we simply take the home production hours in the data as the solution from equation (10) and then go directly into equation (9) to choose the consumption bundle between goods and services.

Proposition 1 *Given the model above, if production functions are time invariant and* $\{A_{g,t}, A_{s,t}, A_{h,t}\}$ *grow at the same rate over time, the time allocation between home production and leisure conditional on employment status is time invariant.*

Proof: The proof follows from the following facts: (1) the utility function is separable between time and leisure and it is log form in consumption; (2) final goods production has constant returns to scale.

This result is important to us since it matches the empirical result that home production hours conditional on employment status and gender are relatively stable over time .

This proposition rests on the assumption that production functions are time invariant. If this is not the case, the result should be revised. Recall Equation (3), which can be rewritten as:

$$w_{m,t} = \alpha_t \cdot A_{g,t}[\alpha_t + (1-\alpha_t)(\frac{n_{f,t}}{n_{m,t}})^{\rho_1}]^{\frac{1-\rho_1}{\rho_1}} \cdot \bar{h}$$

Consider the economy from time t to time τ. In order to keep time allocation invariant, one needs to have:

$$\frac{w_{m,\tau}}{w_{m,t}} = \frac{\alpha_\tau \cdot [\alpha_\tau + (1-\alpha_\tau)(\frac{n_{f,\tau}}{n_{m,\tau}})^{\rho_1}]^{\frac{1-\rho_1}{\rho_1}}}{\alpha_t \cdot [\alpha_t + (1-\alpha_t)(\frac{n_{f,t}}{n_{m,t}})^{\rho_1}]^{\frac{1-\rho_1}{\rho_1}}} \cdot \frac{A_{g,\tau}}{A_{g,t}} = \frac{A_{h,\tau}}{A_{h,t}}$$

That is, to keep the time allocation pattern invariant, there should be an adjustment factor between the growth rates of $\{A_{g,t},\ A_{s,t}\}$ and $A_{h,t}$.

Proposition 2 *Given the model above, assuming equal productivity across two sectors,* $\alpha_t = \beta_t$ *implies* $\frac{Y_{s,t}}{Y_{g,t}} = \frac{S_t}{N_t}$*, i.e., output ratio is equal to labor input ratio.*

Family Problem

Since the work and consumption decisions are decided at the family level rather than the individual level, we present the problem solved by a family. All the families are composed of one male and one female. There are four types of families conditional on gender and employment status. We denote them by $F = \{(e,e),(e,u),(u,e),(e,e)\}$. We assume a family pools all the consumption and maintains their own preference in time use. The subscript

$\{m,\ f\}$ indicates the gender of the individual.

$$\max_{c_{g,t},c_{s,t},c_{h,t},l_t} \sum_{t=0}^{\infty} \{log(c_t) + G_m(l_m) + G_f(h_f)\} \tag{2.11}$$

$$s.t.\ \ c_t = \{\theta c_{g,t}^{\epsilon_1} + (1-\theta)[\mu c_{s,t}^{\epsilon_2} + (1-\mu) c_{h,t}^{\epsilon_2}]^{\frac{\epsilon_1}{\epsilon_2}}\}^{\frac{1}{\epsilon_1}}$$

$$a_{m,t} + a_{f,t} = c_{g,t} + p_t \cdot c_{s,t}$$

$$c_{h,t} = A_{h,t} \cdot (h_{m,t} + h_{f,t})$$

$$\bar{h} \cdot \Pi_{m,t} + h_{m,t} + l_{m,t} = 1$$

$$\bar{h} \cdot \Pi_{f,t} + h_{f,t} + l_{f,t} = 1$$

Proposition 1 applies here as long as $\frac{a_{m,t}}{a_{f,t}}$ is not changing over time, and we maintain this assumption throughout the paper.

Government

Government serves only as an income redistribution institution and there is no government spending. The government imposes a tax on employed workers and transfers the wealth to the non-employed to keep a displacement rate for the unemployed κ.

$$p_m \cdot (1-\tau) \cdot w_{m,e} + (1-p_m) \cdot b_{m,f} + p_f \cdot (1-\tau) \cdot w_{f,e} + (1-p_f) \cdot b_{f,e}$$
$$= p_m \cdot w_{m,e} + p_f \cdot w_{f,e}$$

$$\Rightarrow \kappa = \frac{b_{m,e}}{(1-\tau) \cdot w_{m,e}} = \frac{b_{f,e}}{(1-\tau) \cdot w_{f,e}}$$

Equilibrium

An equilibrium, given relative productivity a_j, sectoral productivity $\{A_{g,t}, A_{s,t}, A_{h,t}\}$, labor force participation rates $\{p_m, p_f\}$, market prices $\{P_t,\ w_{m,t},\ w_{m,t}\}$, and government redistribution scheme κ_t, is the combination of households' decisions $\{c_{g,t}, c_{s,t}, h_{m,t}, h_{f,t}\}$, firms' labor input decisions $\{n_{m,t}, n_{f,t}, s_{m,t}, s_{f,t}\}$, and government's taxing decision τ_t such that:

1. $\{c_{g,t}, c_{s,t}, h_{m,t}, h_{f,t}\}$ solves the household maximization problem.

2. $\{n_{m,t}, n_{f,t}, s_{m,t}, s_{f,t}\}$ solves firms' maximization decision.

3. Government keeps fiscal balance.

4. Markets clear:

a. Goods market:

$$Y_{i,t} = \sum_{j \in F} c_{i,t}$$

where $i \in \{g, s\}$.

b. Labor market: the supply and demand of workers for each sector is cleared.

2.4 Calibration And Accounting Strategy

The model is calibrated to the US in 1980. We take 1980 as the basis and solve the consumption patterns in each type of family. We then feed in the labor force participation rates $\{p_{m,t}, p_{f,t}\}$ for each period, and based on the consumption patterns of different types of families, we can back out the relative demand of market goods and service goods and therefore back out the relative employment share in each sector.

Parameter	A_s	A_g	A_h	$\bar{h}$	ζ	ρ	θ	μ	κ	τ	α	β	ϵ_1	ϵ_2
Value	10	10	2.03	$\frac{1}{3}$	.7739	$\frac{2}{3}$	.7607	0959	.5	.18	.66	.66	.1	5

Table 2.4.1: Calibrated Parameters

First, in order to simplify our analysis, we assume the production functions in market goods and market services are similar up to a difference in productivity, i.e., $\rho_1 = \rho_2 = \rho$ and $\alpha = \beta$. However, since labor is perfectly mobile, any differences in productivity would eventually be reflected in the relative price. Therefore, it makes no difference if we simply assume $A_s = A_g$. The elasticity of substitution of male and female labor in the production function is $\rho = \frac{2}{3}$, which is taken from Ngai and Petrongolo (2013). The employed worker's working hour typical in the literature is $\bar{h} = \frac{1}{3}$, as in Hansen (1985).

The productivity of home production A_h is important in the sense that it determines the relative importance of home production. In the benchmark calibration, we choose A_h such that home production output is equal to 40% of GDP. This leads to a $A_h = 2.03$. We also assume the displacement rate for unemployed workers is 0.5, i.e., an unemployed worker will receive government aid as much as 50% of the labor income received if employed. The fiscal balance condition would pin the tax rate τ down to .18.

Now we turn to the demographics of the population. We have the male and female labor force participation rates from the BLS.

Labor Force Participation Rate (Percentage)	1980	1990	2000	2005
Male	79.4	78.2	76.7	75.8
Female	51.3	58.0	60.6	60.4

Table 2.4.2: Labor Force Participation Rate

From the perspective of family, we also need one more piece of information to pin down the distribution of two-worker families, one-worker families, and zero-worker families. Existing literature reports that about 40 to 60% of working men has a spouse that is working as well. We take the median number, 50%, here. And since our paper is focused on women, we transform this number to be the probability of a working husband conditional on a working wife. This pins down $\zeta = .7739$. This would generate a distribution of different types of families.

Percentage	1980	1990	2000	2005
(e,e)	39.70	44.89	46.90	46.74
(e,u)	39.70	33.31	29.80	29.06
(u,e)	11.60	13.11	13.70	13.66
(u,u)	9.00	8.69	9.60	10.54

Table 2.4.3: Distribution of Family Types

From Ramey (2009), we use the following home production hours for people conditional on gender and employment status. We assume the total disposal time in a week is 100 hours and these numbers are simply the home production hours divided by 100.

Time	$h_{m,e}$	$h_{m,u}$	$h_{f,e}$	$h_{f,u}$
Value	.14	.18	.24	.38

Table 2.4.4: Home Production Hours by Gender and Employment Status

2.5 Results

We solve our model based on the family problem, but solving the model based on the individual problem should not significantly change the results. We calibrate the model as explained in Section 4 and then feed in the distribution of family types in 1990, 2000, and 2005 as in Table 4. Given the distribution of family types, we are able to solve for the labor force participation rate and the aggregate consumption pattern, i.e. the split of consumption between market services and goods. Given the demand of consumption of market services and goods, we can solve for the allocation of workers between sectors using Proposition 2.

Figure 2.5.1 presents the benchmark results. In this benchmark, we choose $\epsilon_1 = 5$ which is a typical number in the literature. ϵ_1 is the elasticity between goods and general services

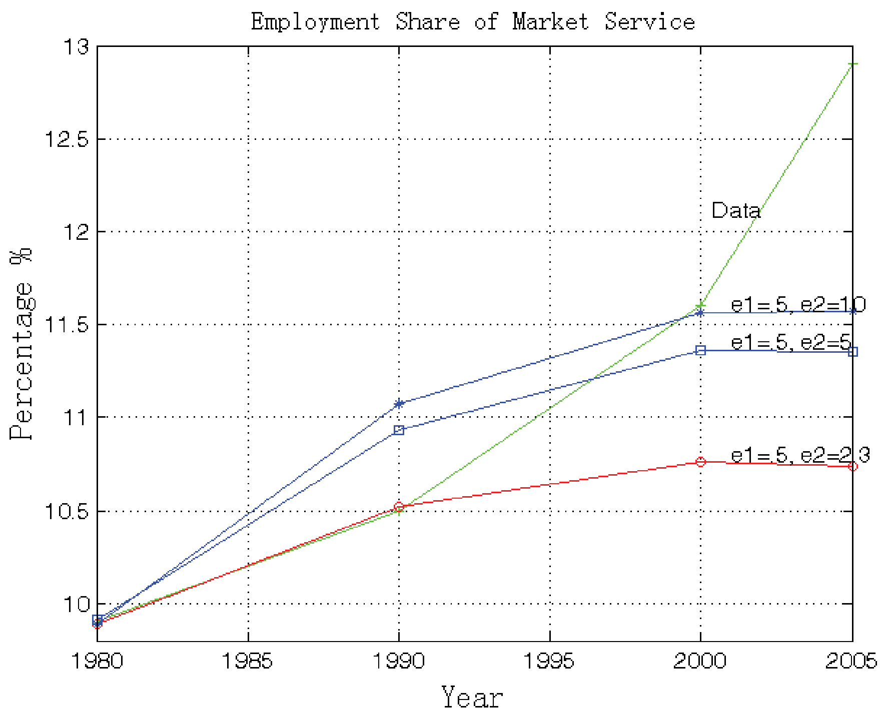


Figure 2.5.1: Benchmark Result

and ϵ_2 is the elasticity between market services and home products (services). In the graph, as ϵ_2 increases, the total amount of growth in low-skilled service jobs that can be explained by more female labor force participation also increases. A high elasticity ϵ_2 implies that market services and home products are close substitutes. Given high elasticity ϵ_2, when females leave home to work, these families have a higher incentive to buy market services. The benchmark parameterization with $(\epsilon_1 = 5, \epsilon_2 = 5)$ shows that this model is able to explain about 50% percent of the growth in low-skilled services jobs.

2.6 Conclusion

In a recent paper,Autor and Dorn (2013) documents that low-skilled service jobs have grown from 9.9% of the total employment to 12.9%. The growth of low-skilled service jobs is a somewhat surprising phenomenon for the US because overall, the US economy increasingly relies on high-skilled workers in all primary, secondary, and tertiary sectors. The traditional SBTC theories use the capital-skill complementarity to explain the growth of high-skilled jobs but are unable to explain the growth of low-skilled service jobs, and Autor and Dorn (2013) attempt to explain this phenomena with an extended SBTC theory.

This paper proposes a possible reason for the growth of low-skilled service jobs. It builds on three empirical facts for the period from 1980 to 2005: there was about 30% growth in low-skilled service jobs; about 9% increase in female labor force participation; and almost constant average home production hours conditional on employment status and gender. We conjecture that the increase in female labor force participation decreases economy-wide home production and leads households to purchase substitutable goods from the market.

We first present empirical results that support our conjecture. Using CEX data, we find that the share of low-skilled services in total family expenditure is positively correlated with the share of adult workers but negatively correlated with the share of female adults and the share of nonworking female adults in the family. All the correlations are statistically significant. On top of these empirical findings, we further develop a simple accounting framework with three sectors: goods, low-skilled services, and home production. We calibrate the model to the US in 1980 and then feed the labor force participation data in 1990, 2000, and 2005 into the model. A benchmark quantitative exercise using this framework shows that this simple theory can explain about 50% of the increase in low-skilled service jobs.

CHAPTER 3

A Simple Theory of Efficient Innovation

Innovation has nothing to do with how many R&D dollars you have. When Apple came up with the Mac, IBM was spending at least 100 times more on R&D. It's not about money. It's about the people you have, how you're led, and how much you get it.

— *Steve Jobs*

3.1 Introduction

What determines the efficiency of innovation?

Before even answering this question, two new questions jump up: 1) What is the definition of innovation efficiency and how do we measure innovation efficiency? 2) On what level do we focus? The enterprise level, the industry level, or the whole economy? Answers may differ depending on the scope we look at this question. I will hold the answer of the first question until the end of this section. For the second question, this paper is about the whole economy. That is, we want to understand how to obtain efficient innovation by allocating resources that are available economy-wide.

Now we turn to our original question. The answer set should include a large number of elements, such as physical capital, human capital, institutions and organizations, market structure, and judicial system, etc.

If we only look at the fundamentals and abstract all typical frictions in a market economy, the answer is probably that creative individuals matter, because after all innovation is about smart human brains. A super creative individual could single-handedly push the whole innovation frontier forward, while a mediocre individual probably can make no contributions at all. Inefficient allocations of brains leads to inefficiency innovation and production, which is the key idea of this paper.

However, market structure, i.e., the incentive schemes, is a fundamental determinant. The incentive schemes decide the allocation of innovative individuals, and thus decide the whole direction of the economic development. In market economies, innovators are usually rewarded by the monopoly power of new patents as discussed in Lambertini (2003). However, whether this is enough to achieve social efficiency is questionable. In fact, the essence of this paper is to show that this reward scheme does not lead to efficiency in the expanding variety model such as in Romer (1990) and Acemoglu (2008).

Physical capital does matter too. However, suppose there is full information of innovators' ability and full mobility of physical capital, we would expect that physical capital would flow towards every single innovator till the level that marginal product of capital of this innovator is equal to the marginal product of any other innovator, and equal to the marginal product of any other usage of the capital. That is, without frictions in the physical capital market, physical capital is efficiently allocated up to the level that the incentive schemes allow for innovators in this economy, and therefore does not matter in determining innovation efficiency. Of course, frictions in physical capital allocation can be a potential problem but it is not the main focus of this paper.

One widely used measure of innovation efficiency is comparing inputs and outputs. Here, inputs can be physical capital, human capital, labor, etc., and outputs can be patents, new products (or services), new techniques, etc. Essentially, all measures of innovation efficiency are related to comparing inputs and outputs to some extent, although they may vary in details. So is this article, although I put more attentions to the heterogeneity of the quality of the human capital input.

Now we talk about where innovators are allocated. Innovations can be classified in different ways, but here I only restrict myself to differences of *process innovation* and *product innovation*, as in Edquist et al. (2001), Frisch and Meschede (2001), and Haustein et al. (1981). The former is on how to reduce the cost of production, while the latter is about introducing new products. Both types of innovations cost social resources, among which human capital, i.e. creative brains, is of great importance. In this paper, I construct a simple model incorporating both types of innovation in two layers of production. On the lower level, an intermediate good is produced using an expanding variety technology. This intermediate good can be understood to be capital, intermediate goods, machine, etc, but I will refer it as capital good in this paper. Innovations occurring on this level of production corresponds to process innovation. On the higher level, consumption goods are produced with capital and labor again, and final output is again aggregated with a expanding variety CES function. Innovation occurs on this level of production is product innovation. In the competitive equilibrium, innovators make decisions on which level to innovate and their choices will be reflected in aggregate output. The setup of the model is different from Rosenkranz (2003), but both papers are concerned with process innovation and product innovation.

This paper assumes process innovation and product innovation are independent, which may be violated in reality. In a seminal paper, Utterback and Abernathy (me 3) provide a dynamic model helping to understand patterns of industrial innovations. They model a three-stage product life cycle: fluid phase, transitional phase, and specific phase. The intensity of process innovation and product innovation vary across periods. Following this paper, Hayes and Wheelwright (1979) develop a two-dimensional product-process matrix linking product life cycle stage and process life cycle for a firm, which is aimed to help firms to make decisions on product and process innovations. Although these papers suggest the inter-dependence of process innovation and product innovation on the industry level, they do not argue such inter-dependence exists on the whole economy level. Even though such inter-dependence exists on the whole economy level, it is hard to claim that such inter-dependence would fundamentally and significantly change the allocation of resources into two innovations. In this paper, I abstract the inter-dependence of process innovation and product innovation to keep model tractable.

The notions of process innovation and product innovation are closely related to the concepts of basic research and applied research in Akcigit et al. (2013). These authors, by quoting NSF, define basic research to be a "systematic study to gain more comprehensive knowledge or understanding of the subject under study without special applications in mind" and applied research to be a "systematic study to gain knowledge or understanding to meet a specific, recognized need". There are no fundamental differences between their concepts and the ones in this paper.

Now we can go back to the first question: what is the efficiency of innovation in our context? In this paper, the efficiency of innovation is about allocating creative brains to *process innovation* and *product innovation* to achieve efficient innovation, which corresponds to the highest level of growth rate of the societal output, and is about why allowing monopoly power to new patents alone does not work.

3.2 Model

Time is discrete and denoted $t = 0, 1, 2, 3, ..., \infty$. There are L measures of individuals born with innovation ability $\phi \sim F(\phi)$ bounded at $[\underline{\phi}, \overline{\phi}]$. For simplicity, I take $\underline{\phi} = 0$.

3.2.1 Production

Production involves two stages: in stage 1, all varieties of capital goods are produced, and then aggregated into a final capital good with a CES aggregator; in stage 2, consumption goods are produced and then aggregated with a CES production function. To avoid confusion, I denote all varieties of capital goods to be "intermediate capital goods" before aggregation and "final capital good" after aggregation, and denote all varieties of consumption goods to be "intermediate consumption goods" before aggregation and "final good" after aggregation. I use the expanding variety model in both production stages.

At the beginning of period t, there are N_t measures of varieties of intermediate capital goods, and M_t measures of variety in stage 2 at the beginning of period t. $\{N_t, M_t\}$ indicates technology level in this economy. In this model, innovation is equivalent to the invention of new varieties of intermediate goods. *Process innovation* means invention of new intermediate capital goods, and *product innovation* refers to invention of new intermediate consumption goods. Both types of innovation occur right before the production of their correspondent intermediate goods.

Innovation uses individual's innovation ability and a fixed amount of labor as inputs. The output of innovation, i.e. the number of new varieties of intermediate goods, are linearly increasing in the innovator's ability. Each individual, based on her own innovative ability, chooses her occupation out of three choices: a process innovator, a product innovator, or a regular worker.

In stage 1, individuals choosing to be a process innovator innovate. This costs f_F units of labor, and brings this innovator $c\phi N_t$ measures of new capital varieties, where c is a parameter measuring the effectiveness of process innovation on the societal level and therefore constant across all individuals. This innovator owns monopoly power in the new output for one period. In the next period, the technology is leaked. One can think that patents expire in one period, and a Bertrand game will lead the price to a perfectly competitive level. After process innovation, the total number of intermediate capital good varieties in the whole economy is now $N_{t+1} = N_t + NI_t$, where $NI_t = cLN_t \cdot \int_0^1 \phi \cdot I_{\{\phi \in I_F\}} dF(\phi)$ is the total measure of newly-invented intermediate capital good varieties in period t. The economy's saving in period t-1 is denoted S_t. In period t, the production of 1 unit of intermediate capital good requires 1 unit of final consumption good saved from previous period as input and therefore S_t is transformed to all varieties of intermediate capital goods:

$$S_t = \int_0^{N_{t+1}} k(\omega) d\omega$$

The aggregate production of capital is calculated using a CES aggregator with elasticity of substitution σ:

$$K_t = \left(\int_0^{N_{t+1}} k(\omega)^{\frac{\sigma-1}{\sigma}} d\omega\right)^{\frac{\sigma}{\sigma-1}} \tag{3.1}$$

In stage 2, individuals choosing to be a product innovator innovate. This costs f_P units of labor, and brings this innovator $d\phi M_t$ measures of new consumption good varieties. As c in the process innovation, d is a parameter measuring the effectiveness of product innovation on the societal level and therefore constant across all individuals. Again, the innovator owns monopoly power of this new variety for one period, and in the next period the market of this particular intermediate consumption good is perfect competitive. After product innovation, the total number of intermediate consumption good varieties in the whole economy is now $M_{t+1} = M_t + MI_t$, where $MI_t = dLM_t \cdot \int_0^1 \phi \cdot I_{\{\phi \in I_P\}} dF(\phi)$ is the total measure of newly-invented intermediate consumption good varieties in period t. Intermediate consumption goods are produced with a Cobb-Douglas production function:

$$F(K, l) = K^{\alpha} l^{1-\alpha} \tag{3.2}$$

where K is final capital goods as an input of production, and l is labor input.

The final output is aggregated with a CES aggregator with elasticity of substitution ε:

$$Y_t = (\int_0^{M_{t+1}} y(\upsilon)^{\frac{\varepsilon-1}{\varepsilon}} d\upsilon)^{\frac{\varepsilon}{\varepsilon-1}} \tag{3.3}$$

3.2.2 Timing

Timing is as shown in Figure 3.2.1. At the beginning of time t, the state of an economy is defined by the triplet $\{S_t, N_t, M_t\}$. The process innovation expands the variety of capital by NI_t. After process innovation, intermediate capital goods are produced and, after aggregation, used by intermediate consumption good producers. Next, product innovation takes place, which expands the measure of consumption good varieties by MI_t. Afterward, consumption goods are produced and aggregated to be final goods. At the end of the period, final goods are consumed or invested (stored for next period), and then the economy enters the next period.

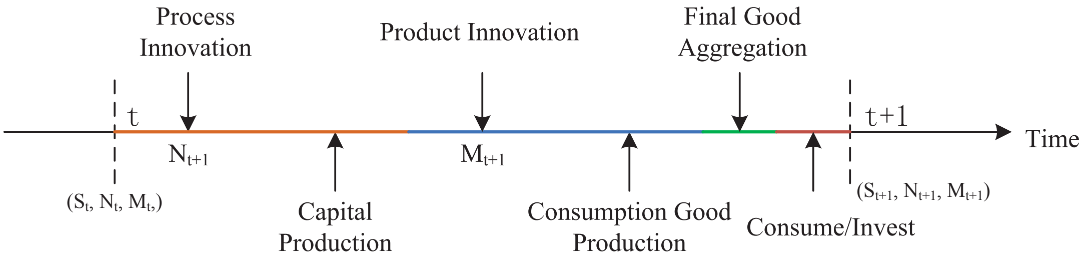


Figure 3.2.1: Timing of the Model

3.2.3 Individual's Work Decision Problem

We start with the static problem. An individual chooses to be a process innovator, a product innovator, or a worker, and receives income $I(\phi)$ according to its innovation ability:

$$I(\phi) = \max \quad \{I_F(\phi), I_P(\phi), w\} \tag{3.4}$$

where $I_F(\phi)$ is the income of a process innovator with ability ϕ, $I_P(\phi)$ is the income of a product innovator with ability ϕ, and w is wage for all workers.

According to the properties of the CES function, a process innovator prices her new variety of capital in the following way:

$$p_k(\omega) = \frac{\sigma}{\sigma - 1} P$$
$$k(\omega) = K \cdot (\frac{p_k(\omega)}{P_K})^{-\sigma}$$

where P is the price of the final good, and P=1 as final goods are used as numeraire, P_K is the price of a unit of final capital good.

The aggregate price and aggregate quantity of capital good is:

$$K = (\int_0^{N+NI} k(\omega)^{\frac{\sigma-1}{\sigma}} dw)^{\frac{\sigma}{\sigma-1}} = (N \cdot k(\omega)^{\frac{\sigma-1}{\sigma}} + NI \cdot k(\omega)^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}$$
$$P_K^{1-\sigma} = (\int_0^{N+NI} p_k(\omega)^{1-\sigma} dw) = (N \cdot p_k(\omega)^{1-\sigma} + NI \cdot p_k(\omega)^{1-\sigma})$$

Note that since the production of all existing intermediate capital goods is perfectly competitive, the prices of these goods are equal to marginal cost P. However, for the newly-invented goods, innovators own some monopoly power and therefore charge a mark-up in the competitive economy. This leads to unequal quantities of existing and newly-invented intermediate capital goods. However, this is not the case in the social planner's problem.

Therefore, every new variety can bring to her innovator a profit $\pi_k(\omega) = \sigma^{-\sigma}(\sigma - 1)^{\sigma-1}P^{1-\sigma}KP_K^{\sigma}$. As a result, a process innovator can receive:

$$I_F(\phi) = cN\pi_k(\omega) \cdot \phi - wf_F \tag{3.5}$$

For a product innovator, she also solves a similar problem, but the production of consumption is assumed Cobb-Douglas. The production of 1 unit of intermediate consumption good is therefore:

$$\begin{aligned} k_c(\upsilon) &= (\frac{w}{1-\alpha})^{1-\alpha}(\frac{r}{\alpha})^{\alpha-1} \\ l_c(\upsilon) &= (\frac{w}{1-\alpha})^{-\alpha}(\frac{r}{\alpha})^{\alpha} \\ MC_c(\upsilon) &= (\frac{w}{1-\alpha})^{1-\alpha}(\frac{r}{\alpha})^{\alpha} \end{aligned}$$

The pricing and profit of a new consumption good variety is therefore:

$$\begin{aligned} p_c(\upsilon) &= \frac{\varepsilon}{\varepsilon-1}MC_c(\upsilon) \\ y(\upsilon) &= Y \cdot (\frac{p_c(\upsilon)}{P})^{-\varepsilon} \\ \pi_c(\upsilon) &= \varepsilon^{-\varepsilon}(\varepsilon-1)^{\varepsilon-1}MC_c(\upsilon)^{1-\varepsilon}YP^{\varepsilon} \end{aligned}$$

And the income of a product innovator is:

$$I_P(\phi) = dM\pi_c(\upsilon) \cdot \phi - wf_P \tag{3.6}$$

Therefore, the aggregate price and aggregate quantity of final goods are:

$$Y = (\int_0^{M+MI} y(\upsilon)^{\frac{\varepsilon-1}{\varepsilon}} d\upsilon)^{\frac{\varepsilon}{\varepsilon-1}} = (M \cdot y(\upsilon)^{\frac{\varepsilon-1}{\varepsilon}} + MI \cdot y(\upsilon)^{\frac{\varepsilon-1}{\varepsilon}})^{\frac{\varepsilon}{\varepsilon-1}}$$

$$P^{1-\varepsilon} = \int_0^{M+MI} p(\upsilon)^{1-\varepsilon} d\upsilon = M \cdot p(\upsilon)^{1-\varepsilon} + MI \cdot p(\upsilon)^{1-\varepsilon}$$

An individual's working decision is determined by equations (4), (5), (6).

3.3 The Competitive Economy

We start by analyzing a static problem and then define the competitive economy in the dynamic horizon.

Note that the income for an innovator is linear in her innovation ability and therefore, sorting exists in the labor market, which can be found in Figure 3.3.1.

Proposition 1 (Sorting in the labor market)**:** Under appropriate assumptions, there exists $\{\phi_1, \phi_2\}$ such that, $[\underline{\phi}, \phi_1)$ are workers, $[\phi_1, \phi_2)$ are product innovators, and $[\phi_2, \overline{\phi}]$ are process innovators.

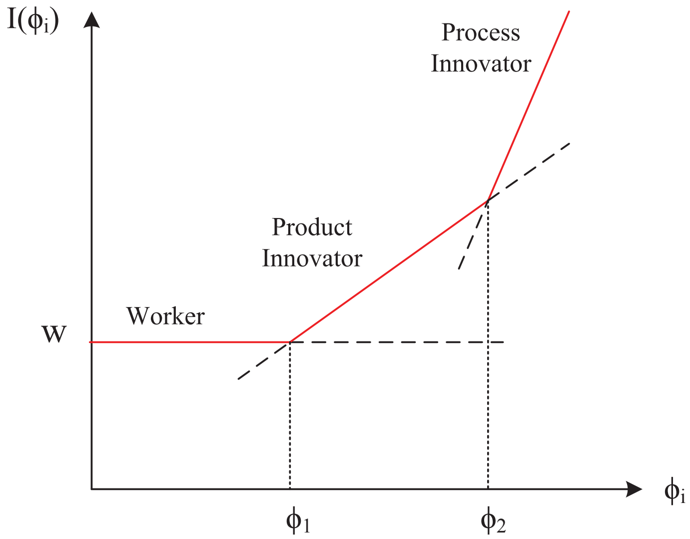


Figure 3.3.1: Work Decision

In this case, the technology level of this economy grows as follows:

$$NI_t = cLN_t \cdot \int_0^1 \phi \cdot I_{\{\phi \in I_F\}} dF(\phi) = cL[1 - F(\phi_2)]N_t$$
$$MI_t = dLM_t \cdot \int_0^1 \phi \cdot I_{\{\phi \in I_P\}} dF(\phi) = dL[F(\phi_2) - F(\phi_1)]M_t$$

Sorting in the labor market exempts us the indicator function inside the integral. The production side of the whole economy is determined after $\{\phi_1, \phi_2\}$ is fixed. This property will also be used in the social planner's case later as well.

Although agents are heterogeneous in innovation ability, I use a representative household on the consumption side. The purpose behind this abstraction is convenience, and validity comes from the following reasoning. Different agents differ in consumption due to income differences and this is one mechanism that the society does not achieve the optimum under the assumption of risk-averse utility, but this is not the key point in this paper. Instead, with certain mechanisms, the economy (the government) can still solve the appropriation problem by redistribution and induce individuals to work as if in a economy with homogeneous agents. One such (weak) equilibrium is to equalize all individuals' incomes. Therefore, assuming logarithm utility form, the representative consumer's problem is as follows:

$$V(S_t \quad ; N_t, M_t) = \max_{C_t, \quad S_{t+1}} \quad \{\log(C_t) + \beta V(S_{t+1} \quad ; N_{t+1}, M_{t+1})$$
$$s.t. \quad C_t + S_{t+1} = F(S_t, N_t, M_t, \phi_{1t}, \phi_{2t}) + (1 - \delta)S_{t+1}$$
$$M_{t+1} = M_t \cdot (1 + Ld \int_{\phi_1}^{\phi_2} \phi dF(\phi))$$
$$N_{t+1} = N_t \cdot (1 + Lc \int_{\phi_2}^{1} \phi dF(\phi))$$

Note that in this case, the representative agent is not able to choose $\{\phi_1, \phi_2\}$. $\{\phi_1, \phi_2\}$ is chosen in the individual's work decision problem. Here, the representative household is only able to choose between consumption and savings. In Appendix B, I discuss the form of the production function $F(S_t, N_t, M_t, \phi_{1t}, \phi_{2t})$.

Competitive Equilibrium

A competitive equilibrium is: an occupation choice function $OC_t(\phi)$, the representative household's decision functions $\{C_t,\ S_{t+1}\}$, a technology growth path $\{M_t, N_t\}$, and prices $\{P_t, P_{K_t}, w_t, r_t\}$ such that:

1. Given prices $\{P_t, P_{k_t}, w_t, r_t\}$, $OC_t(\phi)$ solves individual's work decision problem;

2. Technology growth path $\{M_t, N_t\}$ evolves according to occupation choice $OC_t(\phi)$;

3. Given prices $\{P_t, P_{K_t}, w_t, r_t\}$, decision functions $\{C_t,\ K_{t+1}\}$ solve representative household's problem;

4. All markets clear: labor market, capital rental market, final capital market, intermediate capital market, final consumption good market, and intermediate consumption good markets.

3.4 The Social Planner's Problem: A Closed-Form Solution

Now we turn to the social planner's problem. We first consider the static social planner's production function. The decision of a benevolent social planner involves: (1) allocation of resources, including human capitals, into two different types of innovations; (2) allocation of resources into the production of two different general categories of differentiated intermediate goods.

The complete form of this function is complicated and recorded in the Appendix A. However, after a few steps of simplification which is also available in Appendix A, the production function can be written as follows:

$$
\begin{aligned}
&Y(S_t, N_t, M_t, \phi_{1t}, \phi_{2t}) \\
&= M_t^{\frac{1}{\varepsilon-1}} N_t^{\frac{\alpha}{\sigma-1}} S_t^{\alpha} L^{1-\alpha} \cdot \\
&= \{[1 + Lc \int_{\phi_{2t}}^{1} \phi dF(\phi)]^{\frac{\alpha}{\sigma-1}} [1 + Ld \int_{\phi_{1t}}^{\phi_{2t}} \phi dF(\phi)]^{\frac{1}{\varepsilon-1}} \ldots \\
&\qquad [(1 + f_P)F(\phi_{1t}) + (f_F - f_P)F(\phi_{2t}) - f_F]^{1-\alpha}\} \\
&\equiv \Psi(S_t, N_t, M_t) \cdot G(\phi_{1t}, \phi_{2t})
\end{aligned}
$$

where $\Psi(S_t, N_t, M_t) = M_t^{\frac{1}{\varepsilon-1}} N_t^{\frac{\alpha}{\sigma-1}} S_t^{\alpha} L^{1-\alpha}$ and:

$$
\begin{aligned}
&G(\phi_{1t}, \phi_{2t}) \\
&= \{[1 + Lc \int_{\phi_{2t}}^{1} \phi dF(\phi)]^{\frac{\alpha}{\sigma-1}} [1 + Ld \int_{\phi_{1t}}^{\phi_{2t}} \phi dF(\phi)]^{\frac{1}{\varepsilon-1}} \ldots \\
&\qquad [(1 + f_P)F(\phi_{1t}) + (f_F - f_P)F(\phi_{2t}) - f_F]^{1-\alpha}\}
\end{aligned}
$$

The Social Planner's problem can now be written as:

$$
\begin{aligned}
V(S_t, N_t, M_t, \phi_{1t}, \phi_{2t}) &= \max_{C_t, S_{t+1}, N_t, M_t, \phi_{1t}, \phi_{2t}} \sum_{t=0}^{\infty} \beta^t \log(C_t) \\
s.t. \quad C_t + S_{t+1} &= Y(S_t, N_t, M_t, \phi_{1t}, \phi_{2t}) + (1 - \delta)S_{t+1} \\
M_{t+1} &= M_t \cdot (1 + Ld \int_{\phi_1}^{\phi_2} \phi dF(\phi)) \\
N_{t+1} &= N_t \cdot (1 + Lc \int_{\phi_2}^{1} \phi dF(\phi))
\end{aligned}
$$

As shown in the Appendix C, there exists a balanced growth path for this social planner's problem. Along this path, $\{\phi_1^*, \phi_2^*\}$ are chosen in each period and there exists a closed-form solution for this social planner's problem if we assume full depreciation of capital. The growth rates γ can be written as follows:

$$
\begin{aligned}
M_{t+1}^* &= M_t^* \cdot (1 + Ld \int_{\phi_1^*}^{\phi_2^*} \phi_i dF(\phi_i)) \equiv M_t^* \cdot (1 + g_M) \\
N_{t+1}^* &= N_t^* \cdot (1 + Lc \int_{\phi_2^*}^{1} \phi_i dF(\phi_i)) \equiv N_t^* \cdot (1 + g_N) \\
\gamma \equiv g_Y = g_S = g_C &= \frac{1}{1-\alpha}[\frac{1}{\epsilon - 1} g_M + \frac{\alpha}{\sigma - 1} g_N]
\end{aligned}
$$

And savings and consumption are as follows:

$$
\begin{aligned}
S_{t+1}^* &= \alpha\beta M_{t+1}^{\frac{1}{\varepsilon-1}} N_{t+1}^{\frac{\alpha}{\sigma-1}} S_t^{\alpha} \\
C_t^* &= (1-\alpha\beta) M_{t+1}^{\frac{1}{\varepsilon-1}} N_{t+1}^{\frac{\alpha}{\sigma-1}} S_t^{\alpha}
\end{aligned}
$$

In addition, for any growth path with constant $\{\phi_1, \phi_2\}$, one can calculate the social welfare:

$$
\begin{aligned}
U &= \sum_{t=0}^{\infty} \beta^t \log(C_t) \\
&\propto \log \overline{C} + \frac{\beta}{1-\beta} \log \gamma
\end{aligned}
$$

Note that $\overline{C} = \overline{C}(\phi_1, \phi_2)$ and $\gamma = \gamma(\phi_1, \phi_2)$. Therefore, what matters are only $\{\phi_1, \phi_2\}$. And as already shown before, $\{\phi_1^*, \phi_2^*\}$ maximize the social welfare here.

3.5 The Comparison between CE and SP: Where Does Inefficiency Come From?

There are several sources of inefficiency in the competitive economy.

First, in the static problem, $\{\phi_1, \phi_2\}$ are not chosen at the optimum. The fundamental problem is that process innovators do not get all the marginal benefits they create. Part of their marginal product goes to the profits of product innovators. This makes product innovation over-crowded and process innovation inadequate. Figure 3.5.1 displays the property of the function $G(\phi_1, \phi_2)$. In this graph, $c = 1$, $d = 1$, $L = 1$, $f_F = 3$, $f_P = 2$, $\alpha = .33$, $\sigma = \varepsilon = 2$, $F(\phi_i)$ follows a Pareto distribution with parameter $k = 1.2$.

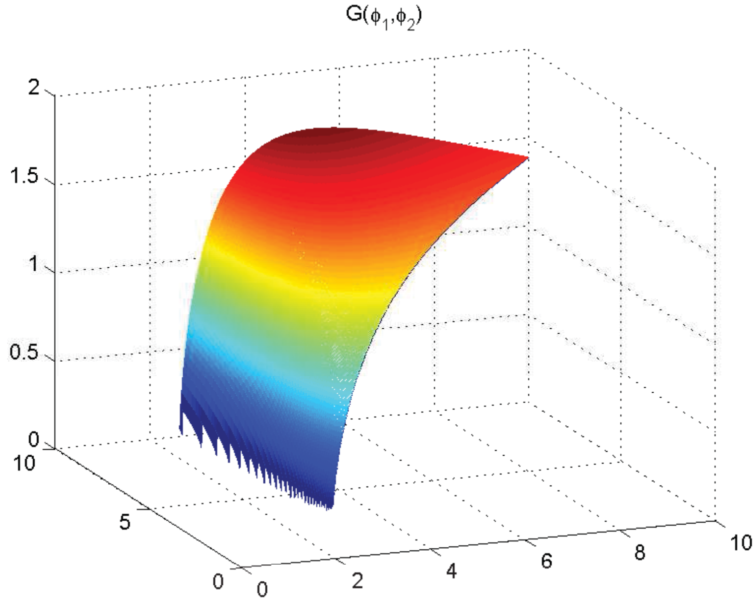


Figure 3.5.1: Function G

Second, the social planner in this paper can efficiently produce each variety of capital good and consumption good. However, in the competitive economy, because the monopoly power owned by the innovators, these new varieties are more expensive than old varieties and therefore are produced at a smaller amount than the efficient value.

Third, in this paper I assume there is a representative household in terms of consumption. This assumption is not necessary. Because of this assumption, there is an additional source of inefficiency in competitive economy, which roots from income inequality.

Fourth, note that even for the social planner in this paper, we still may not achieve the global Pareto optimal solution. The reason is that we only choose $\{M_{t+1}, N_{t+1}\}$ statically and then choose K_{t+1} inter-temporally. However, chances are that the optimal solution lies in the area where $\{M_{t+1}, N_{t+1}\}$ should also be chose inter-temporally. In that case, the social planner should choose to do inefficient innovation statically but this brings more welfare if we look at the whole time sequence.

3.6 Conclusion

In this paper, I develop a theoretical model to discuss issues related to innovation efficiency. In this model, individuals are heterogeneous in innovation ability and the allocation of innovative agents into process innovation and product innovation determines the innovation efficiency and economy-wide growth rate as well. The competitive economy version of this model displays sorting in the labor market, and I also solve for a closed-form social planner's balanced growth path. By comparing the CE and SP, I identify several sources of Inefficiency of the competitive economy. The most important of them is the inefficient allocation of innovation ability into different innovation processes.

3.7 Appendix A: Social Planner's Production Function

The production function of the social planner is:

$$Y(S_t, N_t, M_t, \phi_{1t}, \phi_{2t}) = (\int_0^{M_{t+1}} y(\nu)^{\frac{\varepsilon-1}{\varepsilon}} d\nu)^{\frac{\varepsilon}{\varepsilon-1}}$$

$$s.t. \quad N_{t+1} = N_t + NI_t = (1 + Lc \int_{\phi_{2t}}^{1} \phi dF(\phi))N_t$$

$$S_t = \int_0^{N_{t+1}} k_t(\omega) d\omega$$

$$K_t = (\int_0^{N_{t+1}} k_t(\omega)^{\frac{\sigma-1}{\sigma}} d\omega)^{\frac{\sigma}{\sigma-1}}$$

$$M_{t+1} = M_t + MI_t = (1 + Ld \cdot \int_{\phi_{1t}}^{\phi_{2t}} \phi dF(\phi))M_t$$

$$y_t(\upsilon) = K_t(\upsilon)^{\alpha} l_t(\upsilon)^{1-\alpha}$$

$$K_t = \int_0^{M_{t+1}} K_t(\upsilon) d\upsilon$$

$$\int_0^1 \phi \cdot I_{\{\phi \in I_F\}} dF(\phi) L \cdot (1 + f_F) + \int_0^1 \phi \cdot I_{\{\phi \in I_P\}} dF(\phi) L \cdot (1 + f_P) + L^w = L$$

$$L^w = \int_0^{M_{t+1}} l(\upsilon) d\upsilon$$

By the property of CES function, the maximizer should have the following property:

$$k_t(\omega) = \frac{S_t}{N_{t+1}}$$

$$l_t(\upsilon) = \frac{L^w}{M_{t+1}}$$

$$K_t(\nu) = \frac{K_t}{M_{t+1}}$$

As a result, the total final production is:

$$
\begin{aligned}
& Y(S_t, N_t, M_t, \phi_{1t}, \phi_{2t}) \\
& = M_t^{\frac{1}{\varepsilon-1}} N_t^{\frac{\alpha}{\sigma-1}} S_t^{\alpha} L^{1-\alpha}. \\
& = \{[1 + Lc \int_{\phi_{2t}}^{1} \phi dF(\phi)]^{\frac{\alpha}{\sigma-1}} [1 + Ld \int_{\phi_{1t}}^{\phi_{2t}} \phi dF(\phi)]^{\frac{1}{\varepsilon-1}} \ldots \\
& \qquad [(1 + f_P)F(\phi_{1t}) + (f_F - f_P)F(\phi_{2t}) - f_F]^{1-\alpha}\} \\
& \equiv \Psi(S_t, N_t, M_t) \cdot G(\phi_{1t}, \phi_{2t})
\end{aligned}
$$

where $\Psi(S_t, N_t, M_t) = M_t^{\frac{1}{\varepsilon-1}} N_t^{\frac{\alpha}{\sigma-1}} S_t^{\alpha} L^{1-\alpha}$ and:

$$
\begin{aligned}
& G(\phi_{1t}, \phi_{2t}) \\
& = \{[1 + Lc \int_{\phi_{2t}}^{1} \phi dF(\phi)]^{\frac{\alpha}{\sigma-1}} [1 + Ld \int_{\phi_{1t}}^{\phi_{2t}} \phi dF(\phi)]^{\frac{1}{\varepsilon-1}} \ldots \\
& \qquad [(1 + f_P)F(\phi_{1t}) + (f_F - f_P)F(\phi_{2t}) - f_F]^{1-\alpha}\}
\end{aligned}
$$

Once $\{\phi_{1t}, \phi_{2t}\}$ is chosen endogenously, the progress in technology is fixed as follows:

$$
\begin{aligned}
M_{t+1} &= M_t \cdot (1 + Ld \int_{\phi_1}^{\phi_2} \phi dF(\phi)) \equiv M_t \cdot (1 + g_M) \\
N_{t+1} &= N_t \cdot (1 + Lc \int_{\phi_2}^{1} \phi dF(\phi)) \equiv N_t \cdot (1 + g_N)
\end{aligned}
$$

3.8 Appendix B: Production Function in the Competitive Economy

Production function in the competitive economy is very similar to the one in the social planner's problem. However, there is a major difference between the two due to the monopoly power owned by the innovators on those newly-invented intermediate goods. In this section, I denote existing intermediate capital good varieties with ω and newly-invented intermediate capital good varieties with ω^n. In addition, I denote existing intermediate consumption good varieties with υ and newly-invented intermediate consumption good varieties with υ^n.

First of all, individual's working decision fixes $\{\phi_1, \phi_2\}$, which decides NI and MI.

According to properties of the CES function, a process innovator prices her new variety of capital in the following way:

$$
\begin{aligned}
p_k(\omega) &= \frac{\sigma}{\sigma-1}P \\
k(\omega) &= K \cdot (\frac{p_k(\omega)}{P_K})^{-\sigma}
\end{aligned}
$$

This implies that:

$$
\begin{aligned}
p_k(\omega^n) &= \frac{\sigma}{\sigma-1}P \\
p_k(\omega) &= P \\
k(\omega^n) &= K \cdot (\frac{p_k(\omega^n)}{P_K})^{-\sigma} \\
k(\omega) &= K \cdot (\frac{p_k(\omega)}{P_K})^{-\sigma} \\
&\Rightarrow k(\omega^n) = (\frac{\sigma}{\sigma-1})^{-\sigma} \cdot k(\omega)
\end{aligned}
$$

Note that there is a resource constraint in producing intermediate capital goods:

$$
S = \int_0^{N+NI} k(\omega)d\omega = (N \cdot k(\omega^n) + NI \cdot k(\omega))
$$

One can solve for $\{k(\omega^n),\ p_k(\omega^n),\ k(\omega),\ p_k(\omega)\}$ explicitly according to the above equations. In addition, one can aggregate and solve for $\{K,\ P_K\}$:

$$
\begin{aligned}
K &= (\int_0^{N+NI} k(\omega)^{\frac{\sigma-1}{\sigma}} dw)^{\frac{\sigma}{\sigma-1}} = (N \cdot k(\omega)^{\frac{\sigma-1}{\sigma}} + NI \cdot k(\omega)^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \\
P_K^{1-\sigma} &= (\int_0^{N+NI} p_k(\omega)^{1-\sigma} dw) = (N \cdot p_k(\omega)^{1-\sigma} + NI \cdot p_k(\omega)^{1-\sigma})
\end{aligned}
$$

Following the same logic, we can solve for a product innovator's and calculate the quantity of production:

$$
\begin{aligned}
p_c(\upsilon^n) &= \frac{\varepsilon}{\varepsilon-1} MC_c(\upsilon^n) \\
p_c(\upsilon) &= MC_c(\upsilon) \\
y(\upsilon^n) &= Y \cdot (\frac{p_c(\upsilon^n)}{P})^{-\varepsilon} \\
y(\upsilon) &= Y \cdot (\frac{p_c(\upsilon)}{P})^{-\varepsilon} \\
&\Rightarrow y(\upsilon^n) = (\frac{\varepsilon}{\varepsilon-1})^{-\varepsilon} \cdot y(\upsilon)
\end{aligned}
$$

This implies that:

$$
\begin{aligned}
K(\upsilon^n) &= (\frac{\varepsilon}{\varepsilon-1})^{-\varepsilon} K(\upsilon) \\
l(\upsilon^n) &= (\frac{\varepsilon}{\varepsilon-1})^{-\varepsilon} l(\upsilon)
\end{aligned}
$$

Note that there are also resource constraints on $\{K(\upsilon^n), l(\upsilon^n)\}$:

$$
\begin{aligned}
K &= \int_0^{M+MI} K(\upsilon) d\upsilon \\
L^w &= \int_0^{M+MI} l(\upsilon) d\upsilon
\end{aligned}
$$

According to the above equations, one can explicitly solve for $K(\upsilon)$ and $l(\upsilon)$.

Therefore, the aggregate price and aggregate quantity of final good is:

$$
\begin{aligned}
Y &= (\int_0^{M+MI} y(\upsilon)^{\frac{\varepsilon-1}{\varepsilon}} d\upsilon)^{\frac{\varepsilon}{\varepsilon-1}} = (M \cdot y(\upsilon)^{\frac{\varepsilon-1}{\varepsilon}} + MI \cdot y(\upsilon)^{\frac{\varepsilon-1}{\varepsilon}})^{\frac{\varepsilon}{\varepsilon-1}} \\
P^{1-\varepsilon} &= \int_0^{M+MI} p(\upsilon)^{1-\varepsilon} d\upsilon = M \cdot p(\upsilon)^{1-\varepsilon} + MI \cdot p(\upsilon)^{1-\varepsilon}
\end{aligned}
$$

That is, the aggregate production function is $F(S, N, M, \phi_1, \phi_2) = Y$.

3.9 Appendix C: Balanced Growth Path for the Social Planner

Lagrangian:

$$L = \sum_{t=0}^{+\infty} \beta^t \{\log C_t + \lambda_t [Y(S_t, N_t, M_t, \phi_{1t}, \phi_{2t}) - C_t - S_{t+1}]\}$$

FOC's:

$$\begin{aligned}
\text{Euler Equation} : \frac{1}{C_t} &= \alpha\beta \frac{1}{C_{t+1}} \frac{Y_{t+1}}{S_{t+1}} \\
\phi_{1t} : \frac{1}{C_t} \frac{\partial Y_t}{\partial \phi_{1t}} &+ \beta \frac{1}{C_{t+1}} \left(\frac{\partial Y_{t+1}}{\partial N_{t+1}} \frac{\partial N_{t+1}}{\partial \phi_{1t}} + \frac{\partial Y_{t+1}}{\partial M_{t+1}} \frac{\partial M_{t+1}}{\partial \phi_{1t}} \right) = 0 \\
\phi_{2t} : \frac{1}{C_t} \frac{\partial Y_t}{\partial \phi_{2t}} &+ \beta \frac{1}{C_{t+1}} \left(\frac{\partial Y_{t+1}}{\partial N_{t+1}} \frac{\partial N_{t+1}}{\partial \phi_{2t}} + \frac{\partial Y_{t+1}}{\partial M_{t+1}} \frac{\partial M_{t+1}}{\partial \phi_{2t}} \right) = 0
\end{aligned}$$

where:

$$\begin{aligned}
\frac{\partial Y_t}{\partial N_t} &= \frac{\alpha}{\sigma - 1} \frac{Y_t}{N_t} \\
\frac{\partial Y_t}{\partial M_t} &= \frac{1}{\varepsilon - 1} \frac{Y_t}{M_t} \\
\frac{\partial N_{t+1}}{\partial \phi_{2t}} &= -LcN_t f(\phi_{2t}) \\
\frac{\partial N_{t+1}}{\partial \phi_{1t}} &= 0 \\
\frac{\partial M_{t+1}}{\partial \phi_{2t}} &= LdM_t f(\phi_{2t}) \\
\frac{\partial M_{t+1}}{\partial \phi_{1t}} &= -LdM_t f(\phi_{1t})
\end{aligned}$$

Along the balanced growth path, $\{\phi_{1t}, \phi_{2t}\}$ is constant over time. The above system of equations produce the following two equations of $\{\phi_1, \phi_2\}$:

$$G_1(\phi_1, \phi_2) - \beta \frac{1}{\varepsilon - 1} \frac{G(\phi_1, \phi_2)}{\int_{\phi_1}^{\phi_2} \phi_i dF(\phi_i)} f(\phi_1) = 0$$

$$G_2(\phi_1, \phi_2) + \beta[-\frac{\alpha}{\sigma - 1} \frac{G(\phi_1, \phi_2)}{\int_{\phi_2}^{1} \phi_i dF(\phi_i)} f(\phi_2) + \frac{1}{\varepsilon - 1} \frac{G(\phi_1, \phi_2)}{\int_{\phi_1}^{\phi_2} \phi_i dF(\phi_i)} f(\phi_2)] = 0$$

As mentioned in the paper, I denote the solution of these two equations, i.e., the optimizer of the social planner's problem, to be $\{\phi_1^*, \phi_2^*\}$.

The steady state of this balanced growth path after detrending is (take $\overline{L} = 1$):

$$\overline{S} = [\alpha\beta M_0 N_0 G(\phi_1^*, \phi_2^*)]^{\frac{1}{1-\alpha}}$$
$$\overline{C} = \frac{1-\alpha\beta}{\alpha\beta}\overline{S} = \frac{1-\alpha\beta}{\alpha\beta}[\alpha\beta M_0 N_0 G(\phi_1^*, \phi_2^*)]^{\frac{1}{1-\alpha}}$$
$$\overline{Y} = [M_0 N_0 G(\phi_1^*, \phi_2^*)\alpha^\alpha \beta^\alpha]^{\frac{1}{1-\alpha}}$$

And the trend of growth is therefore:

$$\gamma = \frac{1}{1-\alpha}[\frac{1}{\epsilon-1}g_M + \frac{\alpha}{\sigma-1}g_N]$$
$$= \frac{1}{1-\alpha}[\frac{1}{\epsilon-1}d\int_{\phi_1^*}^{\phi_2^*}\phi dF(\phi) + \frac{\alpha}{\sigma-1}Lc\int_{\phi_2^*}^{1}\phi dF(\phi)]$$

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