# Essays in Growth and Development

by

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ABSTRACT

The dissertation consists of three essays that deal with variations in economic growth and development across space and time. The essays in particular explore the importance of differences in occupational structures in various settings.

The first chapter documents that intergenerational occupational persistence is significantly higher in poor countries even after controlling for cross-country differences in occupational structures. Based on this empirical fact, I posit that high occupational persistence in poor countries is symptomatic of underlying talent misallocation. Constraints on education financing force sons to choose fathers' occupations over the occupations of their comparative advantage. A version of Roy (1951) model of occupational choice is developed to quantify the impact of occupational misallocation on aggregate productivity. I find that output per worker reduces to a third of the benchmark US economy for the country with the highest level of occupational persistence.

In the second chapter, I use occupational prestige as a proxy of social status to estimate intergenerational occupational mobility for 50 countries spanning the breadth of world's income distribution for both sons and daughters. I find that although relative mobility varies significantly across countries, the correlation between relative mobility and GDP per capita is only mildly positive for sons and is close to zero for daughters. I also consider two measures of absolute mobility: the propensity to move across quartiles and the propensity to move relative to father's occupational prestige. Similar to relative mobility, the first measure of absolute mobility is uncorrelated with GDP per capita. The second measure, however, is positively correlated with GDP per capita with correlations being significantly higher for sons compared to daughters.

The third chapter analyses to what extent the growth in productivity witnessed by India during 1983–2004 can be explained by a better allocation of workers across occupations. I first document that the propensity to work in high-skilled occupations relative to high-caste men increased manifold for high-caste women, low-caste men and low-caste women during this period. Given that innate talent in these occupations is likely to be independent across groups, the chapter argues that the occupational distribution in the 1980s represented talent misallocation in which workers from many groups faced significant barriers to practice an occupation of their comparative advantage. I find that these barriers can explain 15–21% of the observed growth in output per worker during the period from 1983–2004.

DEDICATION

To Anila,

for being there with me through it all

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# Chapter 1

# INTERGENERATIONAL OCCUPATIONAL MOBILITY AND LABOR PRODUCTIVITY

## 1.1 Introduction

There are huge variations in labor productivities across countries. For example, output per worker relative to US is a third in Asia, a fourth in Latin America and an eighth in Africa (Duarte and Restuccia (2006)). A key finding of the development accounting literature is that total factor productivity (TFP) differences across countries play a vital role in explaining these gaps in productivity relative to differences in stocks of physical and human capital.[1] A growing body of research is trying to quantify the role of misallocation of resources in explaining the low levels of TFP in poor countries.[2] While most of this literature has investigated the misallocation of capital, the goal of this paper is to study the effects of misallocation of talent in explaining cross-country disparities in productivity.

Using multiple sources, I construct a unique dataset consisting of occupational information on fathers and sons for more than 65 countries. The dataset is then used for comparing cross-country differences in intergenerational occupational persistence. I find that men in poor countries are more likely to be employed in their fathers' occupations as compared to their counterparts in richer countries. For example, in India one out of every two men is employed in the same occupation as his father as compared to one in every seven men in the US. The situation is even more severe in African economies where in some cases more than nine out of ten men pursue the same occupation as their fathers. It is possible that the differences in unconditional persistence stems from differences in occupational structures rather than conscious occupational decisions. I account for this concern and show that intergenerational occupational persistence is significantly higher in poor countries even after controlling

[1] For example, see Klenow and Rodriguez-Clare (1997), Hall and Jones (1999) and Caselli (2005).
[2] Restuccia and Rogerson (2013) provides a survey on this literature.

for cross-country variations in occupational structures.[3]

The thesis of this paper is that the documented high persistence in poor countries is indicative of talent misallocation in which sons follow their fathers' occupations instead of occupations of their comparative advantage. Given that education is essential in transforming innate talent to marketable human capital, a potential factor that influences occupational decisions is the availability of credit to finance education. Weak credit markets in poor countries restrict such education borrowing and a constrained worker gets trained by his father in the father-specific occupation. To formalize the mechanism, I augment the canonical Roy (1951) model to account for frictions specific to education spending.

I begin by assuming that each worker has a different endowment of innate talents across possible occupations which determines his relative productivity across occupations. Workers require occupation-specific education in order to translate talent into marketable skills. Each worker is endowed with a home-based education technology which enables him to get trained by his father in the father-specific occupation. Alternatively, the workers can get educated by buying education goods and services and financing this expenditure through borrowing. Imperfect enforceability of contracts generate financial frictions which restrict workers from getting access to credit. Credit constrained workers get trapped in paternal occupations leading to higher intergenerational occupational persistence. Two channels present in the model generate loss of labor productivity. First, a fraction of the constrained workers choose their fathers' occupations over the occupations of their comparative advantage. Second, a fraction of constrained workers use the inefficient home-based education technology. I adopt the specification used in Buera *et al.* (2011) and Buera *et al.* (2013) to model differences in quality of credit markets.

[3] These facts have been documented in Section 3.2.

To determine the quantitative importance of this mechanism, I calibrate the benchmark model to match key features of the US economy which is assumed to have perfect credit markets. This is in line with previous studies that have found a limited role of credit constraints in explaining college enrollment decisions. The counterfactual poor countries are constructed by making two changes to the benchmark: 1) replacing the US's distribution of fathers across occupations with the poor country-specific distribution of fathers and 2) choosing a level of financial frictions to match the occupational persistence of the poor country.[4] I find that output per worker drops by a factor of three relative to the benchmark when the above features are replicated for the country with highest persistence in the dataset. Decomposition exercise shows that 75% of this loss is explained by financial frictions. Workers allocate to approximately efficient allocation starting from any paternal distribution if the credit markets are perfect. The interaction of the two factors accounts for the residual loss of 25%. An obvious concern of the previous exercise is that the residual measure of financial frictions leaves room for model misspecification. To test the validity of the residual measures I directly measure frictions from one such potential source, specifically the maximum limit on unsecured borrowing, for Tanzania and India. I find that the residual measures are close to the estimated direct measures of frictions in the two countries.

The benchmark model is stylized and makes two assumptions that seem restrictive. First, the model requires all education spending to be financed via borrowing. I relax this by allowing for paternal transfers which can be used for education expenditure. The drop in output per worker is higher for the model with transfers in which workers are able to offset the effects of frictions. This happens because larger frictions are

[4] There is some evidence that credit constraints are instrumental in understanding low human capital observed in poor countries. For example, see Cartiglia (1997) and Ranjan (2001).

necessary to target the same level of persistence in presence of transfers. Secondly, the model assumes that workers receive no intergenerational transfer of talent from fathers in the paternal occupation. I find that decline in output per worker in a modified model with talent transfers is little changed from the decline observed in the benchmark model. In the last robustness exercise, I allow the occupation-specific fixed costs to differ across countries. Lower education intensity in poor countries imply lower barriers to get sorted into occupation of comparative advantage. Opening the misallocation channel via frictions is quantitatively important even after accounting for the differences in education costs.

The chapter is related to three influential strands of literature. First, it relates to the literature that seeks to understand the quantitative effects of resource allocation across possible uses in understanding cross-country differences in incomes. A number of studies within this literature have analyzed the effect of credit market imperfections on aggregate productivity.[5] Similar to the method adopted by Hsieh and Klenow (2009), Bello *et al.* (2011), and Hsieh and Klenow (2014), the estimates of frictions in this paper are backed out as residuals. The paper is most closely related to Hsieh *et al.* (2014) and Lagakos and Waugh (2013), who examine the macroeconomic consequences of talent misallocation. Hsieh *et al.* (2014) find that improved talent allocation can account for 15–20% of the US wage growth seen in the last 50 years.

Second, the chapter aligns with a large literature that has studied the role of credit constraints in limiting investments in human capital. Lochner and Monge-Naranjo (2011) reviews the US evidence on the importance of credit constraints. There is a consensus that credit constraints played a limited role in explaining college attendance

[5]For example, Erosa (2001), Amaral and Quintin (2010), Buera *et al.* (2011) and Midrigan and Xu (2014) analyze the importance of limited enforcement in explaining aggregate TFP losses from misallocation of capital, entrepreneurial talent or both. Also, see Banerjee and Duflo (2005) for a survey on microeconomic evidence.

decisions in the early 1980s (Keane and Wolpin (2001), Carneiro and Heckman (2002), Cameron and Taber (2004)). However, the findings of studies concentrating on recent cohorts have been mixed (Belley and Lochner (2007), Stinebrickner and Stinebrickner (2008), Johnson (2013)). Dearden *et al.* (2004) analyzes the UK data and report that credit constraints were not binding for most of the population. The paper builds on this evidence and extends the analysis to the developing world. Moreover, as many poor countries are implementing programs that enable students to finance education, it is important to understand the potential effects of such policies on aggregate productivity.

Finally, this chapter ties to an extensive literature that has studied the relationship between intergenerational occupational mobility and economic growth. In a much earlier study, Lipset and Bendix (1959) find relatively little difference in mobility rates among the nine industrialized countries. Kerckhoff *et al.* (1985) show that the probability of moving from farming to white collar occupations was higher in the US as compared to Britain. However, in a recent paper Long and Ferrie (2013) report that while the US experienced higher mobility than Britain since the beginning of the 20$^{\text{th}}$ century, most of this gap was erased by the 1950s. Behrman *et al.* (2001) find that mobility is much lower in the Latin American countries when compared the US. In the context of this literature, an empirical contribution of this paper is that it provides mobility measures for a number of countries that are located across the breadth of income distribution and establishes a strong negative relationship between occupational persistence and income. Additionally, the paper proposes a mechanism that can account for this negative relationship.

The rest of the chapter is organized as follows: section 3.2 provides the evidence of negative relationship between intergenerational occupational persistence and incomes. In section 3.3, I present the benchmark model of occupational choice in presence of financial frictions. Following, I calibrate the model and investigate the effects of financial frictions on aggregate productivity in section 3.4. Finally, I show the findings of robustness checks performed on the benchmark model in section 3.5 before concluding.

## 1.2 Occupational persistence and income

In this section, I begin by discussing the data I use for computing occupational persistence across countries followed by defining two measures of occupational persistence. I then document that both measures of occupational persistence are negatively correlated with income. Additionally, I show that the differences in persistences across countries are sizeable.

### *1.2.1 Data*

An ideal dataset for computing occupational persistence consists of a representative sample of workers with information on their occupations together with the occupations of their fathers. The following four sources of data are able to provide this required information. The first two sources provide paternal occupation when the workers were between the ages of 14–22. This roughly corresponds to the prime-age occupation of the fathers. The latter two sources record the occupation that the fathers practiced for most of their lives.

1. European Social Survey (ESS): Data on 27 countries used in the analysis are sourced from the ESS (ESS Round 2 (2004) – ESS Round 5 (2010)). Contrary to the name of the survey, the ESS also covers some of the countries located in the western region of Asia.

2. National Longitudinal Survey of Youth 1979 (NLSY79): I use NLSY79 (Bureau of Labor Statistics (2012)) for the US as it contains occupational

information of respondents and their parents.

3. Indian Human Development Survey (IHDS): The IHDS (Desai *et al.* (2007)) is a nationally representative large sample survey of the households in India.

4. Egypt Labor Market Panel Survey 2012 (ELMPS12): The ELMPS12 (Economic Research Forum (2012)) consists of a representative sample of more than 8,300 households in Egypt.

Occupational persistence is measured for 30 countries using data from the above four sources. The dataset contains some very rich countries (Norway, Switzerland, US) together with some very poor ones (India, Ukraine, Turkey) and there is a considerable variation in incomes across these countries. For example, per-capita-GDP in the US is around 12 times per-capita GDP in India.

The next step is to harmonize the occupational data obtained from the four sources into a common structure. As ESS contains the majority of the countries, the classification used by the ESS serves as a natural starting base. The occupations of the workers in the ESS are reported using the 4-digit International Standard Classification of Occupations 1988 (ISCO-88). However, the 4-digit ISCO-88 coded parental occupation data is available for only 9 countries. Parental occupation information for the non-ISCO coded countries is available in the language the interview was conducted. The nature of responses vary with respect to how narrowly they could be classified on the 4-digit ISCO-88 taxonomy. I map these responses to the finest possible level of detail. The resulting occupational taxonomy is very close to the standard 2-digit ISCO-88 classification as shown in Appendix A. There are a total of 23 occupations in this modified 2-digit ISCO-88 structure, which is four less than the standard 2-digit structure.

For computing occupational persistence, I consider male workers who are at least 25 years of age. The age restriction is made for two reasons: first, most of the schooling is completed by the age of 25 and secondly, the occupational choices when younger could relate to temporary jobs and not to the final choices of workers. The exclusion of female workers stems from severe gaps in data relating to mothers' occupations.

Appendix A contains a more detailed discussion on the construction of the dataset and the occupational structure.

#### 1.2.2 A Simple Measure of Occupational Persistence

I begin by defining a naïve measure $\mathcal{N}^k$ of occupational persistence for a country $k$ which simply measures the proportion of sons employed in their fathers' occupations:

$$\mathcal{N}^k = \frac{\sum_{i=1}^{N^K} \mathcal{I}(j_i^k, j_{if}^k)}{N^k}, \tag{1.1}$$

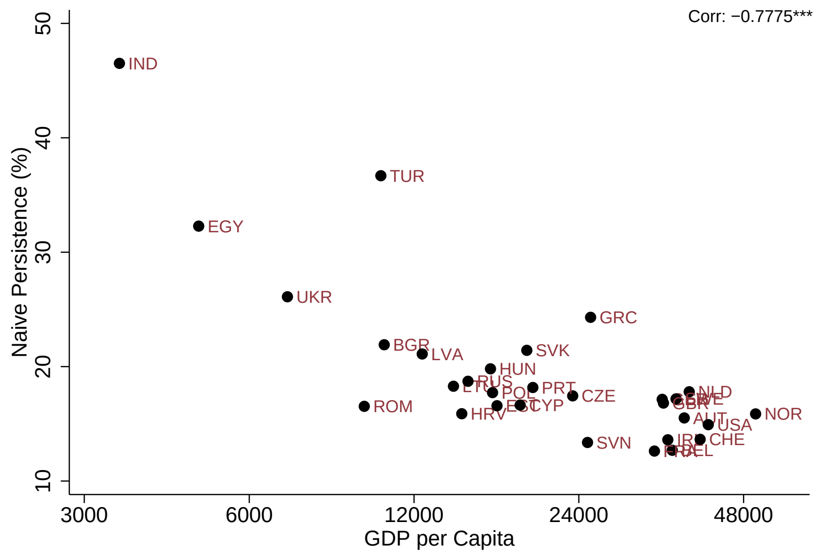
where $j_i^k$ and $j_{if}^k$ denote the occupation of worker $i$ in country $k$ and the occupation of his father respectively, and $N^k$ corresponds to the total number of workers in country $k$. The indicator function $\mathcal{I}(.,.)$ equals 1 when the occupations of a worker and his father are matched ($j_i^k = j_{if}^k$) and equals 0 otherwise.

The relationship between naïve persistence and income is shown in figure 1.1. There is a strong negative correlation between the two variables. Occupational persistence varies over a large range across countries. India, the poorest country in the sample has more than 45% of the workers being employed in their fathers' occupations compared to 32-36% in Egypt and Turkey. Persistence drops further to only about 15% observed for the US and the developed economies of western Europe.

#### 1.2.3 An Adjusted Measure of Persistence

While simple and intuitive, an important drawback of the naïve persistence is that it fails to adjust for differences in occupational structure across countries. The

Figure 1.1: Naive Persistence Across Countries




distribution of workers across occupations is more dispersed in some countries than others.[6] In India, two occupations account for 54% of the workers compared to 37% in the US. Similarly, the two largest occupations employ as much as 75% of the fathers in India compared to only 45% in the US.

Additionally, naïve persistence is likely to be high for countries in which the workers are concentrated in few occupations. For example, consider the occupational structure of some of the African countries in which more than 80% of the population engages in farming. Given such distribution, a random occupational choice by workers will generate naïve persistence in excess of 64% ($0.8 \times 0.8$). Such high persistence does not neccesarily indicate frictions in education or occupational choice. In this light, it is vital that a measure employed to study cross-country variations in persistence should account for such glaring differences in occupational structures.

In order to correct for differences in occupational structure across countries, I

[6]Appendix tables E.9 and E.10 report the distribution of workers and fathers across 1-digit ISCO codes respectively.

construct an adjusted measure of occupational persistence as described below. I begin by estimating occupational persistence $\mathcal{R}^k$ that would be expected if sons made occupational choices independent of their fathers' occupations. Let $p_j^k$ be the fraction of workers employed in occupation $j$ in any country $k$ and $p_{jf}^k$ be the fraction of the workers' fathers employed in the same occupation $j$. Assuming independence of occupational decisions, $p_j^k \cdot p_{jf}^k$ gives the fraction of workers who are employed in occupation $j$ and are matched to their fathers' occupations. Summing over all occupations, $\mathcal{R}_k$ gives the expected occupational persistence if sons made occupational choices independent of their fathers' occupations,

$$\mathcal{R}^k = \sum_{j=1}^{J} p_j^k \cdot p_{jf}^k \tag{1.2}$$

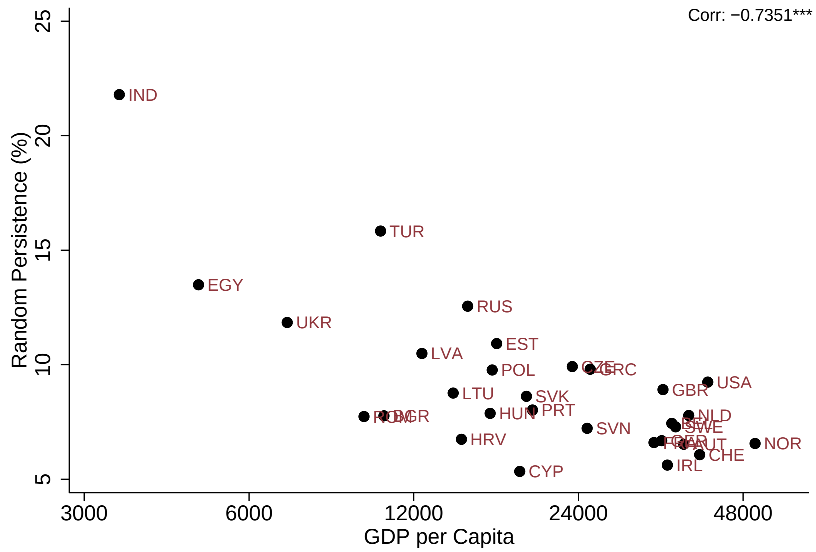
Consistent with the discussion before, I find that there exists a strong negative correlation between $\mathcal{R}^k$ and income as shown in figure 1.2. The goal now is to find out whether occupational persistence is higher in poorer countries even after accounting for this purely compositional effect. To do so, I define the adjusted measure of occupational persistence $\mathcal{P}^k$

$$\mathcal{P}^k = \frac{\mathcal{N}^k - \mathcal{R}^k}{1 - \mathcal{R}^k} \tag{1.3}$$

The adjusted persistence $\mathcal{P}^k$ measures how far a country is located between random sorting (conceptually, a lower bound on the importance of occupational persistence) and perfect sorting (1, an upper bound). In this way, the adjusted persistence $\mathcal{P}^k$ accounts for the differences in occupational structures across countries.

Figure 1.3 describes the relationship between adjusted persistence $\mathcal{P}^k$ and incomes. The correlation between persistence and income is strongly negative and significant at 1%. The poorest country in the sample, India, has an adjusted persistence of over 30% as compared to around 6% observed in the US. This means that India is much

Figure 1.2: Random Persistence Across Countries

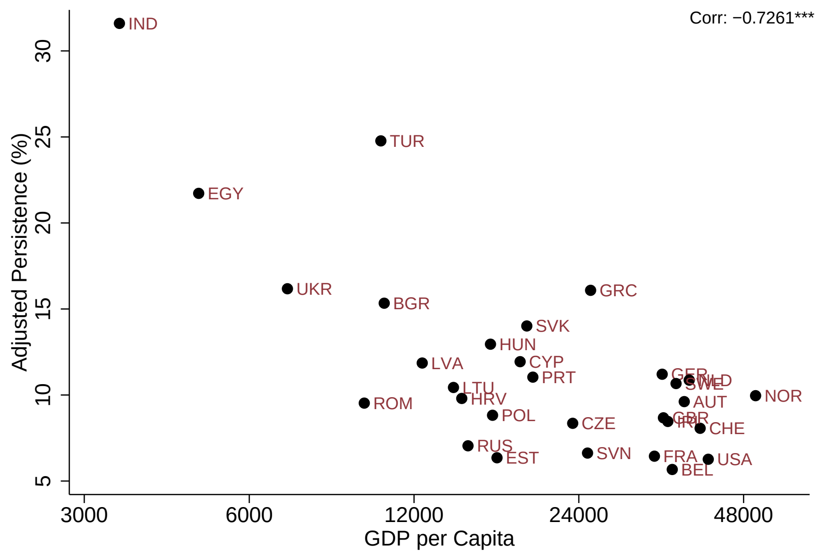



closer to perfect sorting compared to the US even after accounting for the differences in occupational structures across the two countries. The next two poorest countries, Egypt and Ukraine, also have much higher adjusted persistence as compared to persistences observed in many of the developed economies.

### 1.2.4 Census Data: IPUMS-I

A second approach to measure occupational persistences across countries is to consider the household census data from the Integrated Public Use Microdata Series-International (IPUMS-I, Minnesota Population Center (2014)). The father-son matches can be identified using the survey data and occupational persistence can be measured using occupational information of fathers and sons living within the same household. The advantage of using this approach is that I can get persistence measures for a much larger sample including some the poorest countries of the world like Malawi, Guinea, Burkina Faso etc. Additionally, the sample size for a country increases by

Figure 1.3: Explained Persistence Across Countries

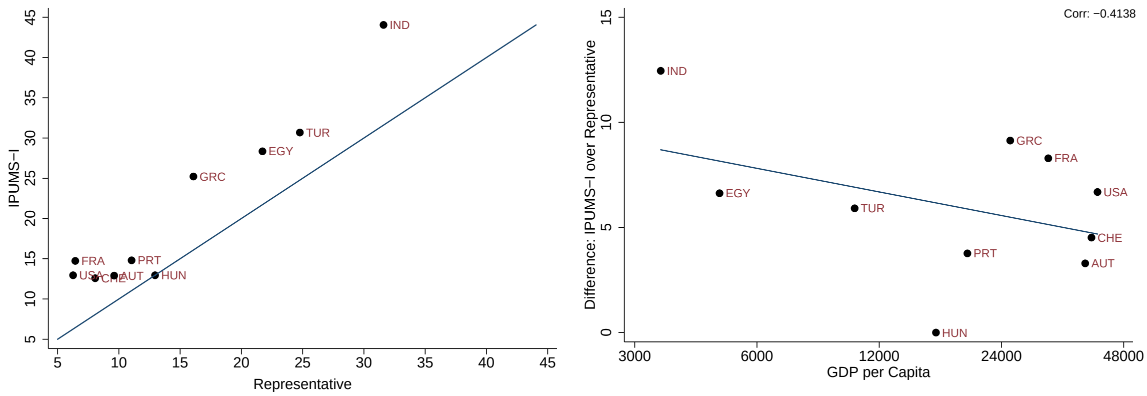



many multiples compared to the representative sample when the census data is used. On the other hand, an obvious limitation of such an approach is that the sample of workers is no longer representative as it only contains sons who live with their fathers.

To determine whether the non-representative nature of census data is a serious limitation, I compare the persistences measured from the representative and the non-representative datasets for the 10 countries that are present in both datasets. Figure 1.4a plots adjusted persistence measured from the representative sample against the non-representative sample. Adjusted persistence measured using the non-representative sample is higher when compared to the representative sample for all countries except Hungary. The regularity of upward bias hints that occupational choice of a son living with his father is closer to his father as compared to a son not living in the same household. The upward bias would pose a problem in determining the relationship between persistence and incomes if the differences in measured persistences from the two datasets were higher for poor countries, thereby inflating persistence for poor

Figure 1.4: Comparing Adjusted Persistence: Representative vs IPUMS-I

(a) Adjusted Persistence (b) Persistence vs Income



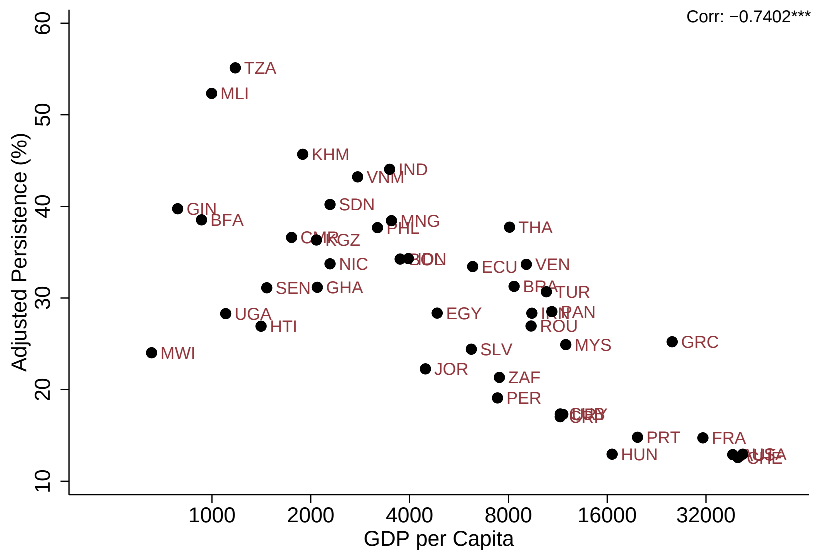

Panel (a) plots the adjusted persistence measured from the IPUMS-I data against the persistence obtained from representative data for the 10 overlapping countries. The persistence from the IPUMS-I data lie above the 45-degree line for most countries indicating a positive bias in persistence. Panel (b) plots this bias against incomes and shows the line of fit.

countries relative to richer ones.

Figure 1.4b shows the difference in persistence across the two datasets together with incomes. The estimates differ by 3-7 percentage points for 6 of the 10 countries including the US, while the maximum discrepancy of 12.5 percentage points is observed for India. The magnitude of bias is negatively correlated with incomes but the relationship is insignificant. Furthermore, this negative relationship is driven by India. Switzerland, Austria, Portugal, Hungary, Turkey and Egypt are poorer than the US and yet report lower discrepancy than that observed in the US.[7] This suggests that even though there is an upward bias in persistence measured using non-representative data, the qualitative relationship between persistence and income is likely to be preserved in this dataset. The raw persistence obtained from the non-representative dataset needs to be corrected for the upward bias. I do this by downward adjusting the persistences using the mean of differences in estimates from the two datasets

[7]See figures E.1 and E.2 in appendix for naïve persistence. The findings for naïve persistence is similar to that of explained persistence.

Figure 1.5: Adjusted Persistence: IPUMS-I




(6.1%).

I find that the negative relationship between persitence and income holds for the extended dataset as shown in Figure 1.5. Tanzania and Mali are located half-way between random sorting and perfect sorting. On the other hand, the adjusted persistence in Burkina Faso relative to other African countries is low as compared to its high naïve persistence (96%). The adjusted persistence in Cambodia, India, Vietnam and Sudan is more than 40% compared to Switzerland, Austria, US and Hungary, all of which have adjusted persistence of less than 13%.

### *1.2.5 Role of Agriculture*

Intergenerational occupational choices are generally more persistent in agriculture. Even in US, 18% of the sons born to fathers in agriculture end up in agriculture. This is 3 percentage points more than the national average. Intergenerational transfer of land may be a reason why agriculture is associated with relatively high persistence.

Given that poorer countries have higher share of employment in agriculture, it is plausible that the higher observed persistence in poor countries is driven mainly by higher persistence in agriculture. In order to assess whether agriculture is instrumental in determining the negative relationship between persistence and incomes, I drop all observations in which paternal occupation pertains to agriculture. Persistence measured hence does not include any agriculture-to-agriculture flow.

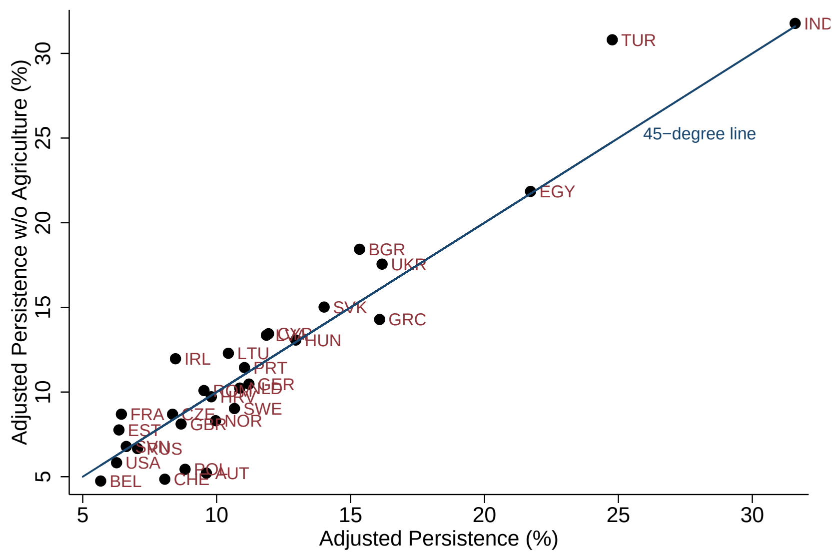
The correlation between explained persistence and income becomes even more negative after dropping these observations. The horizontal and the vertical axes in figure 1.6 show explained persistence calculated with and without agriculture respectively. Interestingly, persistence for half of the countries is larger when agriculture is excluded from the analysis. Barring Egypt, explained persistence in each of the poorest five countries without agriculture is higher than with agriculture. Explained persistence with agriculture exceeds explained persistence without agriculture by more than two percentage points for three countries, two of which are among the five richest countries in the sample. Appendix B contains a detailed discussion on the role of agriculture and similar robustness checks related to dropping of other occupations.

In this section I documented that there is a strong negative relationship between intergenerational occupational persistence and income even after accounting for differences in occupational structures. Additionally, the relationship is robust to exclusion of agriculture. Based on this documented negative relationship, I develop a general equilibrium model of occupational choice in which financial frictions restrict comparative advantage and lead to higher persistence.

## 1.3 Model

The model consists of two periods. The workers are born at the beginning of the first period and develop skills required for work during the first period. The workers

Figure 1.6: Adjusted Persistence with and without Agriculture




supply labor for wages in the second period.

### *1.3.1 Technology*

There is a representative firm in the economy which is endowed with a constant returns to scale production function. The technology aggregates labor inputs from various occupations to produce a composite good. The good produced by the firm can be used for consumption or for repaying the credit taken from the financial intermediary in the first period. The production function is given by

$$Y = \left[ \sum_{j=1}^{J} (A_j H_j)^{\rho} \right]^{\frac{1}{\rho}} \tag{1.4}$$

where $H_j$ is the labor input in occupation $j$ and $A_j$ is the occupation specific productivity parameter. The elasticity of substitution across the $J$ occupational labor inputs is captured by the parameter $\rho$. The good produced by the firm serves as the numeraire. The firm optimization problem is to choose $J$ occupation-specific labor inputs $\{H_j\}_{j=1}^J$ to maximize profits taking wages $\{w_j\}_{j=1}^J$ as given.

$$\max_{\{H_j\}_{j=1}^J} \left[\sum_{j=1}^J (A_j H_j)^\rho\right]^{\frac{1}{\rho}} - \sum_{j=1}^J w_j H_j \tag{1.5}$$

### *1.3.2 Workers*

The economy is populated by a continuum of heterogenous workers of unit mass. At the beginning of the first period, each worker receives an idiosyncratic talent endowment $\boldsymbol{\epsilon} \equiv \{\epsilon_j\}_{j=1}^J$, with $\epsilon_j$ being the talent of the worker in occupation $j$. In the spirit of the Roy (1951) model of occupational choice, it is possible for a worker to be endowed with high talent in a certain occupation but with a low talent in another. The distribution of talent is independent across workers and occupations, and follows the extreme value Fréchet distribution. This specification is borrowed from McFadden (1973) and has also been utilized by Lagakos and Waugh (2013) and Hsieh *et al.* (2014) more recently. Specifically, each worker gets an iid draw of talent endowment $\epsilon_j$ for a given occupation $j$ such that

$$\text{Prob}(\epsilon_j \leq \epsilon) = e^{-\epsilon^{-\theta}}, \quad j = 1, \ldots, J \tag{1.6}$$

The property that the maximum of $N$ Fréchet distribution is also Fréchet distributed eases the computation of the equilibrium. Apart from the talent, the occupation of a worker's father also differentiates him from workers with different paternal occupation. A point to note here is that the talent that a worker receives relates to the comparative advantage before any investments in human capital have taken place.

In order to supply labor to an occupation $j$, the worker requires a human capital investment in the form of fixed education $\bar{\xi}_j$. Conditional on choosing occupation $j$, the human capital of a worker with talent $\boldsymbol{\epsilon}$ is given by

$$h_b(\boldsymbol{\epsilon}, \bar{\xi}_j | j) = \epsilon_j \bar{\xi}_j^{\eta} \tag{1.7}$$

where $\eta$ is the elasticity of human capital with respect to education spending.

Apart from making human capital investments through borrowing in the credit markets, the workers have access to another technology that can be used to create human capital. Specifically, this technology allows the workers to get trained by their fathers. However, the fathers can only train their sons in their own occupation. For example, it is possible for a farmer to teach his son the use of agricultural tools and a potter to teach pottery to his son, but it is not possible for the farmer to teach his son pottery nor it is possible for the potter to teach his son the use of agricultural tools. Conditional on choosing his father's occupation $f$ and using the home-based education technology, a worker's human capital is given by

$$h_h(\boldsymbol{\epsilon}, \bar{\xi}_f | f) = \epsilon_f (\alpha \bar{\xi}_f)^{\eta} \tag{1.8}$$

where $\alpha$ denotes the efficiency of home-based education technology.

### *1.3.3 Credit Markets*

The workers fund their investments in human capital through borrowing in the credit markets. In the benchmark model, the workers have no access to household resources that could be used to partially or fully fund their education. I relax this assumption of necessary borrowing in a robustness exercise later to allow for paternal transfers and show that the main results of the benchmark model are very similar to the results of a modified model with transfers. The credit market is characterized by a perfectly competitive financial intermediary with a sufficient supply of credit to satisfy the demand.

The presence of financial frictions in the credit markets put restrictions on workers' ability to borrow from the financial intermediary. The modeling of financial frictions follows the span of control specification of Buera *et al.* (2011) in which the level of financial frictions in an economy is characterized by the parameter $\phi$ which can take any value in the interval [0,1]. If a worker chooses to renege on the repayment of $\bar{\xi}_j$, the financial intermediary can extract a fraction $\phi$ from his wage income. The worker loses all of his wage income if he reneges in presence of perfect credit markets ($\phi = 1$). On the other extreme, in absence of any credit markets ($\phi = 0$), the workers face no penalty from reneging and end up with all of their wage income. The parameter $\phi$, thus, spans all possible levels of financial frictions.

### *1.3.4 Worker Optimization*

The optimization problem of the workers consists of making the occupational choice decision along with choosing the optimal education technology required to produce the human capital in the chosen occupation. Obviously, the worker can choose the home-based education technology if he decides to practice the same occupation as his father.

#### Optimization: Education through borrowing

In this section, I provide the neccesary condition for a worker to have access to credit and show that the condition weakens as quality of credit markets improve. Suppose that a worker chooses occupation $j$ and accordingly borrows $\bar{\xi}_j$ from the financial intermediary. Then the utility of worker with talent $\boldsymbol{\epsilon}$ is given by:

$$\begin{aligned} \tilde{U}_j^C(\boldsymbol{\epsilon}) &= \max_{c,l}\ \gamma \text{log} c + \log(1-l) \\ \text{subject to, } c + (1+r)\bar{\xi}_j &= w_j h(\boldsymbol{\epsilon}, \bar{\xi}_j) l = w_j \epsilon_j \bar{\xi}_j^{\eta} l \end{aligned} \tag{1.9}$$

The worker chooses consumption $c$ and labor $l$ so as to maximize utility subject to his expenditure on consumption and repayment of $\bar{\xi}_j$ is equal to his wage income, where $r$ is the rate of interest charged on the borrowing. The wage income received by the worker is the product of occupation specific efficiency wage $w_j$ and the efficiency units supplied by the worker $h(\boldsymbol{\epsilon}, \bar{\xi}_j)l$. Hence, $\tilde{U}_j^C(\boldsymbol{\epsilon})$ represents the utility of a worker with talent $\boldsymbol{\epsilon}$ conditional on choosing occupation $j$ and making loan repayment.

However, the worker can renege on repayment of the loan in which case he foregoes a fraction $\phi$ of his wage income. $\tilde{U}_j^R(\boldsymbol{\epsilon})$ denotes the utility of a worker with talent $\boldsymbol{\epsilon}$ conditional on choosing occupation $j$ and reneging on loan repayment:

$$\begin{aligned} \tilde{U}_j^R(\boldsymbol{\epsilon}) &= \max_{c,l}\ \gamma \text{log} c + \log(1-l) \\ \text{subject to, } c &= (1-\phi) w_j h(\boldsymbol{\epsilon}, \bar{\xi}_j) l = (1-\phi) w_j \epsilon_j \bar{\xi}_j^{\eta} l \end{aligned} \tag{1.10}$$

The budget constraint when reneging allows the worker to escape the repayment of after-interest loan $(1+r)\bar{\xi}_j$, but on the other hand he now receives only $(1-\phi)$ fraction of his wage income which like before is a function of occupation specific efficiency wage and efficiency labor units supplied.

The lending by the financial intermediary follows incentive compatibility. In other words, the intermediary denies credit to any worker who has a higher utility from reneging on the repayment of the loan, i.e., $\tilde{U}_j^R(\boldsymbol{\epsilon}) > \tilde{U}_j^C(\boldsymbol{\epsilon})$ assuming that $j$ is the optimal occupation for the worker. It is assumed that the financial intermediary can observe the talent of a worker with certainty.

Hence, loans are granted to only those workers for whom it is optimal to follow the repayment contract and as such, there are no defaults in the equilibrium. The conditional optimization of the workers lead to the following two propositions.

**Proposition 1:** *For a given level of $\phi$, there exists a threshold level of talent $\epsilon^*_{j\phi}$ for each occupation $j$, such that all workers with talent $\epsilon_j < \epsilon^*_{j\phi}$ are denied loans conditional on choosing occupation $j$.*

**Proof:** See appendix.

**Proposition 2:** *The threshold talent level $\epsilon^*_{j\phi}$ is decreasing in the friction parameter $\phi$, i.e., the measure of workers satisfying incentive compatibility decreases with increases in financial frictions.*

**Proof:** See appendix.

The first proposition identifies the lowest possible talent in any occupation $j$ (for a given level of $\phi$) that a worker must have in order to borrow from the financial intermediary. The threshold level of talent varies across occupations. The second proposition states that more and more workers get credit constrained with increases in financial frictions.

### Optimization: Home-based education

In the previous section I identified conditions under which a worker has access to credit. The only alternative available for constrained workers is to choose their fathers' occupations. However, it may be optimal for workers to choose home-based education even when they have access to credit. In this section, I discuss conditions under which it is optimal for a worker to use home-based technology.

Instead of borrowing to obtain education, the workers can use the home-based education technology to produce human capital. Additionally, the home-based technology is costless and hence, there is no borrowing required. The utility of a worker with talent $\boldsymbol{\epsilon}$ conditional on choosing his father's occupation is given by $\hat{U}(\boldsymbol{\epsilon}, f)$

$$\hat{U}(\boldsymbol{\epsilon}, f) = \max_{c,l} \gamma \log c + \log(1-l)$$
$$\text{subject to, } c = w_f h_h(\boldsymbol{\epsilon}, \bar{\xi}_f) l = w_f \epsilon_f (\alpha \bar{\xi}_f)^{\eta} l \tag{1.11}$$

The home-based education technology is available to all workers and is not conditional on a worker being credit constrained. Relatedly, it is possible for a worker to choose home-based education technology because his returns from investment in human capital through borrowing is not high enough to compensate the costs owing to his low level of talent. This is summed up in proposition 3.

**Proposition 3:** *There exists a talent level $\epsilon_f^*$ such that any worker with talent $\epsilon_f < \epsilon_f^*$ optimally chooses home-based education technology conditional on choosing his father's occupation $f$.*

**Proof:** See appendix.

Note that there are some workers who are credit constrained even when the credit markets are perfect. However, the optimal decision for these workers is to obtain education at home which makes borrowing constraints redundant. This result has been formalized in the following corollary.

*Corollary: When the credit markets are perfect ($\phi = 1$), all workers for whom it is optimal to borrow are able to borrow in the credit markets. In other words, incentive compatibility holds for all such workers.*

The occupational choice of a worker is a maximization over $J+1$ conditional utilities

$$U(\boldsymbol{\epsilon}, f) = \max \left\{ \max_j \; \{\tilde{U}_j^C(\boldsymbol{\epsilon}).\mathcal{I}_j(\boldsymbol{\epsilon})\}_{j=1}^J, \hat{U}(\boldsymbol{\epsilon}, f) \right\}$$

where $\mathcal{I}_j(\boldsymbol{\epsilon}) = 1$ if incentive compatibility is met, $\tilde{U}_j^C(\boldsymbol{\epsilon}) \geq \tilde{U}_j^R(\boldsymbol{\epsilon})$, else $\mathcal{I}_j(\boldsymbol{\epsilon}) = -\infty$.

### 1.3.5 Equilibrium

A competitive equilibrium of the economy consists of optimal occupational choice $j^*(\boldsymbol{\epsilon}, f)$, conditional consumption choice $\{c^*(\boldsymbol{\epsilon}, f|j)\}_{j=1}^J$, $c_h^*(\boldsymbol{\epsilon}, f)$, conditional labor supply $\{l^*(\boldsymbol{\epsilon}, f|j)\}_{j=1}^J$, $l_h^*(\boldsymbol{\epsilon}, f)$, total efficiency units of labor in each occupation $\{H_j^*\}_{j=1}^J$ and efficiency wage rate in each occupation $\{w_j^*\}_{j=1}^J$ such that:

1. Conditional on an occupation choice $j$ and taking $w_j$ as given, $c^*(\boldsymbol{\epsilon}, f|j)$ and $l^*(\boldsymbol{\epsilon}, f|j)$ are solutions to 1.9

2. Taking $w_f$ as given, $c_h^*(\boldsymbol{\epsilon}, f)$ and $l_h^*(\boldsymbol{\epsilon}, f)$ are solutions to 1.11

3. The optimal occupational choice $j^*(\boldsymbol{\epsilon}, f)$ is given by

$$j^*(\boldsymbol{\epsilon}, f) = \begin{cases} \arg\max\limits_j \{\tilde{U}_j^C(\boldsymbol{\epsilon}, f).\mathcal{I}(\boldsymbol{\epsilon}, f)\} & \text{if } \max\limits_j \{\tilde{U}_j^C(\boldsymbol{\epsilon}, f).\mathcal{I}(\boldsymbol{\epsilon}, f)\} > \hat{U}(\boldsymbol{\epsilon}, f) \\ f & \text{if } \max\limits_j \{\tilde{U}_j^C(\boldsymbol{\epsilon}, f).\mathcal{I}(\boldsymbol{\epsilon}, f)\} \leq \hat{U}(\boldsymbol{\epsilon}, f) \end{cases}$$

4. Taking efficiency wage rate in each occupation $\{w_j^*\}_{j=1}^J$ as given, the representative firm's optimal choice of efficiency units $\{H_j^*\}_{j=1}^J$ solves 3.3

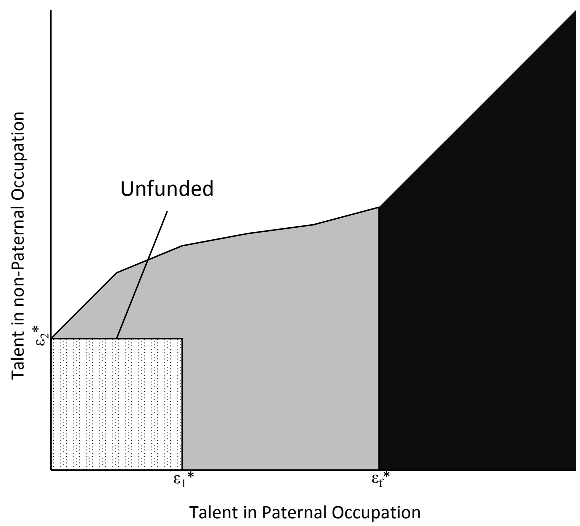
5. The occupational wage rate $w_j$ clears the labor market in each occupation.

### 1.3.6 Mechanism

A simple two-occupation case can explain the channels through which productivity loss occurs in the presence of financial frictions. Figure 1.7 shows the optimal allocation of talent across the occupations under perfect credit markets. The two axes correspond to the talent of workers in the 2 occupations. For simplicity, assume that all workers have the same paternal occupation and this occupation corresponds to the one whose talent is measured on the horizontal axis.

Conditional on choosing his father's occupation, it is optimal for a worker to choose

Figure 1.7: Optimal Allocation Under Perfect Credit Markets




Workers in the black region choose paternal occupation and obtain education via borrowing, while workers in the white region choose the non-paternal occupation. The gray region represents workers who choose to get trained by their fathers and the shaded region shows workers who don't have access to credit.

home-based education technology if his talent is less than the threshold level $\epsilon_f^*$. The black region shows the talent combinations for which the father's occupation is the occupation of comparative advantage, but the home-based education technology is not optimal. The white region demarcates the talent combinations for which the non-paternal occupation is the occupation of comparative advantage. The regions (dotted and gray) to the bottom-left of these regions show the talent combinations for which the father's occupation together with home-based education is the optimal choice. Note that while it is true a worker with talent less than $\epsilon_f^*$ would find home-based education optimal conditional on choosing his father's occupation, it is possible that he may draw a higher talent draw in the other occupation making borrowing and choosing non-paternal occupation optimal. These talent combinations lie in the white region to the left of $\epsilon_f^*$.

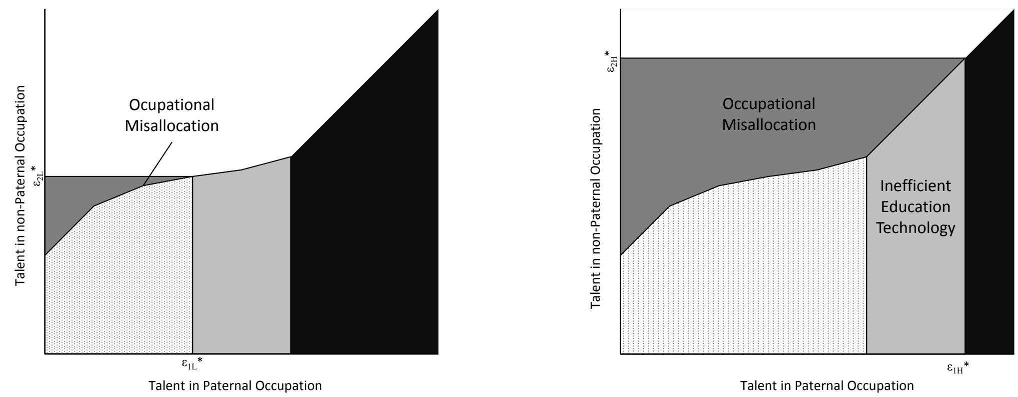
There is a set of talent combinations for which incentive compatibility fails even when the credit markets are perfect. The dotted region represents such talent combinations. $\epsilon_1^*$ and $\epsilon_2^*$ correspond to the threshold talent level $\epsilon_{j\phi}^*$ in proposition 2 that a worker must have in any occupation to satisfy incentive compatibility. Hence, any worker with talent less than $\epsilon_1^*$ in father's occupation or with talent less than $\epsilon_2^*$ in non-paternal occupation is denied credit conditional on choosing the occupation. However, note that the dotted region of talent combinations for which incentive compatibility fails is contained within the gray region of talent combinations and as such the adoption of home-based education technology is optimal for these combinations. While there are some workers who can't get education financing even when the markets are perfect, there are no inefficiencies in the system.

Figure 1.8a represents an economy with imperfect credit markets, albeit with low level of financial frictions. In line with proposition 2, the threshold talent level $\epsilon_{j\phi}^*$ a worker must have to borrow in the credit markets increases with increase in financial frictions (a decline in the $\phi$). The threshold talent for paternal occupation increases from $\epsilon_1^*$ to $\epsilon_{1L}^*$ and from $\epsilon_2^*$ to $\epsilon_{2L}^*$. Consequently, the set of talent combinations for which incentive compatibility fails (dotted and dark gray) become larger. Unlike an economy with perfect credit markets, the allocation of talent is no longer efficient. It would be optimal for talent combinations in the dark gray region to borrow and choose the non-paternal occupation. The presence of frictions restricts the optimal occupational choice for these talent combinations leading to an occupational misallocation.

As financial frictions increase, the set of constrained talent combinations become larger as shown in figure 1.8b. Now, a larger set of talent combinations are occupationally misallocated as compared to when the level of financial frictions were lower. However, with sufficient rise in frictions, another source of inefficiency becomes opera-

Figure 1.8: Allocation in Presence of Frictions

(a) Low level of frictions (b) High level of frictions




Panel (a) shows occupational allocation at low levels of frictions. Workers located in the dark gray region are forced to choose paternal occupation and are occupationally misallocated. Occupational allocation at high levels of frictions is shown in panel (b). Workers in the gray region have comparative advantage in paternal occupation but use the inefficient home-based education technology.

tional. The workers who have comparative advantage in their father's occupation and have talent in paternal occupation in excess of $\epsilon_f^*$ would want to borrow in the credit markets instead of getting home-based education. Although these workers are not occupationally misallocated, they use the *inefficient education technology* to produce human capital.

In summary, productivity loss propogates in the model through two channels: a fraction of credit constrained workers choose their fathers' occupation over the occupation of their comparative advantage and a fraction of credit constrained workers use the inefficient human capital technology.

## 1.4 Quantitative Analysis

The previous section outlined the mechanism through which inefficiency propogates in the presence of financial frictions. In this section, I quantitatively analyze the impact of allocation inefficiencies on labor productivity.

### 1.4.1 *Calibration*

I begin the quantitative exercise by calibrating the model to match key features of the US economy which is assumed to have perfect credit markets, i.e. $\phi^{US} = 1$. The calibration is performed jointly to estimate the $5+2J$ parameters of the model. In the next step, I construct counterfactual countries by making two changes to the benchmark: 1) replacing the US distribution of fathers across occupations with the country-specific distribution of fathers and 2) choosing a level of financial frictions to match the occupational persistence of the country. The quantitative effect of the mechanism is then identified by the difference in output per worker between the two economies.

**Non-Occupation specific parameters**

The human capital function parameter $\eta$ represents the elasticity of human capital with respect to education spending. There are estimates available for this parameter from related literature focussing on human capital process. In line with estimates reported in Erosa *et al.* (2010) and Manuelli and Seshadri (2014), $\eta$ is assigned a value of 0.400. The shape parameter $\theta$ on the Fréchet talent distribution directly relates to variance in wage income of the workers. As such, $\theta$ is calibrated in order to match variance of wage income to that observed in the US data.

The utility parameter $\gamma$ is the geometric weight on consumption relative to leisure. When $\gamma$ is lower, workers value leisure more as compared to consumption leading to a decrease in labor supplied. Accordingly, the value of $\gamma$ is pinned down by matching the average time allocated to labor.

A son can choose to get educated by his father in the paternal occupation using the home-based technology. The parameter $\alpha$ captures the efficiency of this technology. Conditional on choosing his father's occupation, it is always optimal for a worker to use the home-based technology irrespective of his talent in his father's occupation if $\alpha$ is at least as large as 1. An increase in $\alpha$ leads to more sons choosing their fathers' occupations. Any decrease in earnings resulting from low talent in father's occupation if offset by saved expenditure on education goods and services. Hence, $\alpha$ is chosen to pin down the naïve persistence observed in the US. Note that this calibration technique does not ex-ante restricts $\alpha$ to be less than 1.

The only non-occupation specific parameter left to be estimated is $\rho$. The parameter chracterizes the elasticity of substitution across the occupation specific labor inputs in aggregating the composite good. Due to a lack of guidance on the estimate of $\rho$, I pick $\rho = 2/3$ in line with Hsieh *et al.* (2014). The benchmark is tested for robustness by varying the chosen level of elasticity $\rho$.

### Occupation-specific parameters

### Productivity parameters $\{A_j\}$

The marginal product of labor in any occupation $j$ depends on the occupation specific productivity $A_j$. Likewise, the relative wage of an occupation $j$ increases with an increase in $A_j$, leading to more workers choosing it. Using this, these parameters are pinned down in equilibrium by matching the distribution of workers across the $J$ occupations. A robust feature of these estimates is that the distribution of workers in the model remains very close to the actual distribution of workers even when the distribution of fathers across occupation is altered.

### Education parameters $\{\bar{\xi}_j\}$

The only parameters left to be calibrated are the $J$ occupation-specific fixed cost $\bar{\xi}_j$. These fixed costs are lifetime expenditure on all education related goods and services, incurred on average by a worker in any given occupation. I use the variation in schooling intensity across occupations to pin down these parameters. To implement this, I assume the occupation-specific cost $\bar{\xi}_j$ to be a function of average years of schooling observed in the occupation $j$. Moreover, the cost of an addition year of schooling at college level is allowed to be different from the cost of an additional year of schooling at pre-college level.

I begin by decomposing the fixed cost of education in any occupation $\bar{\xi}_j$ into expenses incurred during pre-tertiary and tertiary schooling years. Specifically, the fixed education cost in any occupation is given by

$$\bar{\xi}_j = \bar{\xi}_{Pj} + \bar{\xi}_{Tj} \tag{1.12}$$

where $\bar{\xi}_{Pj}$ and $\bar{\xi}_{Tj}$ represents pre-tertiary and tertiary cost respectively. I then assume that each year of pre-tertiary and tertiary education in any occupation costs $\bar{\xi}_P$ and $\bar{\xi}_T$ respectively. Then, the fixed education cost for any occupation $\bar{\xi}_j$ is given by

$$\bar{\xi}_j = \bar{\xi}_P \int_0^{s_{Pj}} e^{-Rt} dt + \bar{\xi}_T \int_{s_{Pj}}^{s_{Tj}} e^{-Rt} dt \tag{1.13}$$

where $s_{Pj}$ and $s_{Tj}$ are the pre-tertiary and tertiary schooling years required for an occupation $j$ and $R$ is the yearly rate of interest charged on education loans charged by the financial intermediary.

I assume that the first 12 years of schooling belong to the pre-tertiary education and the remaining years correspond to tertiary education. It follows that the maximum number of years of pre-tertiary schooling that an occupation can have is 12 and tertiary schooling does not apply for occupations having less than 12 years of schooling.[8] I use mean years of schooling in any occupation as a measure of total number of years schooling required. Hence, the task of estimating $J$ occupation specific education parameters is reduced to estimating two parameters: $\bar{\xi}_P$ and $\bar{\xi}_T$. These parameters are pinned down by matching pre-tertiary and tertiary spending-to-GDP ratios of 4.7% and 2.6% respectively (LaRock (2012)). Table 1.1 summarizes the calibration exercise.

Table 1.1: Calibration: Estimate and Target/Source

| **Parameter(s)** | **Value** | **Target/Source** |
|---|---|---|
| | Parameters from related literature | |
| $\eta$: Elasticity of human capital* | 0.40 | Erosa *et al.* (2010) |
| | | Manuelli and Seshadri (2014) |
| $\rho$: Elasticity of substitution in production* | 2/3 | Hsieh *et al.* (2014) |
| | Jointly Calibrated Parameters | |
| $\theta$: Talent variance | 3.25 | Variance of earnings |
| $\gamma$: Weight on consumption | 0.47 | Hours worked |
| $\alpha$: Efficiency of home-based education | 0.61 | Adjusted persistence |
| $\bar{\xi}_P$: Cost of a year of pre-tertiary schooling | 0.003 | Pre-tertiary Spending-to-GDP |
| $\bar{\xi}_T$: Cost of a year of tertiary schooling | 0.023 | Tertiary Spending-to-GDP |
| | Occupation Specific Parameters | |
| $\{A_j\}$: Occupation-specific productivity | - | Distribution of workers across occupations |

Benchmark economy calibrated to match moments in the US data using the US as a proxy for an economy with no financial frictions. The parameters in blue are taken from related literature with sources listed. All other parameters are calibrated jointly.
*Robustness checks performed.

[8] Agriculture (2-digit ISCO 61) is the only occupation having no years of tertiary education. Please see appendix for mean years of schooling by occupation.

### *1.4.2 Baseline Results*

The objective is to quantitatively measure the effect of model's mechanism on labor productivity. The calibrated model represents the US economy which is assumed to have perfect credit markets. In order to obtain productivity measures of other countries, I make two changes to the calibrated US economy : 1) replace the US's distribution of fathers across occupations with the country-specific distribution of fathers and 2) pick a value of financial friction parameter $\phi$ that pin downs the adjusted persistence for the country. Table 1.2 shows the result of the exercise for Tanzania (country with the highest persistence in the non-representative dataset) and India (country with the highest persistence in the representative dataset). Appendix tables E.1 and E.2 list the results for all countries in the two datasets.

Table 1.2: Productivity Relative to US

| | $\phi$ (1) | Relative $Y$ (2) | Relative $Y/H$ (3) |
|---|---|---|---|
| Tanzania | 0.12 | 0.32 | 0.33 |
| India | 0.26 | 0.77 | 0.79 |

Columns 2 and 3 report the output and output per hour worked in a country relative to US respectively, while column 1 reports the level of financial friction parameter $\phi$ for the given country. Both measures of productivity drop by about a factor of three when I match the adjusted persistence observed in Tanzania together with the country-specific distribution of fathers across occupations. Output and output per hour worked declines by 23% and 21% respectively for India. Output per hour worked declines somewhat less compared to output because workers supply less labor due to an associated drop in returns to human capital. The levels of financial frictions $\phi$ that target the adjusted persistences for the two countries are much lower than the frictionless US economy, but are still some distance away from the other extreme of no credit markets.

Table 1.3: Decomposing the Productivity Gains

| | Relative $Y$ | | |
|---|---|---|---|
| | Distribution (1) | Frictions (2) | **Baseline** (3) |
| Tanzania | 0.99 | 0.48 | 0.32 |
| India | 1.00 | 0.81 | 0.77 |

Column 1 reports output per worker relative to US when the distribution of fathers is changed to country-specific distribution keeping the credit markets perfect. Column 2 reports output per worker relative to US when $\phi$ is changed to country-specific level using the US distribution.

The loss in aggregate productivity is driven by presence of financial frictions and potentially also by the denser distribution of fathers in poor countries. To understand the relative importance of these two factors, I perform a decomposition exercise to deduce the relative importance of the two factors. Column 1 in table 1.3 reports output relative to the benchmark US economy when I replace the US distribution of fathers across occupations with the country-specific distribution. There is almost no change in productivity for either country. This means that the initial distribution of fathers has no effect on the efficient occupational matching as long as workers have access to well functioning credit markets. Column 2 gives the relative output when country-specific level of frictions is used keeping the occupational distribution of fathers fixed to the US case, while column 3 reports relative output when both changes are made together. The results show that bulk of the loss in productivity is driven by the presence of financial frictions alone with frictions accounting for around $4/5^{\text{th}}$ of the total drop. Unlike frictionless case, the paternal occupational distribution also makes sizable contribution to the mechanism in presence of frictions and explains

22% and 17% of productivity loss for Tanzania and India respectively. In the next section, I discuss the sensitivity of the baseline results.

## 1.5 Sensitivity

In order to generate output loss, the model requires workers to be credit constrained while financing education expenditure and have comparative advantage outside paternal occupation. The benchmark model abstracts from certain features that may weaken credit constraints or positively affects the returns from choosing paternal occupation. First, the constraints are bound to be weaker in presence of paternal transfers that could be used for education spending. Second, workers may receive intergenerational transfer of talents from their fathers making the father-specific occupation more likely to be aligned as the occupation of comparative advantage. Lastly, the costs of education may be lower in poor countries making it easier to escape financial constraints. I check the sensitivity of the baseline results reported in table 1.2 by modifying the model to account for the aforementioned channels. Moreover, the magnitude of misallocation depends critically on the value of the financial friction parameter $\phi$. The values of $\phi$ are backed out as residuals by matching the persistence and this strategy leaves room for model misspecification. In the last robustness exercise, I test the validity of the residual measures by directly measuring frictions from the data.

The baseline results are also found to be robust to changes in elasticity parameters $\eta$ and $\rho$. Appendix D.3 discusses these findings in detail.

### *1.5.1 Paternal Transfers*

A feature of the benchmark model is that any worker who chooses to develop human capital through education spending $\bar{\xi}_j$ does so through borrowing. This seems a harsh restriction as household resources could be used to fund such spending. Specifically, it is possible that sons born in rich households in poor country could use household resources to alleviate the impact of credit constraints. To consider such a setting, I allow for paternal transfers that can be used for education spending or consumption. In period 1, together with talent endowment the workers also receive paternal transfers $b_f(> 0)$ which depends on the father's occupation $f$. Any excess of transfers over education spending can be deposited with the financial intermediary. The transfers also serves as collateral when borrowing from the financial intermediary.

The Inada conditions cease to hold in presence of transfers as workers with low talent across occupations can choose not to work. In order to induce all talent draws to work, I abstract from labor-leisure trade-off and assume that labor is supplied inelastically.

Conditional on choosing occupation $j$ and repaying (when $b_f < \bar{\xi}_j$), the utility of a worker with talent $\boldsymbol{\epsilon}$ and father's occupation $f$ is simply his consumption in period 2 and is given by

$$\tilde{U}_j^C(\boldsymbol{\epsilon}, f) = w_j \epsilon_j \bar{\xi}_j^{\eta} + (1+r)(b_f - \bar{\xi}_j) \tag{1.14}$$

Alternatively, the worker can renege on repayment when $b_f < \bar{\xi}_j$, in which case he looses a fraction $\phi$ of his wage income and all of paternal bequest $b_f$. Thus, his utility from reneging is given by

$$\tilde{U}_j^R(\boldsymbol{\epsilon}, f) = (1-\phi) w_j \epsilon_j \bar{\xi}_j^{\eta} \tag{1.15}$$

The utility of a worker with talent $\boldsymbol{\epsilon}$ conditional on choosing his father's occupation $f$ and using home-based education is given by

$$\hat{U}(\boldsymbol{\epsilon}, f) = w_f \epsilon_f (\alpha \bar{\xi}_f)^{\eta} + (1+r) b_f \tag{1.16}$$

Like before, the occupational choice of a worker is a maximization over $J+1$ conditional utilities

$$U(\boldsymbol{\epsilon}, f) = \max \left\{ \max_j \, \{\tilde{U}_j^C(\boldsymbol{\epsilon}, f) \cdot \mathcal{I}_j(\boldsymbol{\epsilon}, f)\}_{j=1}^J, \; \hat{U}(\boldsymbol{\epsilon}, f) \right\} \tag{1.17}$$

where $\mathcal{I}_j(\boldsymbol{\epsilon}, f) = 1$ if incentive compatibility is met, i.e., $\tilde{U}_j^C(\boldsymbol{\epsilon}, f) \geq \tilde{U}_j^R(\boldsymbol{\epsilon}, f)$, else $\mathcal{I}_j(\boldsymbol{\epsilon}, f) = -\infty$.

The model with bequests is recalibrated independent of the benchmark model. The independent calibration is done using the same targets as outlined in table 1.1. The calibration of transfer parameters $\{b_j\}$ is discussed below.

### Calibration and results

The parameter $b_j$ captures the amount of resources that are available to a son with a paternal occupation $j$. In absence of any direct measures of such transfers, I adapt the following simplifying procedure. Let $\pi_j$ be the mean income of fathers in occupation $j$. Then, the transfers left by a father in occupation $j$ is assumed to be proportional to the mean income $\pi_j$. This accounts for richer fathers leaving larger transfers for their sons. Hence, the occupation specific transfer $b_j$ could be written as

$$b_j = \pi_j B \tag{1.18}$$

An increase in the scaling parameter $B$ raises parental transfers for everyone, thereby reducing the borrowing requirements. The parameter is calibrated to match the percentage of students receiving education loans in the US. This calibration probably overestimates $B$ as some students may use other sources of debt like credit cards, to cover for low borrowing requirements resulting from scholarships, part-time work etc.

The calibrated $B$ implies that paternal transfers received by workers are on average as large as 14% of their lifetime earnings. The robustness of results to the choice of $B$ is shown in the appendix.

Table 1.4: Productivity Relative to US: Baseline vs. Transfers

| | **Baseline** | | **With Transfers** | | | |
|---|---|---|---|---|---|---|
| | | | Same Frictions | | Higher Frictions | |
| | $\boldsymbol{\phi}$ (1) | Relative $Y$ (2) | $\boldsymbol{\phi}$ (3) | Relative $Y$ (4) | $\boldsymbol{\phi}$ (5) | Relative $Y$ (6) |
| Tanzania | 0.12 | 0.32 | 0.12 | 0.40 | 0.09 | 0.20 |
| India | 0.26 | 0.77 | 0.26 | 0.80 | 0.13 | 0.67 |

Column 4 in table 1.4 reports relative output when workers receive transfers and frictions $\phi$ are unchanged. The drop in output is 8 and 3 percentage points less for Tanzania and India respectively. Less workers are constrained at same level of frictions as compared to the benchmark model resulting in lower persistence than that observed in data. Hence, higher levels of frictions are required to match the persistence. Column 6 reports relative output when adjusted persistence in matched in presence of frictions. The extended model requires $\phi$ to be 0.09 and 0.13 compared to 0.12 and 0.26 to match the persistences observed in Tanzania and India respectively. The drop in output is 12 percentage points more for Tanzania and 10 percentage points more for India in presence of paternal transfers. The output drops more in presence of transfers because sons of poor fathers are more likely to be constrained compared to sons of rich fathers. Moreover, the costs of being trapped in fathers occupations is higher for sons of poor fathers who are poor partially due to the low productivity of their occupations.

The quantitative findings of the model with transfers are within close range to those obtained in the benchmark model. As such, the assumption of unavoidable borrowing though appearing restrictive, is rather an innocuous one.

### *1.5.2 Intergenerational Persistence of Talents*

The benchmark model assumes that talent drawn in any occupation by a worker is independent of his father's occupation. Yet, it seems reasonable that the probability of drawing higher talent in an occupation would be higher for a worker whose father was employed in that occupation as compared to someone whose father practiced an occupation other than that.[9] In order to test the quantitative importance of such intergenerational persistence in talents, I estimate the wage premium earned by workers employed in their fathers' occupations using the regression,

$$\log(W) = \alpha + \sum_j \beta_j d_j + \mu M + \varepsilon \tag{1.19}$$

where $W$ is the wage income, $d_j$'s are the occupation dummies and $M$ is the dummy indicating a father-son occupation match. Table 1.5 reports the results of the regression. The unconditional wage premium for matched workers in US is 3.4% and the coefficient is not significant. The wage premium increases to 10.7% controlled for occupations and does not change much when agricultural workers are dropped. This suggests that matched workers in an occupation have higher human capital than unmatched workers. Consequently, it could be argued that such differences in human capital stem from intergenerational persistence in talent from fathers to sons. On

[9] For example, if fathers had chosen their occupations based on their comparative advantage, then fathers who chose farming are more likely to be physically strong as compared to fathers who chose clerical jobs because physical strength is likely to be an important contributor to productivity in agriculture. Consequently, the stronger fathers in agriculture are more likely to have stronger sons more suited to farming as compared to sons of fathers in other occupations.

the other hand, on average matched workers earn 50% less than unmatched workers in India. Even after controlling for occupations and ignoring agriculture, unmatched workers earn 13–16% more than matched workers. Such reversal in gap hints that only highly talented workers' are able to leave their fathers' occupations in poor countries.

Table 1.5: Wage Gap Between Matched and Unmatched Workers

| | without Occupation Dummies (1) | (2) | without Agriculture (3) |
|---|---|---|---|
| | | **United States** | |
| Wage Gap | 0.034 | 0.107* | 0.108* |
| *Std Error* | *0.061* | *0.060* | *0.060* |
| | | **India** | |
| Wage Gap | -0.503* | -0.163** | -0.131** |
| *Std Error* | *0.211* | *0.051* | *0.047* |

**Significant at 5%. *Significant at 10%.

To account for such talent transfer, I assume that a worker's talent in his father's occupation is drawn from a distribution with a higher mean. This talent draw is still independent of draws in other occupations and follows Fréchet, albeit with a higher mean

$$\text{Prob}(\epsilon_j \leq \epsilon) = e^{-(\epsilon-\mu)^{-\theta}} \tag{1.20}$$

if occupation $j$ is the same as the occupation of the worker's father $f$.

### Calibration and results

Like in the previous extention, the model with talent adjustment is recalibrated independent of the benchmark calibration, targeting the same moments outlined in table 1.1. The only additional talent distribution parameter $\mu$ is calibrated to target a wage premium of 11%. Next, I compare compare the quantitative findings of this extended model to the findings of the benchmark model.

Table 1.6: Productivity Relative to US: Baseline vs. Talent persistence

| | **Baseline** | | **With Talent Persistence** | |
|---|---|---|---|---|
| | $\phi$ | Relative $Y$ | $\phi$ | Relative $Y$ |
| | (1) | (2) | (3) | (4) |
| Tanzania | 0.12 | 0.32 | 0.13 | 0.35 |
| India | 0.26 | 0.77 | 0.27 | 0.80 |

Table 1.6 compares the results of the extension with the results of the benchmark model. The productivity loss reported by the extended model is less than that reported by the baseline model. The difference in output loss reported by the two models varies in the range of 2–3 percentage points for the two countries. Returns to following paternal occupation increase with higher expected talent in father's occupation and this leads to higher occupational persistence at the same level of frictions. Hence, lower level of frictions are required in presence of talent persistence if the same level of persistences are to be matched. The extended model requires $\phi$ to be 0.13 and 0.27 compared to 0.12 and 0.26 to match the persistences observed in Tanzania and India respectively.

Another way to analyze the importance of talent persistence is to endow economies with perfect credit markets and increase the talent parameter $\mu$ to match the level of country-specific persistence.[10] Performing this exercise for India, I find that matched workers earn 17% more than unmatched workers after controlling for occupations. This is in stark contrast to the negative wage gap of 16% reported in table 1.5. Allowing for a worker's expected talent in his father's occupation to be higher than

[10]It is also improbable that the level of intergenerational talent transfers depends on persistence.

his expected talent in any other occupation only mildly dampens the effect of the mechanism on productivity.

### 1.5.3 Differences in Education Intensity

The baseline model specifies that occupation-specific education costs $\{\bar{\xi}_j\}$ are invariable across countries. This specification allows me to isolate the effect of frictions independent of any loss in output due to low education intensity seen in poor countries. However, lower education intensity implies that the constraints in getting employed in the occupation of comparative advantage are also lower in poor countries. It is possible then that the output losses due to frictions may be lower after accounting for these differences.

In this exercise I allow occupation-specific fixed costs to differ across countries. Let the mean years of pre-tertiary and tertiary schooling in occupation $j$ and country $k$ be $s^k_{Pj}$ and $s^k_{Tj}$ respectively, then the occupation-specific cost $\bar{\xi}^k_j$ is given by

$$\bar{\xi}^k_j = \bar{\xi}_P \int_0^{s^k_{Pj}} e^{-Rt} dt + \bar{\xi}_T \int_{s^k_{Pj}}^{s^k_{Tj}} e^{-Rt} dt \tag{1.21}$$

The per-year schooling expenditure, $\bar{\xi}_P$ and $\bar{\xi}_T$ are fixed at the US level. I recalculate the output loss after allowing the barriers to be lower in poor countries. Table 1.7 reports the results of the exercise.

Column 1 reports relative output when both education intensity and frictions are allowed to differ across countries. As expected, the loss in output is much larger compared to the baseline case. In order to separate the loss generated by differences in education intensity, I estimate the relative output when only education intensity is allowed to change. I find that differences in education intensity can cause output to drop by 30% in Tanzania and 25% in India. Opening the misallocation channel is still quantitatively important as output contracts by another 50% and 19% for Tanzania and India respectively in presence of frictions.

Table 1.7: Productivity Relative to US: Differences in School Intensity

| | Relative $Y$ | | |
|---|---|---|---|
| | Intensity + Frictions (1) | Intensity only (2) | **Baseline** (3) |
| Tanzania | 0.20 | 0.70 | 0.32 |
| India | 0.56 | 0.75 | 0.77 |

Column 1 reports output per worker relative to US when education costs are lowered in presence of frictions. Column 2 reports output per worker relative to US when costs are lowered keeping the credit markets perfect.

### *1.5.4 Direct Measure of Frictions*

The country-specific measure of frictions in the baseline results were estimated as residuals while matching the occupational persistence. An obvious concern is whether such values of financial frictions are close to what one would obtain if one was to directly measure these frictions from the data. The challenge here is that direct measures of these frictions are difficult to obtain from the data and to obtain a measure that reasonably captures all potential distortions might not be possible. Following, I estimate direct measures of frictions from one such potential source to test for the validity of the residual measures. I find that the residual measures lie close to the estimated direct measures for the two countries.

To directly estimate $\phi$ from the data, I make a slight adjustment to the benchmark model. Specifically, I abstract from the labor-leisure choice and assume that labor is supplied inelastically.[11] Under this specification $\phi$ maps as a limit on borrowing against the future wage income. To see this, let consumption while repaying be given by $C^C = Y - D$ and consumption under reneging be $C^R = (1-\phi)Y$, where $Y$ is income and $D$ is education debt. Incentive compatibility requires, $C^C \geq C^R \Rightarrow D \leq \phi Y$. This implies that borrowing is bounded by a fraction $\phi$ of income $Y$. The estimation strategy to pin down $\phi$ entails finding what fraction of lifetime earnings could be borrowed via unsecured loan for a given country. Next, I outline the process of estimating frictions directly for the two countries using this interpretation of $\phi$.

**Frictions in India**

The present loan system follows the guidelines of Education Loan Scheme announced by the government in the budget of 2000–01. A maximum of Rs. 400,0000 (∼\$7,000) can be granted collateral-free under the scheme. However, the scheme requires the parents or guardian of the student to be treated as co-applicants and as such, the loan is not only borne by the student. More importantly, this maximum grant is multiples less than actual cost of attending college, and in many cases factors less than the tuition fees. For example, the I-Tenable (2006) study on education loans reported that more than 80% of students receiving education loans were enrolled in professional degree courses. The maximum grant is highly insufficient to cover the total costs of attending these programs. Not surprisingly, loan adoption is a rare phenomenon and only 2–3% of the graduating students in any year use education loans as a source of financing (Agarwal, 2006).[12] The paper also reports that default rates on education loans are very low at 1.1%. This finding is in line with my model

[11] The results of the benchmark model are preserved under inelastic labor supply as shown in appendix table E.7.

[12] In comparison, Titus (2002) report that 28% of all undergraduate students received federal Stafford loans or Supplemental Loans to Students in 1999–2000. The percentages were much higher for 4-year programs (public: 38% and private, not-for-profit: 47%).

which precludes defaults in light of incentive compatibility.

Given this loan structures, financial friction parameter $\phi$ is pinned down by estimating the collateral-free borrowing as a fraction of lifetime earnings. I assume that loans are taken at age 20 and workers complete college at age 24 and work till age 65. Then, using the age-earnings profile of workers, I estimate the present value of lifetime earnings at age 20 when the loan is taken. I calculate the lifetime earnings of Indian men using the data from IHDS. As returns to college education are high, I restrict my attention to men who at some point in their life attended college irrespective of completing the college program. I find that the estimated $\phi$ ranges between 0.13–0.19 depending on the choice of discount rate (2–4%) and is lower than the residual estimate of 0.26.

**Frictions in Tanzania**

The Higher Education Students' Loans Board provides loans to students based on a means testing system due to a severe shortage of funds. The system takes into account numerous characteristics of loan applicants and chances of getting loans are higher for students pursuing science-based programs. In my estimation exercise, I use a maximum limit of Tzs 3.1 million ($\sim$\$1,850) which applies to students of medicine related courses. This choice provides the most conservative estimate of frictions since loan financing varies across programs with medicine getting the largest funding. In contrast to the Indian system, the board favors the students from poor households and requires no co-signers.[13] I use data from Integrated Labour Force Survey 2006 (National Bureau of Statistics (2006)) to generate age-earnings profiles of Tanzanian men. For Tanzania, I consider profiles of only those men who had completed at least 12 years of schooling. Similar to the previous case, the estimated $\phi$ for Tanzania is

[13] See Board (2009) and Board (2014) for details.

lower than the residual measure and ranges from 0.03–0.05 depending on the discount rate.

Table 1.8: Residual and Direct Measures of Frictions

| | **Residual** | **Direct** | |
|---|---|---|---|
| | | Discount Rate | |
| | | 2% | 4% |
| | (1) | (2) | (3) |
| Tanzania | 0.12 | 0.03 | 0.05 |
| India | 0.26 | 0.13 | 0.19 |

The direct estimates of $\phi$ for the two countries are similar, though somewhat lower than the residual values used in the baseline analysis. The external evidence suggests that the residual measures of financial frictions are not arbitrarily large and in absence of direct measures can be used to analyze the quantitative impact on aggregate productivity. In summary, the results of the benchmark model are robust to a number of alternative specifications.

## 1.6 Conclusion

The paper documents that intergenerational occupational persistence is significantly higher in poor countries. One out of every two sons in India is employed in the same occupation as his father. However, a simple measure of persistence is unable to account for the differences in the occupational structures across countries. I develop an adjusted measure that corrects this and find that poor countries exhibit higher persitence even after controlling for differences in in occupational structures. The key idea of the paper is that such high level of occupational persistence is symptomatic of talent misallocation in which sons end up in their fathers' occupations instead of pursuing an occupation in which they hold a comparitive advantage.

Financial frictions seems an important factor that can restrict efficient occupational allocation in poor countries. Education is both costly and essential in order to transform innate talent to human capital and credit constraints hinder workers from borrowing in order to pay for their education. The only alternative for these credit constrained workers is to get trained by their fathers and follow their fathers' occupations. In this spirit, a version of Roy (1951) model of occupational choice in presence of financial frictions is developed. Two mechanisms present in the model cause productivity loss in presence of frictions: 1) a fraction of constrained workers choose their fathers' occupations over the occupations of their comparative advantage and 2) a fraction of constrained workers use the inefficient home-based education technology.

The model is calibrated to match the key features of the US economy assuming that the credit markets in US are perfect. Productivity drops by a factor of three relative to the benchmark US economy for the country with the highest level of occupational persistence. The baseline results are robust to a number of alternative specifications.

Chapter 2

# CROSS-COUNTRY DIFFERENCES IN INTERGENERATIONAL OCCUPATIONAL MOBILITY

## 2.1 Introduction

Most people would argue that higher rates of intergenerational mobility is good for a society in which family background does not play a pivotal role in determining the success of a child. In this regard it is important to know how mobility differs across countries. Do the richest and most developed economies of the world have higher mobility when compared to their poorest and least developed counterparts? For the most part, research on intergenerational mobility has considered cross-country variations within the developed world. This is partly because there is a general paucity of income or consumption data spanning generations from the developing economies. To overcome this obstacle, I use occupational prestige as a proxy of social status to estimate intergenerational occupational mobility measures for countries located across the world's income distribution. The main finding of the paper is that while mobility measures vary significantly across countries, there is little evidence of any meaningful relationship between intergenerational occupational mobility and GDP per capita.

The data used are sourced from multiple sources and and the resulting dataset consists of 50 countries. The dataset contains the richest economies (Netherlands, Switzerland, US) together with the poorest economies (Guinea, Mali, Uganda) of the world. This results in a considerable variation in incomes across these sample countries. For example, per-capita-GDP in the US is more than 40 times higher than per-capita GDP in Mali.

The occupational structure that harmonizes occupational information across countries is derived from the 4-digit International Standard Classification of Occupations 1988 (ISCO-88) taxonomy. I begin by assigning each occupation of the harmonized structure a prestige score using the National Opinion Research Center (NORC) ratings. I normalize the prestige scores on a scale of 1–100 so that the occupation with highest score receives a score of 100 and the one with the lowest score receives a score of 1.

There are two scales that can be used to normalize prestige scores: an Absolute scale which is same across countries and, an Adjusted Scale which normalizes scores based on country-specific occupations with highest and lowest score. Mobility measures that assess the outcomes of children of fathers with low occupational prestige relative to children of fathers with high occupational prestige will report lower mobility for countries that have higher occupational inequality is the Absolute Scale is used. The Adjusted Scale helps in controlling for differences in occupational inequality across countries and generations.

I consider both relative and absolute measures of occupational mobility. In line with previous research (Solon, 1999), I obtain my relative measure of persistence by estimating the elasticity of child's occupational prestige to father's occupational prestige. I find that the occupational elasticity for both sons and daughters varies significantly across countries irrespective of the scale used. For example when the Adjusted Scale is used, occupational elasticity is more than 0.40 in five and six countries for sons and daughters respectively compared to an elasticity of 0.19 and 0.15 for sons and daughters observed in the US. However, I find that there exists no relationship between elasticity and GDP per capita for daughters. For sons there is a mild negative correlation between the two variables (-0.21) when the Absolute Scale is used but the association is not significant. The association becomes significant when the Adjusted Scale is used but the magnitude of correlation still remains below 0.30. Another finding here is that mobility in the US is among the highest for both sons and daughters when the Absolute Scale is used. Comparisons using estimates based on the Adjusted Scale move some nations above the US in terms of exhibiting higher mobility.

The absolute measures of mobility evaluate the outcomes of children of fathers with low occupational prestige in absolute terms. I consider two measures of absolute mobility in this paper: the propensity to move across quartiles (Corak and Heisz (1999), Hertz (2006)) and the propensity to move relative to father's occupational prestige. I find that the transitional probability of moving from the bottom to the top quartile for sons across countries is uncorrelated with GDP per capita. The transitional probability decreases slightly with GDP per capita for daughters, but the relationship is not significant. Taking into account differences in downward transitional probability, I find that although children in poor countries don't have a higher probability of moving up from bottom quartile, they face a higher probability of the adverse outcome of moving to the bottom from the top quartile. The findings using the second measure of absolute mobility differs significantly from the other measures. I find that not only the propensity to move up but also the propensity to move down relative to father's occupational prestige is positive correlated with GDP per capita. The correlations are particularly higher for sons relative to daughters. I also find that the correlation is not driven by possible narrow partitions of occupations in rich countries as the average gain (loss) in occupational prestige is correlated with the propensity to move up (down).

An important comment to be made here is that the prestige scores used in this paper are based on respondents' evaluations of occupation titles that were conducted in 1989. This raises concern to the comparability of occupational prestige scores across space and time. Though previous research has found little evidence of variability across either dimension, the results of this paper must be read with such issues in mind.

The paper is related to an extensive literature that has explored how intergenerational mobility varies across countries (Black and Devereux (2011)). Several studies have used occupations to measure intergenerational mobility (Ermisch and Francesconi (2002), Carmichael (2000), Ferrie (2005)). While most of these deal with mobility in developed nations, the focus of this paper is to get mobility estimates for developing countries for which multi-generational data is usually not available. Hertz *et al.* (2007) consider educational attainment of fathers and sons and find huge variations in the intergenerational persistence across countries. Similar to the findings of this paper, the persistence in their paper is uncorrelated with GDP per capita. More recently researchers have started using first names and surnames to find variations in intergenerational mobility across space and time (Güell *et al.* (2007), Clark and Cummins (2012), Olivetti and Paserman (2015)). In particular, examining surnames Clark (2014) finds that mobility rates observed in Communist China were similar to those seen in modern US.

The rest of the paper is organized as follows: section 3.2 discusses the data and the construction of occupational prestige scores. Following, I estimate mobility for the set of 50 countries used in the analysis and document how intergenerational occupational mobility varies across countries. Section 3.3 reports the findings on relative mobility while section 3.4 relates to findings on absolute mobility. The last section concludes the paper.

## 2.2 Data

The data used in this chapter is identical to the one used in the previous chapter. The dataset contains occupational information of children and their fathers. The occupational information across countries and generations is harmonized using the 4-digit ISCO-88 taxonomy. The harmonized occupational structure uses the finest mapping possible to the ISCO-88 taxonomy. As a result, certain occupational mappings are done at a 2-digit or 1-digit level for some countries.

Multiple sources have been used to construct this dataset. I briefly discuss these sources below.

### 2.2.1 Sources

1. National Longitudinal Survey of Youth 1979 (NLSY79): The NLSY79 (Bureau of Labor Statistics, 2012) is a nationally representative longitudinal survey of US youth born between 1957–64. The survey contains the current occupation of respondents together with principal occupation of fathers at the time of the first interview. The respondents were between the ages of 14 and 22 at that time.

2. European Social Survey (ESS): The ESS (ESS Round 2 (2004) – ESS Round 5 (2010)) covers countries located within Europe as well as some countries in the western region of Asia. The respondents were asked to list the principal occupation of their fathers when the respondents were 14 years of age.

3. Household Surveys from Integrated Public Use Microdata Series - International (Minnesota Population Center, 2014): The household surveys have occupational information of the respondents. The father-child matches can be identified in the data and occupational mobility can be measured using occupational choices of fathers and children living within the same household.[1] Using these surveys allow me to obtain mobility estimates for some of the poorest countries in the world like Guinea, Mali, Uganda etc. The surveys report the current principal occupation of children and their fathers.

[1]This means that the sample of workers used for measuring mobility is not representative. Only those fathers and children are considered who are living in the same household.

4. Other Sources: Two large sample household surveys – Egyptian Labor Market Survey 2012 (Economic Research Forum, 2012) and Integrated Human Development Survey (Desai *et al.*, 2007), are used for Egypt and India respectively. Both of these sources contain information on the principal lifetime occupation of fathers.

The next step is to assign each occupation a prestige score using the scores provided by the NORC.

### *2.2.2 Occupational Prestige*

The NORC provides prestige scores for all 503 occupation titles that comprise the 1980 US Census classification of occupations. The prestige scores are based on respondents' evaluations of occupation titles conducted in 1989 (Nakao and Treas, 1989). In order to reduce the burden of rating all 503 occupations, the sample of 1500 respondents were randomly divided into 12 groups. Each respondent was then asked to distribute 110 of the 503 occupation titles on a scale of 1 to 9 with 9 representing the highest prestige level. The first 40 occupations formed core occupations that were same across all groups while the next 70 occupations were unique to each group. Table 2.1 reports the occupational prestige scores associated with the five highest and the five lowest ranked occupations.

There are two comments to be made here with regards to using the NORC prestige scores. First, the prestige associated with an occupation is not time invariant. It is possible that over time some occupations may gain prestige while other occupations lose it. Hodge *et al.* (1964) report that while small changes in occupational prestige occurred during the 1947–63 period in the US with scientific occupations gaining in prestige, the overall occupational structure was stable during the period. Second, it is possible that the occupational prestige measured in a country is not a representation

Table 2.1: Occupational Prestige Scores

| Highest Ranked | Score | Lowest Ranked | Score |
|---|---|---|---|
| Physicians | 86.05 | Food Preparation Occupations | 16.78 |
| Lawyers | 74.77 | News Vendors | 19.38 |
| Computer Systems Analysts | 73.70 | Vehicle Washers & Cleaners | 19.38 |
| Environmental Science Teachers | 73.51 | Ushers | 20.03 |
| Biological Science Teachers | 73.51 | Maids & Housemen | 20.05 |

of prestige associated with occupations in other countries. However, Treiman (2013) finds that occupational evaluations are fairly constant across countries with the mean correlation of occupational ratings for a pair of countries being 0.79. Nonetheless, it is still possible that evaluations changed from 1989 to present and that evaluations in some countries considered here are different from the evaluations observed in the US. The results of this paper must be read with these caveats in mind.

The occupations that are used in this paper are derived from the 4-digit ISCO-88 structure as discussed before. In order to assign an occupation a prestige score, I map each 4-digit occupation to one or more occupations in the 1980 US Census structure. When an occupation is mapped to more than one Census occupation, I assign the mean of Census occupations prestige score to that occupation.[2] For the 1-digit, 2-digit and 3-digit aggregated occupations, I use the mean prestige score of the occupations that constitute the aggregated occupation.

Once I have prestige scores for all occupations, I normalize them on a scale of 1–100 so that the highest ranked occupation receives a score of 100 and the lowest ranked receives a score of 1. There are two scales that I use to normalize occupations.

[2]For example, the 4-digit ISCO-88 occupation 2147 (mining engineers, metallurgists and related professionals) is mapped to Census occupations 45 (metallurgical and materials engineers, prestige score 61) and 46 (mining engineers, prestige score 60). The mean prestige score the two Census occupations (60.5) is assigned to ISCO-88 occupation 2147.

First, the Absolute Scale: which uses the occupations with highest and lowest prestige from all possible occupations across countries. Second, the Adjusted Scale which uses the occupations with highest and lowest prestige from all possible occupations within a country. Measures of mobility based on the Absolute Scale assume that an individual's occupational choice set includes all possible occupations whereas measures based on the Adjusted Scale restrict an individual's occupational choice to occupations present in his or her own country. Mobility measures that assess the outcomes of children of fathers with low occupational prestige relative to children of fathers with high occupational prestige will report lower mobility for countries that have higher occupational inequality is the Absolute Scale is used. The Adjusted Scale helps in controlling for differences in occupational inequality across countries and generations.

I consider different measures of mobility that can be classified into two categories based on whether they illustrate differences in relative mobility or absolute mobility. The measure of relative mobility seek to understand how different are the outcomes of children of fathers with low occupational prestige relative to the outcomes of children of high prestige fathers. On the other hand, measures of absolute mobility evaluate the outcomes of children of fathers with low occupational prestige in absolute terms. In the next two sections, I show how the different measures of relative and absolute intergenerational mobility vary across countries.

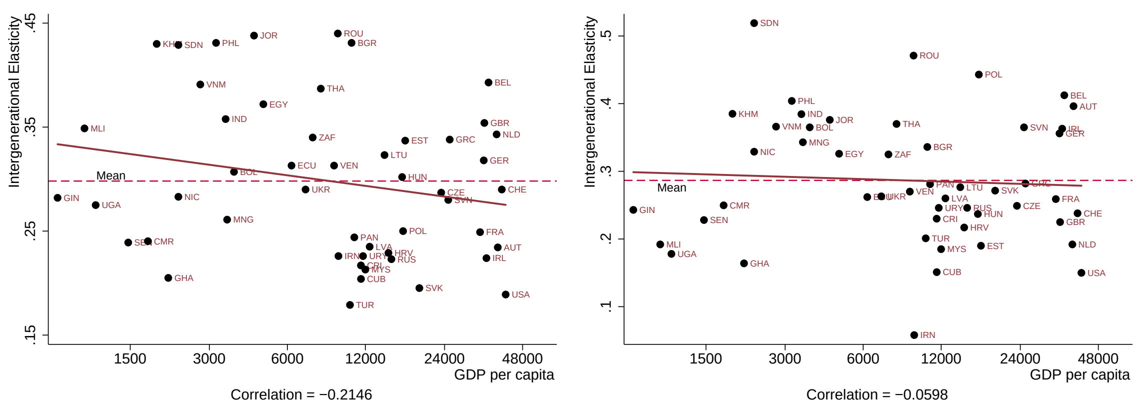
## 2.3 Relative Mobility Across Countries

For the most part, previous literature analyzing differences in mobility across space and time has considered differences in relative mobility using income and consumption data across generations. The goal is to estimate the elasticity of child's income or consumption to parent's income or consumption. Isomorphic to such definition, I regress the log of child $i$'s occupational prestige score $S_i$ on the log of occupational prestige score $P_i$ of $i$'s father to obtain the intergenerational occupational elasticity $\xi$:

$$\log(S_i) = \alpha + \xi \log(P_i) + \epsilon_i \tag{2.1}$$

The elasticity $\xi$ measures the expected percentage increase in a child's prestige given a 1% increase in father's prestige. As such, higher elasticity is related with lower relative mobility in which a father's occupation play a larger role in determining a child's outcome.

Figure 2.1: Intergenerational Occupational Elasticity Across Countries (Absolute Scale)




(a) Sons (b) Daughters

Figures 2.1a and 2.1b plots the intergenerational elasticity estimated using the Absolute Scale against GDP per capita taken from Penn World Tables (Heston *et al.*, 2012) for sons and daughters respectively. I find that elasticity varies significantly across countries. For example, elasticity for sons is as low as 0.19 in the US compared to being more than 0.40 in as many as six countries. The variance in elasticity extends for daughters also. The elasticity for daughters in the US is estimated to be 0.15 compared to the highs of more than 0.40 in five countries. However, the more striking result is that there seems to be no systematic relationship between mobility and income. Mobility and income exhibit a mild positive correlation for sons but the relationship is not significant. For daughters, the correlation drops to almost zero as evidenced by the near concurrence of the lines of linear fit and mean elasticity. Another important observation is that mobility in the US is among the highest for both sons and daughters. The only countries with higher mobility for sons and daughters than the US are Turkey and Iran respectively.

Figure 2.2: Intergenerational Elasticity, Sons vs Daughters (Absolute Scale)

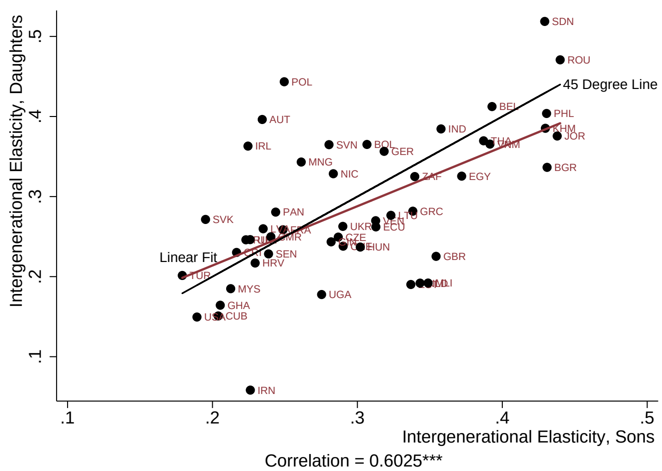


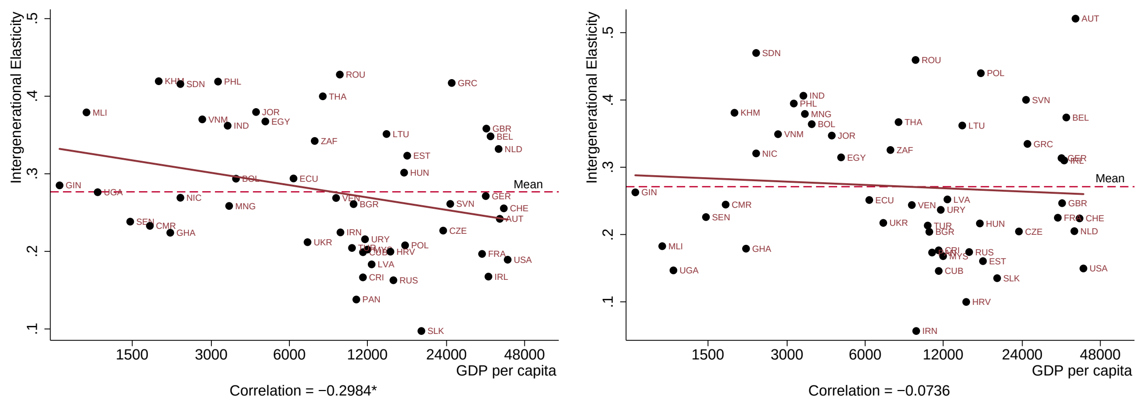

Figure 2.2 shows a positive correlation between mobility of sons and daughters across countries. However, there are huge differences in relative mobility of sons and daughters for some countries. Mobility for sons is high relative to daughters in Poland and Austria whereas Iran, Mali and Netherlands have much lower relative mobility for sons compared to daughters. Of the eight developed countries, I find that elasticity for sons is higher than daughters in four countries and around the same as daughter in two of them.[3]

As explained before, the relative mobility measures estimated using the Absolute Scale do not account for cross-country differences in occupational inequality. The

[3] Jäntti *et al.* (2006) found intergenerational elasticity to be higher for sons in five of the six developed economies considered by them.

elasticity for a country with higher occupational inequality would be larger. To check whether the findings above are robust to the choice of scale, I estimate elasticity using the Adjusted Scale. Figures 2.3a and 2.3b report the result of the exercise.

Figure 2.3: Intergenerational Occupational Elasticity Across Countries (Adjusted Scale)

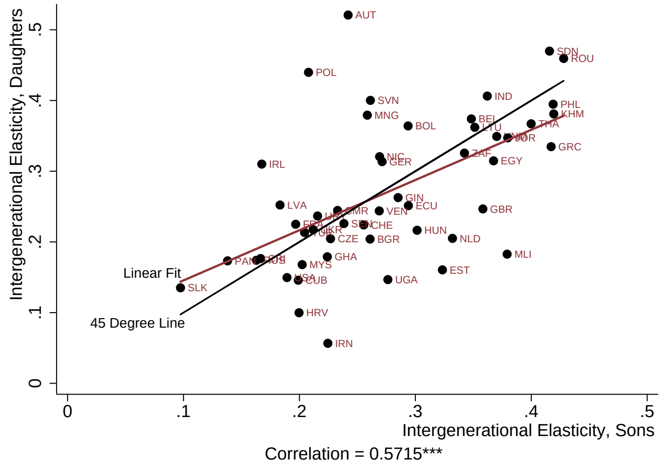



(a) Sons (b) Daughters

I find that correlation between mobility and income increases marginally for daughters but is still very close to zero. In contrast, the strength of negative association between persistence and income increases quite a bit for sons and is now significant at 10% level. However, the magnitude of correlation still remains below 0.3 and as such the relationship between mobility and income can at best be regarded as weak. The US loses a couple of places to other nations who display higher mobility under the Adjusted Scale but still has higher mobility than most countries. The relationship between mobility of sons and daughters across countries is still positive and close to that observed before.

In summary, I find that although relative mobility varies significantly across countries, the relationship between relative mobility and income can at best be described as a weak one. Also, the US displays higher mobility for both sons and daughters compared to most countries. Now, I begin my discussion on measures of absolute

Figure 2.4: Intergenerational Elasticity, Sons vs Daughters (Adjusted Scale)




mobility.

## 2.4 Absolute Mobility Across Countries

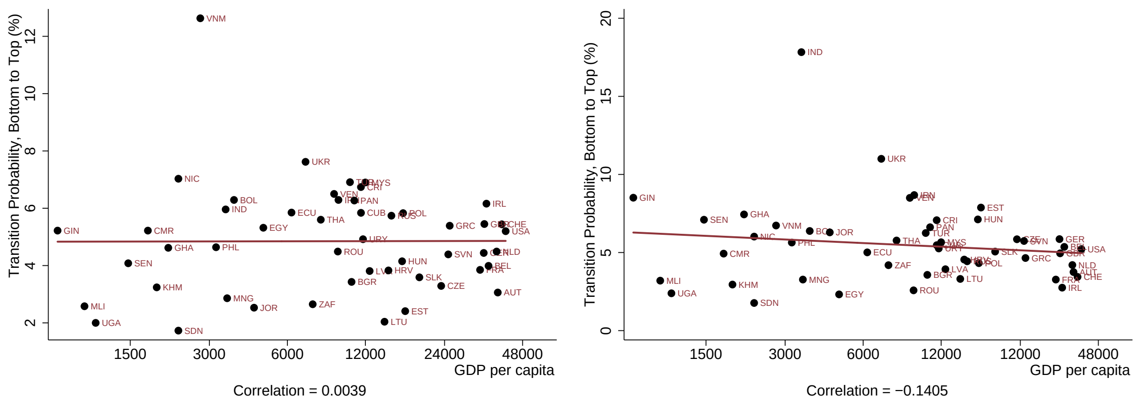
The absolute measures of mobility seek to understand how outcomes in absolute terms vary across countries for children being born to fathers with low occupational prestige. As pointed by Chetty *et al.* (2014), higher relative mobility can be a product of worse outcomes for children of high prestige fathers rather than better outcomes for children of low prestige fathers. On the other hand, fixing absolute mobility at all levels together with higher absolute mobility at any given prestige level is a definite sign of betterment.

I consider two measures of absolute mobility: propensity to move across quartiles and propensity to move relative to father's occupational prestige.

### *2.4.1 Propensity to Move Across Quartiles*

The fathers are grouped into four bins according to their occupational prestige rank with respect to all fathers within a country. Similarly, all sons and daughters are grouped in different bins based on their occupational standing relative to all sons and daughters within the same country. Then I calculate the probability of a child from a father located in the bottom quartile to the top quartile of his or her generation. I also calculate the probabilities of moving from top quartile of father's distribution to bottom quartile of child's distribution.

Figure 2.5: Propensity to Move from Bottom to Top Quartile




(a) Sons

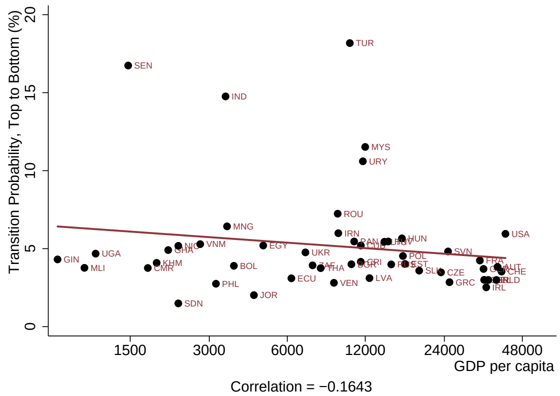
(b) Daughters

Figures 2.5a and 2.5b show the relationship between transition probability of moving from bottom to top and GDP per capita for sons and daughters respectively. I find that transition probability of moving from bottom to top quartile for sons is uncorrelated with income. For daughters, the probability decreases slightly with income but the relationship is not significant.[4]

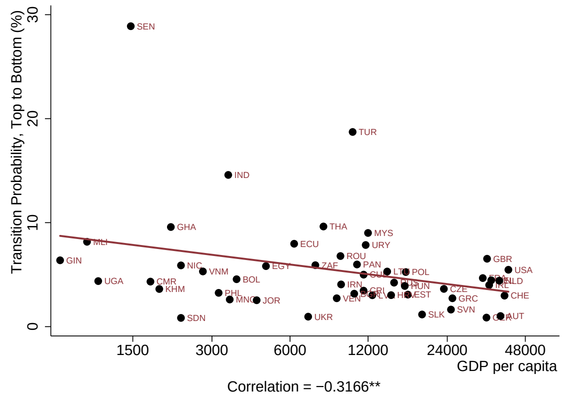
The relationship between downward transition probability and income is slightly negative for sons but is insignificant as evidenced in figure 2.6a. The correlation for daughters is even more negative compared to upward transitional probability and is significant at 10% level (figure 2.6b). However, this significance is driven by high transitional probability observed in Sudan. Based on this it can be concluded that

[4]The magnitude of negative correlation is driven by India. The correlation (in absolute terms) drops to -0.08 when India is excluded.

Figure 2.6: Propensity to Move from Top to Bottom Quartile




(a) Sons




(b) Daughters

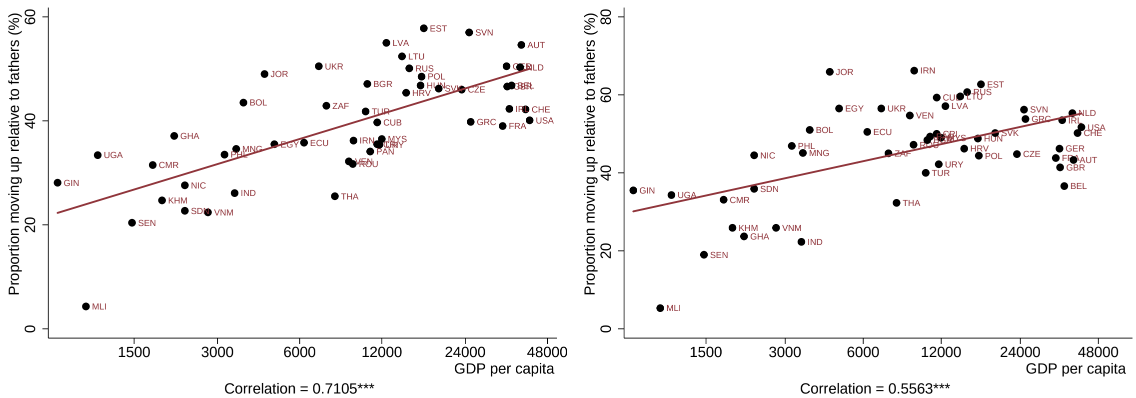
while children in poor countries don't have a higher probability of moving from bottom to top quartile relative to children in rich countries, they face a higher probability of the adverse outcome of moving to the bottom from the top quartile.

Unlike relative mobility, the transitional probabilities are not high in the US compared to other countries. In fact, the US is located at near median of country distribution for both sons and daughters when upward transitional mobility is considered. The US also displays very little variance in transitional probability, both upward and downward, of sons and daughters.

### 2.4.2 *Propensity to Move Relative to Father's Prestige*

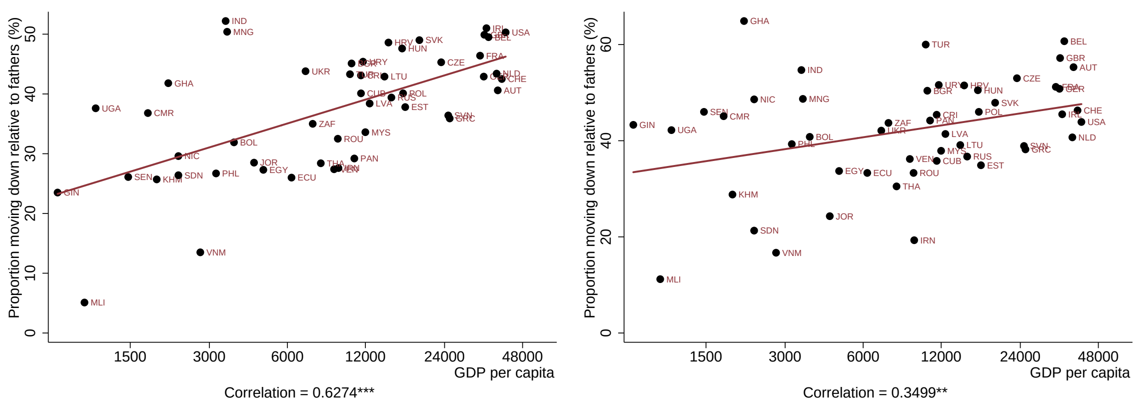
The last measure of absolute mobility that I consider is the fraction of children whose occupational prestige exceeds that of their fathers. Figures 2.7a and 2.7b plots this measure against GDP per capita. I find that propensity to move up relative to father's occupational prestige is strongly correlated with income for both sons and daughters unlike all measures of mobility considered earlier. It is possible that such association is driven by general macroeconomic conditions in which higher growth (or development) in rich countries lead to better outcomes for all children irrespective of father's profile. A test of this hypothesis is to look at the propensity of children to move down relative to father's occupational prestige.[5]

Figure 2.7: Propensity to Move Up Relative to Fathers




(a) Sons (b) Daughters

Figure 2.8: Propensity to Move Down Relative to Fathers

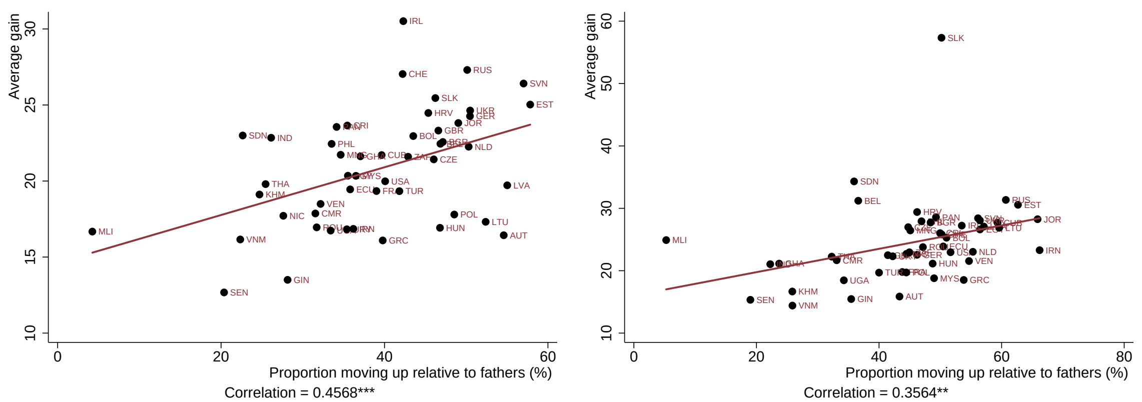



(a) Sons (b) Daughters

[5] The sum of upward and downward mobility relative to father's occupational prestige does not necessarily add up to 1. This is because there are children who end up being employed in the same occupation as their fathers or in occupations that have the same occupational prestige. More importantly, the fraction of such children vary significantly across countries.

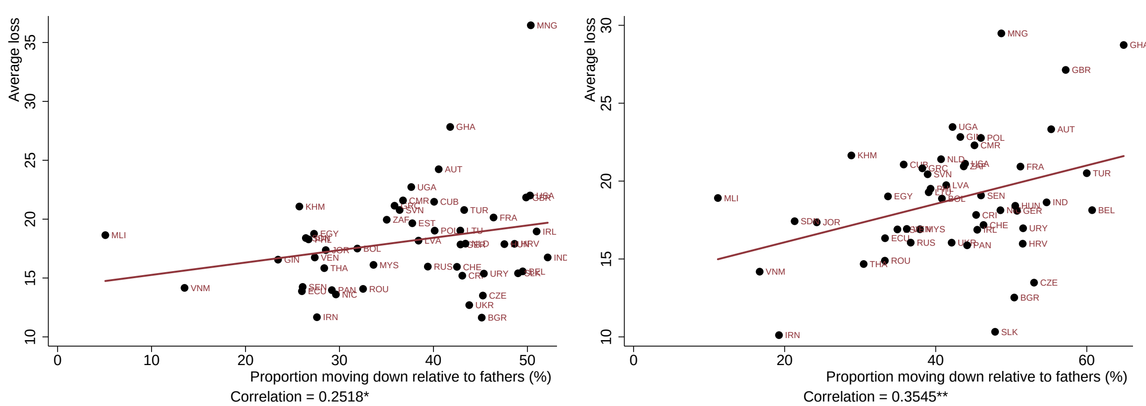
I find that not only the propensity to move up but also the propensity to move down relative to father's prestige is positively correlated with GDP per capita (figures 2.8a and 2.8b). While general improvements in economic and social conditions can explain more children moving up relative to their father's prestige in rich countries, it cannot explain the higher downward propensity observed in rich countries. Hence, it appears that forces other than economic growth and development are important in driving higher propensity in rich countries.

Figure 2.9: Average Gain in Occupational Prestige (Adjusted Scale)




(a) Sons (b) Daughters

Figure 2.10: Average Loss in Occupational Prestige (Adjusted Scale)




(a) Sons (b) Daughters

While it is true that more children in rich countries end up higher (lower) relative to their father's occupational prestige, it is possible that higher absolute mobility is driven by narrow partitions of occupations in rich countries and that the average gain (loss) is actually insignificant. As seen in figures 2.9a and 2.9b, the average gains in occupational prestige for both sons and daughters is positively correlated with the propensity to move up relative to father's prestige. On average, a 10 percentage point increase in the propensity is associated with an increase of 1.6 prestige points for sons and an increase of 1.9 prestige points for daughters when the Adjusted Scale for measuring occupation prestige is used.[6] The relationship between average loss and the propensity to move down is a little less for sons compared to average gain and the propensity to move up (figure 2.10a). In contrast, the correlation between average loss and the propensity to move down for daughters is almost equal to correlation between average gain and the propensity to move up (figure 2.10b).

## 2.5 Conclusion

A cross-country study of intergenerational mobility featuring developing countries is restricted due to a general paucity of income or consumption data spanning generations from these countries. In this paper, I use occupational prestige as a proxy of social status to estimate intergenerational occupational mobility measures for 50 countries located across the world's income distribution.

In order to compare mobility across countries, I consider both the relative and the absolute measures of mobility. I find that although relative mobility varies significantly across countries, the correlation between relative mobility and GDP per capita is only mildly positive for sons and is very close to zero for daughters. I also consider

[6]Appendix figures G.1a and G.1b show the relationship between average gain and propensity for sons and daughters when the Absolute Scale is used. The correlation between the variables is higher when the Absolute Scale is used.

two measures of absolute mobility: propensity to move across quartiles and propensity to move relative to father's occupational prestige. Similar to relative mobility, the first measure of absolute mobility is independent to the level of GDP per capita. The second measure, on the other hand, is positively correlated with GDP per capita with correlations being significantly higher for sons compared to daughters. It also appears that high propensity to move up in rich countries cannot be explained by a general improvement in economic and social conditions in these countries.

The prestige scores used in this paper are based on respondents' evaluations of occupation titles that were conducted in 1989. This raises concern to the comparability of occupational prestige scores across space and time. Though previous research has found little evidence of variability across either dimension, the results of this paper must be read with such issues in mind.

The main finding of the paper is that though mobility differs significantly across countries differences in occupational mobility cannot be explained by differences in income. In future work, I intend to isolate factors that can explain the huge variations in mobility across countries.

Chapter 3

# ALLOCATION OF TALENT AND INDIAN ECONOMIC GROWTH

## 3.1 Introduction

GDP per capita in India more than doubled during the period 1983–2004. There was a massive change in occupational distribution of women and low-caste men during the same period. For example in 1983, a high-caste woman was 1/10 times as likely as a high-caste man to work as an engineer while a low-caste man was 1/7 times as likely. In 2004, the propensity for high-caste women and low-caste men to work in engineering occupations relative to high-caste men increased to 1/6 and 1/2 respectively. The relative propensity of low-caste women in engineering in 2004 was at a dismal 1/16, but it was still an improvement considering that no low-caste woman in the sample was an engineer in 1983. Women and low-caste men saw dramatic increase in their relative propensity to work in many other high-skill occupations.[1]

Hsieh *et al.* (2014) argue that innate talent in most occupations is unlikely to differ across gender-race groups. In this paper I extend their argument to India. The analogous idea presented here is that the occupational distribution in 1980's India represented massive occupational talent misallocation in which women workers from both caste groups as well as low-caste men faced barriers to practice an occupation of their comparative advantage. The goal of this paper is to understand the effects of changes in these barriers on aggregate productivity. I employ the Hsieh *et al.* (2014) model of occupational choice to study talent misallocation in India.

The defining feature of the model is that workers have different levels of innate talent across possible occupations and the endowed talent is critical in determining the relative productivity of a worker in any occupation relative to other occupations.

[1] Other studies have also found convergence in outcomes of these groups relative to high-caste men. For example, Hnatkovska *et al.* (2012) find a significant convergence in education, wages and consumption levels of low-caste workers toward high-caste workers. They also find a convergence in occupational distribution using three broad occupations: white collar, blue collar and agrarian. In this paper, I consider a much finer classification of occupations.

Three forces present in the model lead to differences in occupational outcomes across groups. First, workers of certain groups face wage discrimination in the labor market and earn a lower per unit efficiency wage compared to high-caste men. Banerjee and Knight (1985) and Madheswaran and Attewell (2007) find evidence of such wage discrimination against Scheduled Caste and Schedule Tribe workers. Ito (2009) show that workers from these groups faced higher transaction costs with regards to landing regular employment positions which have significantly higher wages than the other casual employment opportunities. Second, workers of certain groups face frictions in human capital accumulation which increases their cost of investments relative to high-caste men. A variety of reasons can give rise to such frictions: relatively lower investments in daughters' education as compared to sons' education, increased resource cost of attending schools for children from geographically segregated low-caste households etc. For example, Munshi and Rosenzweig (2006) find that boys from the lower caste households have a higher propensity of being enrolled in local language school which limits their chances of being employed in white collar occupations. Muralidharan and Prakash (2013) show that girls enrollment in secondary school increased when they were provided with free bicycles conditional on enrolling. They attribute this increase in enrollment to increased safety in attending school as well as to changes in patriarchal social norms. Third, the model also allows for differences in distribution of talent across groups. For example, the higher propensity of men relative to women in *brawny* occupations may be driven by their natural comparative advantage based on physical strength.[2] Only the first two forces create distortions in occupational choices and engenders talent misallocation. Taken together, these three forces represent the gross frictions faced by the disadvantageous groups in any occupation and in turn lead to differences in occupational distribution across groups.

[2]Pitt *et al.* (2012) study the role of nutrition on occupational choices of women and men.

The distribution of talent follows the extreme value Fréchet distribution with different mean parameters across groups and occupations, but common variance parameter. An important implication of this specification is that the wage gap between any two groups in any occupation is independent of any group-specific gross frictions. Data on wage gaps and relative propensity across occupations finds evidence of no systematic relationship between the two variables. Moreover, I also find that changes in two variables over time are also uncorrelated with each other. The Fréchet specification also allows for closed-form estimation of gross frictions given data on worker wages and occupational choices. However, the decomposition of gross frictions to its constituents is not possible before making further assumptions. The objective of the paper is to estimate the role played by decreasing frictions in explaining the growth in productivity during the period. To this end, I consider four different decomposition of gross frictions.

I find that the model can explain 15–21% of the observed growth in output per worker during the period from 1983–2004. My estimates of frictions show that even in 2004 frictions faced by women from both groups were far from zero. Hence, I ask how much would productivity increase if frictions are reduced to absolute zero in all occupations. The potential increase in output per worker ranges from 10–14.5% depending on the decomposition used. I conclude the quantitative section by showing that the estimates of productivity gains are robust to a wide range of parameter values.

The rest of the paper is organized as follows: section 3.2 discusses the data and reports the extent of convergence in occupational distribution of various groups to that of high-caste men over the period from 1983–2004. In section 3.3, I present the occupational choice model in which frictions in labor market and human capital accumulation, and differences in distribution of talent drive differences in occupational distribution between groups. Following, I estimate gross frictions from data in section 3.4 and show how they change over time for across different groups. Finally, I quantify the effect of talent misallocation on aggregate productivity in section 3.5 and discuss the main results in detail before concluding.

## 3.2 Data and Occupational Similarity

I use the large sample employment survey data from 1983, 1993 and 2004 which is obtained from the Integrated Public Use Microdata Series-International (IPUMS-I, Minnesota Population Center (2014)).[3] With respect to caste groups, I divide the population into two groups: Scheduled Caste or Scheduled Tribe (SC/ST) and non-SC/ST. The caste groups are then crossed with gender groups. As such, the four groups considered for analysis are: non-SC/ST men (high-caste men), non-SC/ST women (high-caste women), SC/ST men (low-caste men) and SC/ST women (low-caste women). High-caste men have the best economic outcomes relative to other groups and hence serve as the benchmark against which outcomes of other groups are measured. I restrict my attention to workers who are between the ages of 25 and 55. The age restriction is made for two reasons: first, most of the schooling is completed by the age of 25 and secondly, the occupational choices when younger (older) could relate to temporary jobs and not necessarily to the final (principal) choices of workers.

The yearly surveys report the occupations using a single classification structure which is comparable across years. This classification consists of more than 400 occupations. I use an aggregated version of this classification that contains 72 occupations. For example, physicists, chemists, geologists, geophysicists and meteorologists are grouped in a single occupation: physical scientists. The respondents who reported working in the week previous to the survey were asked to list the main occupation in which they worked in the prior week.

[3]The most recent data available is for the year 2004.

The propensity of a group to work in an occupation relative to high-caste men can be calculated using the occupational distribution. Specifically, if $p_{jg}$ denotes the proportion of workers in group $g$ that are employed in occupation $j$, then the relative propensity of group $g$ to work in occupation $j$ is given by $\dfrac{p_{jg}}{p_{j,hm}}$. Comparing relative propensities across time presents interesting trends. In 1983, a high-caste woman was 1/10 times as likely than a high-caste man to work as an engineer while a low-caste man was 1/7 times as likely. In 2004, the relative propensities for high-caste women and low-caste men in engineering occupations reduced to 1/6 and 1/2 respectively. The relative propensity of low-caste women in engineering in 2004 was a dismal 1/16, but it was still an improvement considering that no woman from the sample group was an engineer in 1983. The trends in other high-skilled occupations are similar to that observed in engineering.

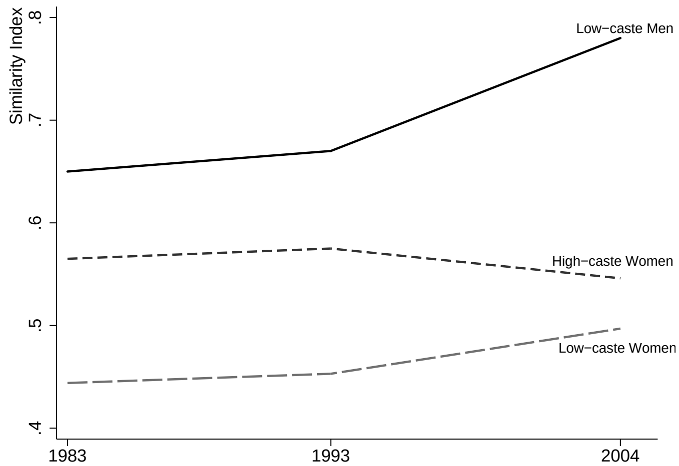
I use the measure of occupational similarity proposed in Hsieh *et al.* (2014) to see whether there has been a convergence in occupational distribution of various groups to that of high-caste men. The similarity index $\psi_g$ for a group $g$ is given by:

$$\psi_g = 1 - \frac{1}{2}\sum_{j=1}^{J} |p_{jg} - p_{j,hm}| \tag{3.1}$$

The similarity index is equal to 1 when the relative propensity is 1 for all occupations implying a perfect overlap, whereas a similarity index of 0 corresponds to no overlap in occupational distribution. Figure 3.1 shows the trend in similarity index for the different groups.

Occupational distribution of low-caste men was closer to high-caste men in 1983 compared to the other groups. Both low-caste groups witnessed occupational convergence relative to high-caste men, though the gain for men was almost thrice as large compared to women. Also, most of the gain in occupational convergence happened

Figure 3.1: Similarity Index: 1983–2004




The figure shows occupational similarity index for various groups in 1983, 1993 and 2004. A higher index value indicates higher overlap with occupational distribution of high-caste men.

during the latter decade with similarity index of all groups changing little during 1983–1993. The similarity index for high-caste women declined slightly during the entire period implying higher divergence in 2004. It is important to note that some difference in occupational distribution between women and men is driven by the possible changes in comparative advantage of men over women in occupations requiring physical strength. Moreover, the similarity index in 2004 for low-caste men is very close to similarity index of black men relative to white men obtained by Hsieh *et al.* (2014) in 2008. The analogy translates to white women and high-caste women as well as black women and low-caste women.

In the next section, I discuss the model of occupational choice used to analyze the effect of frictions on aggregate productivity.

## 3.3 A Model of Occupational Sorting

### *3.3.1 Technology*

There is a representative firm in the economy which is endowed with a constant returns to scale production function. The technology aggregates labor inputs from various occupations to produce a composite good which is either used for consumption or for human capital creation. The production function is given by

$$Y = \left[ \sum_{j=1}^{J} (A_j H_j)^{(\sigma-1)/\sigma} \right]^{\frac{\sigma}{\sigma-1}} \tag{3.2}$$

where $H_j$ is the labor input in occupation $j$ and $A_j$ is the occupation specific productivity parameter. The elasticity of substitution across the $J$ occupational labor inputs is captured by the parameter $\sigma$. The composite good serves as the numeraire and the firm optimization problem consists of choosing $J$ occupation-specific labor inputs $\{H_j\}_{j=1}^{J}$ to maximize profits taking wages $\{w_j\}_{j=1}^{J}$ as given.

$$\max_{\{H_j\}_{j=1}^{J}} \left[ \sum_{j=1}^{J} (A_j H_j)^{(\sigma-1)/\sigma} \right]^{\frac{\sigma}{\sigma-1}} - \sum_{j=1}^{J} w_j H_j \tag{3.3}$$

### *3.3.2 Workers*

The economy is populated with a unit continuum of workers and each worker is a member of one of the four groups: high-caste men (hm), high-caste women (hw), low-caste men (lm) or low-caste women (lw). The utility of a worker depends on his/her consumption $c$ and is given by the strictly monotonic function $u(c)$.

Each worker is endowed with a unit of time. A fraction $s$ of this time is spent at school while the remaining fraction is supplied as labor to earn wage income. The human capital accumulated by a worker is a function of the schooling time $s$ and goods $e$, and is given by

$$h_j(s, e) = s^{\phi_j} e^{\eta} \tag{3.4}$$

where $\phi_j$ and $\eta$ are elasticities of human capital with respect to schooling time and education expenditure respectively. Schooling elasticities $\phi_j$ vary across occupations and hence allow for schooling to have a larger impact on human capital accumulation in certain occupations as compared to others.

### *3.3.3 Occupational Talent*

A defining feature of the model is that workers have different levels of innate talent across all the possible occupations. This endowed talent is critical in determining the relative productivity of a worker in any occupation with respect to other occupations. The differences in talent across occupations capture the notion that workers can be relatively better in certain occupations. For example, it is possible for someone to become a highly productive engineer but not a very productive hairdresser. Specifically, each worker receives a talent endowment $\boldsymbol{\epsilon} \equiv \{\epsilon_j\}_{j=1}^{J}$, where $\epsilon_j$ denotes the level of innate talent in occupation $j$. Given schooling time $s$ and education goods $e$, the efficiency units supplied by a worker in an occupation $j$ is given by

$$h_j(s, e)\epsilon_j(1 - s) = s^{\phi_j} e^{\eta} \epsilon_j (1 - s) \tag{3.5}$$

The distribution of talent is assumed to be independent across occupations and follows the extreme value Fréchet distribution. The talent in an occupation $j$ for any worker in group $g$ follows

$$\text{Prob}(\epsilon_{jg} \leq \epsilon) = e^{-T_{jg}\epsilon^{-\theta}} \tag{3.6}$$

where $\theta$ is the shape parameter that controls the variance of talent with a higher value denoting lower variance. The differences in $T'$s allows for workers from certain groups to be highly productive in an occupation as compared to workers from other groups in general. It is possible that men are more productive in occupations where physical strength is valuable compared to women. In such cases, differences in $T'$s leads to differences in relative weights of men and women in these occupations.

There are two types of frictions present in the model. The first friction occurs in the labor market that leads to different wages being paid to workers from different groups. Specifically, a worker from a group $g$ receives an efficiency wage of $(1-\tau^w_{jg})w_j$ if choosing occupation $j$. The other friction is related to accumulation of human capital in which workers from different groups pay different prices for the education good $e$. A worker from group $g$ spends $(1+\tau^e_{jg})$ for each unit of the education good $e$. A variety of reasons can give rise to these frictions: relatively lower investments in daughters' education as compared to sons' education, increased expenditure of attending school for the geographically segregated low-caste households, caste and gender based discrimination with respect to admission in schools and colleges etc. Taking all the frictions into account, the budget constraint of a worker reduces to consumption being equal to after-friction wage income less after-friction expenditure on schooling

$$c = (1-\tau^w_{jg})w_j\epsilon_j s^{\phi_j} e^{\eta}(1-s) - (1+\tau^e_{jg})e \tag{3.7}$$

In the next step, I set-up the worker's optimization problem and present the findings of the occupational choice problem.

### *3.3.4 Worker Optimization*

The worker's optimization problem consists of two steps: choosing an occupation from the $J$ possible occupations and choosing optimal schooling time $s$ and expenditure in education goods $e$ conditional on occupational choice. Conditional on choosing an occupation $j$, the worker needs to solve

$$\max_{s,e} c \equiv \max_{s,e} (1-\tau^w_{jg})w_j\epsilon_j s^{\phi_j} e^{\eta}(1-s) - (1+\tau^e_{jg})e \tag{3.8}$$

Solving the first order conditions of the above optimization problem yields the following expressions of optimal $s$ and $e$:

$$s^*_j = \frac{\phi_j}{1+\phi_j} \tag{3.9}$$

$$e^*_{jg}(\boldsymbol{\epsilon}|j) = \left(\eta w_j \epsilon_j s_j^{*\phi_j}(1-s^*_j)\frac{1-\tau^w_{jg}}{1+\tau^e_{jg}}\right)^{\frac{1}{1-\eta}} \tag{3.10}$$

Using the expressions of optimal education spending $e^*_{jg}$ and optimal schooling time $s^*_j$ from above, and substituting them in the budget constraint gives the following expression for consumption conditional on choosing any occupation $j$:

$$c^*_{jg}(\boldsymbol{\epsilon}|j) = \left[\frac{w_j\hat{\phi}_j^{\phi_j}(1-\hat{\phi}_j)\eta^{\eta}(1-\eta)^{\eta}\epsilon_j}{(1+\tau^e_{jg})^{\eta}/(1-\tau^w_{jg})}\right]^{\frac{1}{1-\eta}} \tag{3.11}$$

where $\hat{\phi}_j = s^*_j = \dfrac{\phi_j}{1+\phi_j}$. The occupational choice entails comparing these conditional consumption across occupations and picking the one that generates the largest $c^*_{jg}$. The specification that talent follows Fréchet distribution results in the $c^*_{jg}(\epsilon) \equiv \max_j c_{jg}^{*1/(1-\eta)}$ also being Fréchet distributed. This result helps in isolating a closed-form expression for the fraction of workers from a group $g$ working in an occupation $j$ given by $p_{jg}$.[4]

[4] The choice of Fréchet distribution is borrowed from McFadden (1973) which has been exploited for its nice properties in other studies that have analyzed heterogeneity in talent across occupations (Lagakos and Waugh (2013), Young (2014) etc.).

**Proposition 1:** *The fraction of workers in group $g$ that work in occupation $j$ is given by*

$$p_{jg} = \frac{\bar{w}_{jg}^{\theta} T_{jg}}{\sum_{s=1}^{J} \bar{w}_{sg}^{\theta} T_{sg}} \text{ where } \bar{w}_{jg} = \frac{w_j \hat{\phi}_j^{\phi_j} (1 - \hat{\phi}_j) \eta^{\eta} (1-\eta)^{1-\eta}}{(1+\tau_{jg}^{e})^{\eta} / (1-\tau_{jg}^{w})} \tag{3.12}$$

**Proof:** See appendix.

The above result helps in identifying what factors affect the flow of workers into any occupation. An increase in efficiency wage $w_j$ leads to an increase in flows, but in line with intuition there is no change in occupational decisions if wages in all occupations rise proportionally. An increase in either of the two frictions leads to flows out of that occupation. The flows are also increasing with an increase in mean talent parameter $T_{jg}$. The mean talent parameter of a group can change over time due to technological changes. An occupation that traditionally relies on physical strength may become less reliant on it due to invention of new machinery, thereby increasing $T_j$'s in favor of women. The following proposition establishes the relationship between average wages earned by different groups across various occupations and serves as a basis for evaluating the model.

**Proposition 2:** *Let $\overline{\text{inc}}_{jg}$ denote the average wage income of a group $g$ in an occupation $j$. Then, the relative wages of any two groups is given by*

$$\frac{\overline{\text{inc}}_{jg}}{\overline{\text{inc}}_{j,hm}} = \left[ \frac{\sum_{s=0}^{J} \bar{w}_{sg}^{\theta} T_{sg}}{\sum_{s=0}^{J} \bar{w}_{s,hm}^{\theta} T_{s,hm}} \right]^{\frac{1}{\theta(1-\eta)}} \tag{3.13}$$

*and is same across all occupations.*

**Proof:** See appendix.

An important implication of the above result is that wage gaps across occupations between groups are independent of frictions. The wage income of incumbent workers increase with a decline in frictions. However, a decline in frictions also leads to new workers relocating from other occupations. The talent of entrants is lower than the talent of incumbent group and this exactly offsets the upward pressure on average income exerted by increased wage income of incumbent workers.

The propensity of a group to work in an occupation relative to any group is obtained using equations 3.12 and 3.13 and is given by

$$\frac{p_{jg}}{p_{j,hm}} = \frac{T_{jg}}{T_{j,hm}} \left( \frac{\tau_{jg}}{\tau_{j,hm}} \right)^{-\theta} \left( \frac{\overline{\text{inc}}_{jg}}{\overline{\text{inc}}_{j,hg}} \right)^{-\theta(1-\eta)} \tag{3.14}$$

where $\tau_{jg} = \dfrac{(1+\tau^e_{jg})^\eta}{1-\tau^w_{jg}}$. The relative propensity increases with an increase in relative mean talent and relative mean wages while decreases with a increase in relative frictions. I use the above equation, together with data on the relative propensities and relative mean wages to estimate frictions later in the paper.

### *3.3.5 Equilibrium*

A competitive equilibrium for the economy consists of optimal occupational choice $j^*_g(\boldsymbol{\epsilon})$, conditional consumption $\{c^*_{jg}(\boldsymbol{\epsilon}|j)\}_{j=1}^J$, conditional schooling time $\{s^*_j\}_{j=1}^J$, conditional education goods consumption $\{e^*_{jg}(\boldsymbol{\epsilon}|j)\}_{j=1}^J$, total efficiency units of labor in each occupation $\{H^*_j\}_{j=1}^J$ and efficiency wage in each occupation $\{w_j\}_{j=1}^J$ such that

1. Conditional on choosing occupation $j$ and taking $w_j$ as given, $c^*_{jg}(\boldsymbol{\epsilon}|j)$, $s^*_j$ and $e^*_{jg}(\boldsymbol{\epsilon}|j)$ are solutions to the following optimization problem

$$\max_{c,e,s} c \text{ such that } c = (1-\tau^w_{jg}) w_j \epsilon_j s^{\phi_j} e^\eta (1-s) - (1+\tau^e_{jg}) e \tag{3.15}$$

2. The optimal occupational choice $j^*_g(\boldsymbol{\epsilon})$ is given by

$$j^*_g(\boldsymbol{\epsilon}) = \arg\max_j \{c^*_{jg}(\boldsymbol{\epsilon}|j)\}_{j=1}^J \tag{3.16}$$

3. Taking efficiency wage rate in each occupation $\{w_j^*\}_{j=1}^J$ as given, the representative firm's optimal choice of efficiency units $\{H_j^*\}_{j=1}^J$ solves 3.3.

4. The occupational wage rate $w_j$ clears the labor market in each occupation.

### *3.3.6 Model Evaluation*

Proposition 2 presents a strong result of the model. According to equation 3.13, the wage gaps between two groups are same across all occupations. Any increase in wage per efficiency unit due to declining frictions in an occupation is exactly offset by entry of lower talent workers. The exact cancellation of the two forces is an extreme characterization and is unlikely to hold true in reality. However, a related implication is that wage gaps are not necessarily smaller in occupations in which workers from disadvantageous groups have higher relative propensity to work. Additionally, the convergence in wage gaps over time are also independent of changes in relative propensity to work across occupations. These two claims can be tested using data on average incomes and relative weights of groups across occupations.

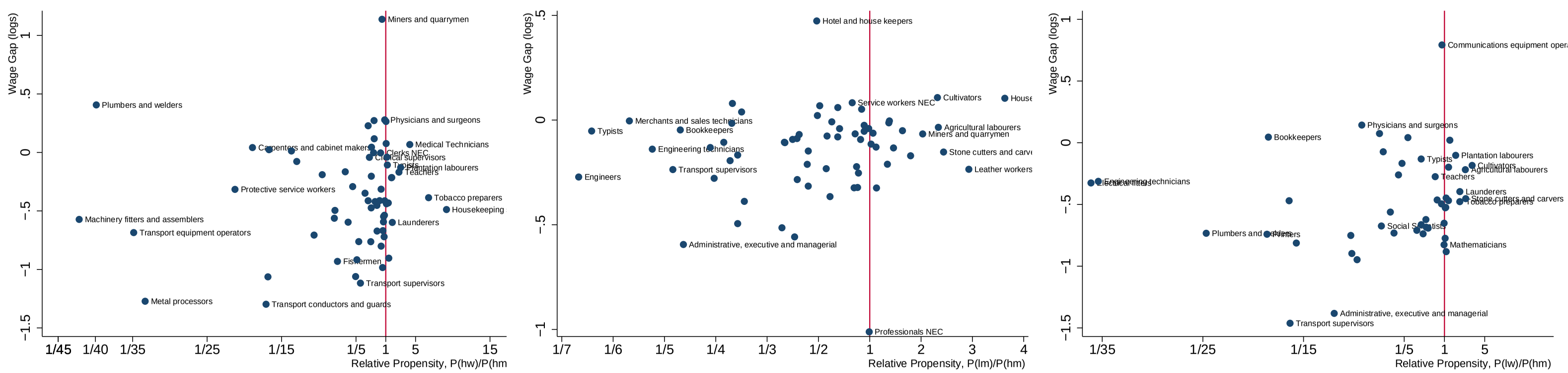
Figures 3.2 and 3.3 plot the log wage gaps of high-caste women, low-caste men and low-caste women relative to high-caste men together with their relative propensity to work across occupations in 1983 and 2004 respectively. A high-caste woman was 9 times more likely to be employed in housekeeping services relative to a high-caste man compared to being only 1/7 times as likely to be employed in wood and paper related craft work in 1983. However, the wage gaps in these occupations was approximately 50% even with such huge variation in relative propensity. Similarly in 2004, high-caste women in tailoring and dressmaking occupations as well as communication equipment operation earned 50% less than high-caste men counterparts even though they were 7 times more like to be a tailor relative to men while only 1/13 times as likely to be a communication equipment operator. More generally, the correlation between wage gaps and relative propensity across groups and years is never more than 0.15 in magnitude and is always insignificant.[5]

Next, I check whether changes in wage gaps over time bear any systematic relationship with changes in relative propensities. Figure 3.4 re-affirms the model's prediction that changes in relative propensities are independent of changes in wage gaps in the sense that higher net flows doesn't occur in and out of occupations that witness larger convergence in wage gaps. For example, figure 3.4a shows that change in wage gaps in wood and paper work, cooking, and carpentry for high-caste women were similar even though there were huge variations in change in relative propensity for these occupations. Similarly for low-caste men, propensity to become a physician or a surgeon more than doubled during the period compared to a three-factor decline in propensity to become a launderer. Yet, the convergence in wage gap for the two occupations varied in the narrow range of 25–40%. The correlation between the change in wage gaps and change in relative propensity across different groups is never more than 0.19 in magnitude and is always insignificant.

The above discussion lends support to the selection mechanism of the model in which mean wage in an occupation is insulated to any flow of workers in or out of that occupation. The next section discusses the estimation of friction parameters.

[5] The correlation magnitudes are higher in 1983 compared to 2004.

Figure 3.2: Occupational Wage Gaps: 1983

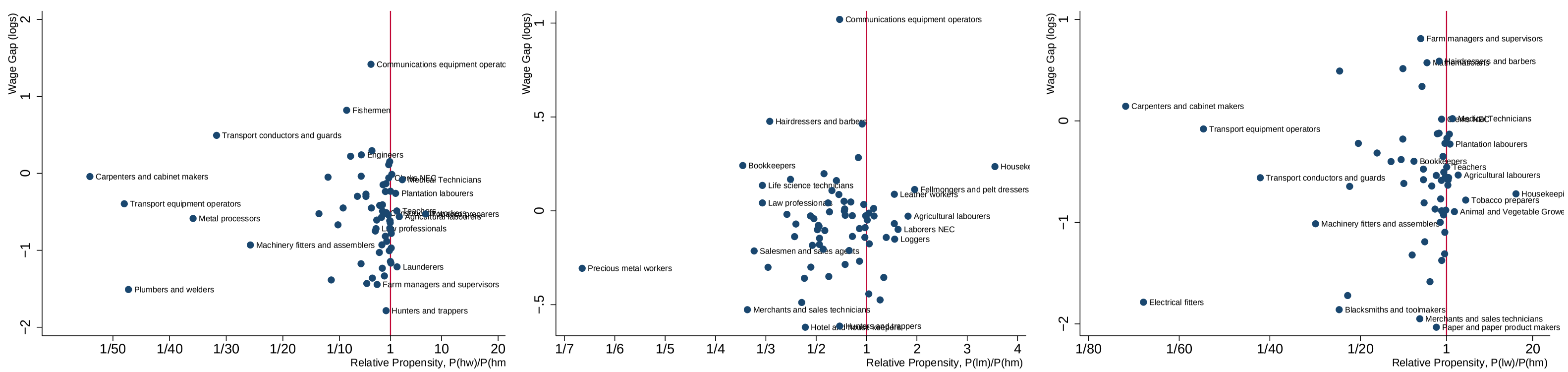



(a) High-caste women

(b) Low-caste men

(c) Low-caste women

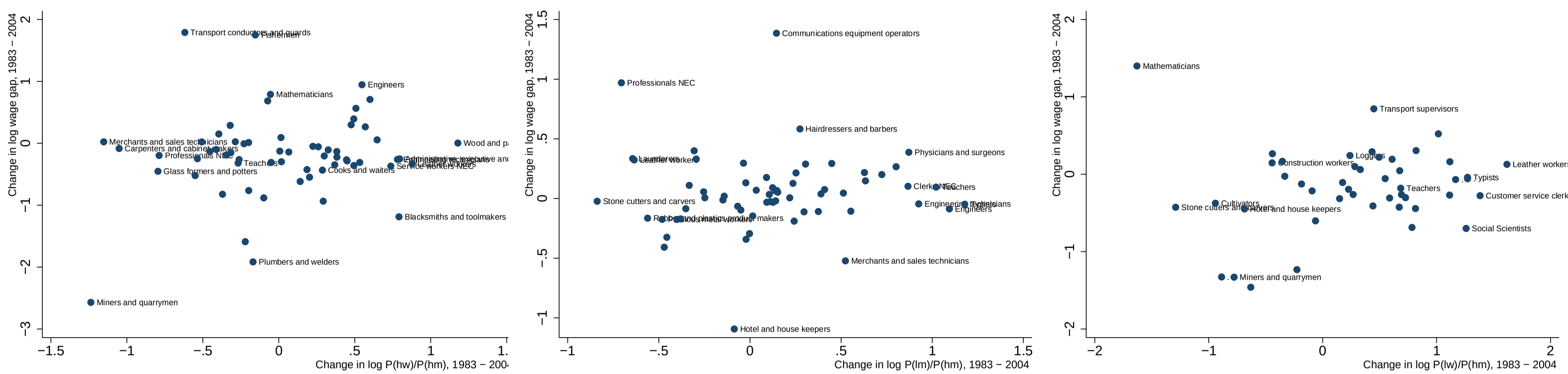
Figure 3.3: Occupational Wage Gaps: 2004




(a) High-caste women (b) Low-caste men (c) Low-caste women

The figures above show the relationship between log wage gap of a group relative to high-caste men and the relative propensity of a worker from a group of working in any occupation relative to high-caste men $P(g)/P(hm)$. In line with the model, the two variables are uncorrelated across all cases.

Figure 3.4: Change in Occupational Wage Gaps: 1980 – 2004




(a) High-caste women

(b) Low-caste men

(c) Low-caste women

The figures above show the relationship between log wage gap of a group relative to high-caste men and the relative propensity of a worker from a group of working in any occupation relative to high-caste men $P(g)/P(hm)$. In line with the model, the two variables are uncorrelated across all cases.

## 3.4 Frictions

In this section, I use data on relative propensities and relative wage incomes to estimate frictions and discuss how they have changed over time for various groups. Rearranging the terms of equation 3.14, I get

$$\hat{\tau}_{jg} \equiv \left(\frac{T_{jg}}{T_{j,hm}}\right)^{\frac{1}{\theta}} \frac{\tau_{jg}}{\tau_{j,hm}} = \left(\frac{p_{jg}}{p_{j,hm}}\right)^{-\frac{1}{\theta}} \left(\frac{\overline{\text{inc}}_{jg}}{\overline{\text{inc}}_{j,hm}}\right)^{-(1-\eta)} \tag{3.17}$$

where $\hat{\tau}_{jg}$ denote the gross frictions that a group $g$ faces in an occupation $j$ that takes into account differences in mean talent across groups for an occupation on top of differences in frictions pertaining to labor market and human capital accumulation. High-caste men (hm) serve as the base group relative to whom gross frictions in other groups are estimated. The right-hand side of the above equation would be high if either the relative propensity of a group is low compared to high-caste men or there is a huge gap in mean income earned by that group relative to high-caste men (or both).

The two parameter values that are required in order to estimate gross frictions are those of Fréchet shape parameter $\theta$ and elasticity of human capital with respect to education goods $\eta$. The variance of wage income $\sigma^2_{\text{inc}}$ and the mean income $\overline{\text{inc}}$ within any occupation are related as follows:

$$\frac{\sigma^2_{\text{inc}}}{\overline{\text{inc}}^2} = \frac{\Gamma\left(1 - \frac{2}{\theta(1-\eta)}\right)}{\left(\Gamma\left(1 - \frac{1}{\theta(1-\eta)}\right)\right)^2} - 1 \tag{3.18}$$

I use the above equation to pin down the value of $\theta(1-\eta)$. First, I collect the residuals from the regression of log of wage income on a set of occupation-group dummies and education attainment. The occupation-group dummies control for occupation related returns as well as any contribution of frictions. The mean and variance of the residuals are then used to obtain the value of $\theta(1-\eta)$ by finding the solution to the above equation. Using the three cross-sections, I obtain three estimates of $\theta(1-\eta)$ and use the highest among these (2.96) for my numerical exercises which translates to being the most conservative estimate for the variation of innate talents.[6] The estimate of the elasticity of human capital with respect to education spending $\eta$ is taken from literature. In line with estimates used in Erosa *et al.* (2010) and Manuelli and Seshadri (2014), I assign $\eta$ a value of 0.40. Using this value of $\eta$ and the expression $\theta(1-\eta) = 2.96$, I back out the value of the Fréchet shape parameter $\theta$.

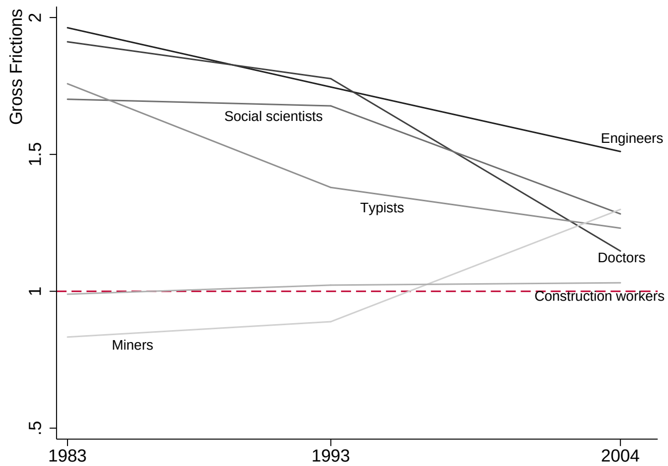
Figure 3.5 plots the gross frictions faced by low-caste men in a few selected occupations.[7] Gross frictions were just under 2 for low-caste men in engineering and medical professions in 1983 and declined strongly over the next 20 years. The decline was particularly impressive for low-caste doctor men for whom gross frictions stayed just above unity in 2004. Frictions pertaining to social scientists and typists also reduced significantly over the 20 year period. While the major drop in frictions for engineers, doctors and social scientists happened during 1993 – 2004, typists saw frictions dropping sharply in the earlier decade. I also find that gross frictions didn't decline for low-caste men across occupations as evidenced by increasing frictions in mining. Low-caste male construction workers started with a frictionless state in 1983 and remained near frictionless over the next two decades.

Figures 3.6a and 3.6b plot frictions experienced by high-caste and low-caste women respectively. Gross frictions for high-caste women declined from more than 3 in 1983 to just under 1.5 in 2004 in engineering occupations, a value lower than that estimated for low-caste men. The frictions for low-caste women in engineering

[6] Please see appendix for the estimated gross frictions at $\theta(1-\eta)$ being equal to 3.44, the value used by Hsieh *et al.* (2014).

[7] Appendix table I.2 lists estimated frictions for all occupations.

Figure 3.5: Estimated Gross Frictions: Low-caste men

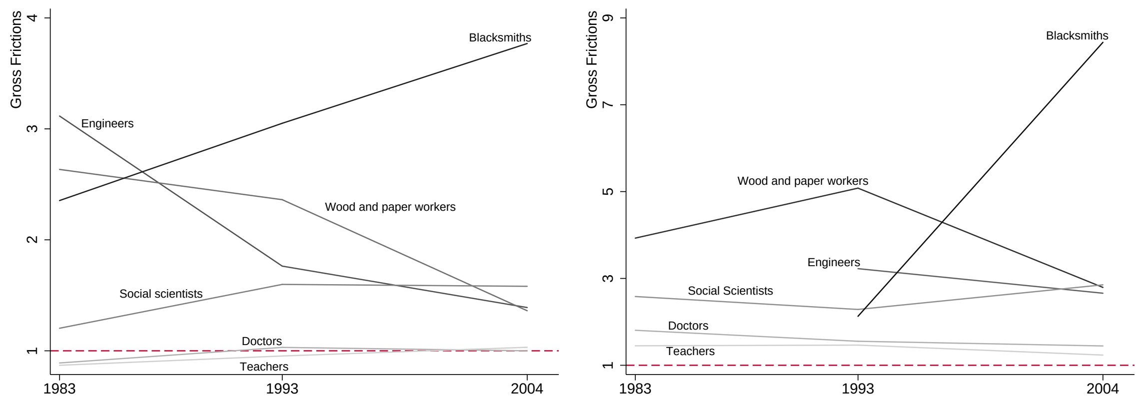



also declined from 1993 to 2004[8], but still remained above 2.5. Interestingly, frictions in social science occupations for women in both caste groups were higher in 2004 as compared to frictions in 1983. High-caste women in medicine and teaching enjoyed gross frictions of less than 1 in 1983, but frictions increased gradually in both these occupations for high-caste women and stood close to 1 by 2004. An important point to note here is that high-caste women were almost thrice as likely to be in teaching in 1983, but a lot of this advantage was offset by them earning 15% less than high-caste men. In contrast, the frictions in medicine and teaching for low-caste women decreased during the period but stayed well above 1 in 2004. Women blacksmiths from both groups saw a drastic increase in frictions. The high gross frictions in this occupation may be driven by the physical demands of the job instead of labor market and human capital accumulation frictions. However, the much higher gross frictions for low-caste women relative to high-caste women is less likely to be driven by differences in mean talent. In the quantitative exercises performed in the next section, I allow for talent differences across gender groups in *brawny* occupations but

[8]There were no women from low-caste engaged in engineering occupations in 1983.

not across caste groups for the same gender. This implies that the talent distribution of men in any occupation is independent of caste affiliations.

Figure 3.6: Estimated Gross Frictions




(a) High-caste women

(b) Low-caste women

In this section, I discussed how gross frictions can be estimated using the model. The gross frictions can be higher for a group both due to differences in fundamental endowment of talent as well as because of labor market and human capital accumulation frictions. In the next section, I introduce four different interpretations of these gross frictions and show what fraction of growth experienced by India from 1983 – 2004 is explained by changing frictions under each interpretation.

## 3.5 Productivity Gains

I begin this section with details on the calibration procedure. The calibration is carried out separately for each year matching the key moments for each year. The calibrated economies are then exploited to yield estimates of productivity gain.

### 3.5.1 *Calibration*

The parameters of the model can be divided into two groups: ones that remain invariant over time and ones that change over time. The three parameters that do not change over time are $\eta, \theta$ and $\sigma$. The estimation of $\eta$ and $\theta$ has been discussed in detail in the previous section. The parameter $\sigma$ characterizes the elasticity of substitution across the $J$ occupation-specific labor inputs. Due to a lack of guidance on the estimate of $\sigma$, I pick $\sigma = 3$ in line with Hsieh *et al.* (2014). I also check the sensitivity of results to this choice of $\sigma$.

The parameters that change over time are the friction parameters $\tau^w_{jg}$'s and $\tau^e_{jg}$'s, the mean talent parameters $T_{jg}$'s, the occupation-specific productivity parameters $A_j$'s and the elasticities of human capital with respect to schooling time $\phi_j$'s. I use equation 3.9 in order to identify $\phi_j$'s by calculating mean years of schooling in each occupation. The productivity parameters are calibrated in equilibrium by matching the distribution of workers across occupations to that observed in the data. An increase in $A_j$ for any occupation raises the returns to that occupation relative to others and leads to flows of workers into the occupation. The only parameters left to be calibrated are the ones that constitute the gross frictions $\hat{\tau}_{jg}$.

The first step in isolating these parameters is to assume that high-caste men do not face any frictions, i.e., $\tau^w_{j,hm} = \tau^e_{j,hm} = 0$ for all $j = 1, \ldots, J$. Without loss of any generality, the mean talent parameters of high-caste white men can be normalized to 1 relative to which I can estimate mean talents for other groups. After these adjustments, I consider the following four extreme cases:

1. There are no differences in mean talents across groups and no frictions in human capital accumulation, i.e., $T_{jg} = 1$ and $\tau^e_{jg} = 0$ for all $j = 1, \ldots, J$ and $g = \{hm, hw, lm, lw\}$. Such specification leads to all gross frictions being attributed

to labor market distortions. The next case is very similar to the present one in which all distortions are restricted in accumulation of human capital.

2. There are no differences in mean talents across groups and no frictions in labor markets, i.e., $T_{jg} = 1$ and $\tau^w_{jg} = 0$ for all $j = 1, \ldots, J$ and $g = \{hm, hw, lm, lw\}$. This leads to all gross frictions being attributed to distortions in human capital accumulation.

3. High-caste women face neither labor market nor human capital accumulation frictions in *brawny* occupations[9] so that all gross frictions experienced by high-caste women are explained by differences in mean talents. Also, the mean talents in any occupation are same across gender groups. Moreover, the means talents are same across all groups for all non-*brawn* occupations and all gross frictions in these occupations are explained for by labor market distortions. In summary, $\tau^w_{b,hw} = \tau^e_{b,hw} = 0$ if $b$ is a *brawny* occupation, $T_{n,g} = 1$ and $T_{j,lm} = 1$, $\tau^e_{j,g} = 0$ if $n$ is a non-*brawn* occupation and $T_{j,hw} = T_{j,lw}$ for all $j = 1, \ldots, J$ and $g = \{hm, hw, lm, lw\}$.

4. All conditions of the above case remain except that in non-*brawn* occupations all gross frictions are attributed to distortions in human capital accumulation instead of distortions in labor market. In summary, $\tau^w_{b,hw} = \tau^e_{b,hw} = 0$ if $b$ is a *brawny* occupation, $T_{n,g} = 1$ and $T_{j,lm} = 1$, $\tau^w_{n,g} = 0$ if $n$ is a non-*brawn* occupation and $T_{j,hw} = T_{j,lw}$ for all $j = 1, \ldots, J$ and $g = \{hm, hw, lm, lw\}$.

[9]See appendix table 3.1 for the list of *brawny* occupations. These relate to agricultural work, craft work in building construction and metal, and others requiring strength-based unskilled labor.

### 3.5.2 *Results*

Output per worker in India nearly doubled in 2004 from its 1983 level (Heston *et al.*, 2012). In the first exercise I explore how much of this productivity gain can be explained by a better allocation of talent across occupations. I consider each of the four specifications listed above and estimate $A_j$'s and $\phi_j$'s separately for 1983 and 2004 under each specification by matching the relevant moments. The growth in output per worker during this period is estimated using chaining. This entails estimating growth by changing frictions from 1983 levels to 2004 levels when $A_j$'s and $\phi_j$'s are fixed at either 1983 or 2004 levels and then taking the geometric mean of the two growth rates. Table 3.1 reports the result of the exercise for all four specifications. Row 1 corresponds to specifications 1 and 2 while gains explained under specifications 3 and 4 are listed in row 2.

Table 3.1: Productivity Gains Explained Due to Frictions

| | Frictions in | |
|---|---|---|
| | Labor Market only | Human Capital only |
| Frictions in all occupations | 19.7 | 21.1 |
| No frictions in *brawny* occupations | 15.5 | 16.4 |

The table reports the fraction of growth in GDP per worker during 1983 – 2004 that is explained by changing frictions over time. The *brawny* occupations are the ones corresponding to agricultural work, craft work in building construction and metal, and others requiring strength-based unskilled labor.

The model can explain 15 – 21% of the observed growth in output per worker during the period from 1983–2004. Not surprisingly, the explained fraction declines when frictions are assumed to be absent in *brawny* occupations. However, the drop is not very large with specifications 3 and 4 still accounting for more than $3/4^{\text{th}}$ of gains explained by specifications 1 and 2 respectively. Frictions in human capital only are able to account for slightly larger growth in productivity as compared to the case where there are frictions present in labor markets only.

Next, I isolate the growth in productivity that results from changing frictions during the period. To do this, I estimate the growth in output per worker when the productivity parameters $A_j$'s and human capital elasticities $\phi_j$'s are allowed to change but the frictions are kept fixed at 1983 levels. The gap in growth rate between the baseline case and one obtained here can be attributed to changing frictions alone. Table 3.2 reports the result of the exercise.

Table 3.2: Decomposing Growth in Output per Worker

| | Baseline (1) | Constant Frictions (2) | Gap (3) |
|---|---|---|---|
| | Frictions in Labor Market Only | | |
| Frictions in all occupations | 18.5 | 9.4 | 9.1 |
| No frictions in *brawny* occupations | 14.6 | 7.6 | 7.0 |
| | Frictions in Human Capital Only | | |
| Frictions in all occupations | 19.8 | 9.7 | 10.1 |
| No frictions in *brawny* occupations | 15.4 | 7.5 | 7.9 |

This table decomposes the growth in productivity to its potential sources. Column (1) reports the growth in output when frictions are allowed to change in presence of changes in $A_j$'s and $\phi_j$'s. Column (2) reports growth when frictions are fixed at 1983 levels and column (3) reports the difference in growth between the first two columns.

The main finding here is while changes in $A_j$'s and $\phi_j$'s are important in understanding growth in output per worker, changes in frictions over time also have a significant impact on productivity. In the case where all frictions apply in the labor market, changes in frictions account for just under half of growth in output per worker. In contrast when all frictions are contained in human capital accumulation, changes in frictions become the dominant source of productivity growth.

Lastly, I ask how much would productivity increase if frictions are reduced to absolute zero in all occupations. To perform this counterfactual, the frictions are exogenously set to zero keeping all other parameters at the 2004 level. Like before I consider the four cases that determine the nature of gross frictions. Table 3.3 reports the results of the exercise. Depending on the specification, the potential increase in output per worker ranges from 10–14.5%. As seen before, estimated increase in productivity is higher when frictions create distortions in human capital accumulation.

Table 3.3: Potential Increase in Output per Worker

| | Frictions in Labor Market only | Frictions in Human Capital only |
|---|---|---|
| Frictions in all occupations | 11.3 | 14.5 |
| No frictions in *brawny* occupations | 9.7 | 13.4 |

The table reports the counterfactual increase in output per worker from the 2004 level if frictions across occupations are reduced to zero leaving all other parameters unchanged.

I conclude the quantitative discussion by examining the robustness of the results to alternative values of $\eta$ and $\sigma$.

### *3.5.3 Robustness*

The value of the elasticity of human capital with respect to education spending $\eta$ is taken to be 0.400 based on Erosa *et al.* (2010) and Manuelli and Seshadri (2014). Table 3.4 shows the sensitivity of results when alternative values of $\eta$ are considered. The model can account for slightly larger gains in productivity when a higher value of $\eta$ is considered and all frictions are attributed to the labor market distortions. However, the model's capacity to explain productivity gains do not change much and remains within 2% of the gains explained by the benchmark specification. The results of the benchmark specification are more robust to changes in $\eta$ when all frictions are attributed to distortions in the human capital accumulation.

Table 3.4: Productivity Gains Explained Due to Frictions: Changing $\eta$

| Frictions in | Baseline (1) | $\eta = 1/100$ (2) | $\eta = 1/2$ (3) |
|---|---|---|---|
| Labor Market only | 19.7 | 18.1 | 21.3 |
| Human Capital only | 21.1 | 20.3 | 21.0 |

The value of elasticity of substitution parameter $\rho$ has been set to 3 following Hsieh *et al.* (2014). Table 3.5 reports the sensitivity of results with respect to $\rho$. The share of growth explained increases to 22.4% as occupations are made near perfect substitutes ($\sigma = 20$) and decreases to 15.3% as occupations are made near imperfect substitutes when all frictions are restricted in the labor market. Changes in explained gains in productivity are less responsive to changes in value of $\sigma$ when distortions are restricted in human capital accumulation. A possible reason for this may be that with an increase in $\sigma$, there is a general increase in human capital accumulation in all occupations and this in turn makes misallocation more costly.

Table 3.5: Productivity Gains Explained Due to Frictions: Changing $\sigma$

| Frictions in | Baseline (1) | $\sigma = 0.1$ (2) | $\sigma = 20$ (3) |
|---|---|---|---|
| Labor Market only | 19.7 | 15.3 | 22.4 |
| Human Capital only | 21.1 | 20.3 | 21.8 |

## 3.6 Conclusion

Output per worker in India nearly doubled in 2004 from its 1983 level. During the same period, there occurred a sea change in the occupational distribution of high-caste women, low-caste men and low-caste women relative to high caste men. Workers from these groups had a much higher propensity to work in high-skilled occupations relative to high-caste men in 2004 compared to 1984. Given that innate talent in these occupations is likely to be independent across groups, the paper argues that the occupational distribution in the 1980s represented talent misallocation in which workers from many groups faced significant barriers to practice an occupation of their comparative advantage.

Three forces present in the model lead to differences in occupational outcomes across groups. First, workers of certain groups face wage discrimination in the labor market and earn a lower per unit efficiency wage compared to high-caste men. Second, workers of certain groups face frictions in human capital accumulation which increases their cost of investments relative to high-caste men. Third, the model also allows for differences in distribution of talent across groups. I employ the Hsieh *et al.* (2014) model of occupational choice to estimate what proportion of the massive productivity growth that happened in India is attributable to changes in talent allocation across occupations.

I calibrate the model to match the key moments observed in the data over time. I find that the model can explain 15–21% of the observed growth in output per worker during the period from 1983–2004. Additionally, my estimates of frictions show that even in 2004 frictions faced by different groups were far from zero. I also find that output per worker has a potential to increase by another 10–15% if frictions reduce to absolute zero in all occupations.

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# APPENDIX A

## CHAPTER 1: CONSTRUCTION OF DATASET AND OCCUPATIONAL STRUCTURE

The data for the analysis is sourced from the sources listed below.

European Social Survey (ESS): The survey is conducted in 36 countries. The survey contains data on a number of respondent's characteristics like jobs, education, beliefs etc. Critical to the analysis of the relationship between intergenerational occupational mobility and economic development, the survey reports the occupations of a respondent's parents when the respondent was of 14 years of age. This parental occupation data is available for 27 of the 36 countries in the ESS.

The 4-digit ISCO-88 parental occupation codes are available for 10 of the 27 countries containing information on parental occupations. Data for the remaining 18 countries are available in the form of text responses conveyed by the respondents. The textual responses are often provided in the language the interview was conducted. There are instances when the responses are in different languages for the same country. For example, in Belgium the parental occupations are listed in Dutch, French and German. The responses have been translated into English using Google Translate and on few occasions using Babylon translation software.

The nature of these responses vary substantially in their level of detail and many responses cannot be mapped to a 3 or 4-digit ISCO-88 level. However, most of the responses could be mapped to a 2-digit ISCO-88 level. Still there are responses that fail to make this cut. For instance, many responses note the parental occupation as "clerk". However, in order to map this response to a 2-digit level, I need to know whether this refers to "Office Clerks" or "Customer service clerks". Such responses would be dropped if persistence is constructed using the standard 2-digit ISCO taxonomy. Table A.2 lists the 1-digit and 2-digit ISCO-881 occupations. The modified 2-digit classification is derived by making the following 3 alterations to the standard 2-digit taxonomy:

Table A.1: Countries in the European Social Survey

| **Code available** | **Self Coded** | |
|---|---|---|
| Czech Republic | Austria | Portugal |
| Estonia | Belgium | Romania |
| Germany | Bulgaria | Slovakia |
| Greece | Croatia | Switzerland |
| Netherlands | Cyprus | Turkey |
| Norway | France | Ukraine |
| Poland | Hungary | United Kingdom |
| Russia | Ireland | |
| Slovenia | Latvia | |
| Sweden | Lithuania | |

1. 2-digit ISCO code 12 and 13 are merged into one occupation level "12"
2. 2-digit ISCO codes 41 and 42 are merged into one occupation level "40"

3. 2-digit ISCO codes 81, 82 and 83 are merged into one occupation level "80"

As a result, there are a total of 24 occupations present in the modified 2-digit ISCO structure compared to a total of 28 occupations in the standard 2-digit ISCO structure.

National Longitudinal Survey of Youth 1979 (NLSY79): The NLSY79 is a longitudinal survey of youth that began in 1979 when the respondents were 14-22 years of age. At the inception, the occupations of the youth's mother and father were recorded. The occupational data of the respondents are available for the later waves of the survey.

Indian Human Development Survey (IHDS): The IHDS is a nationally representative survey of 41,554 households across India. The male head of households were asked about their father's principal occupation which helps compute occupational persistence for India.

Egypt Labor Market Panel Survey 2012 (ELMPS12): The ELMPS12 is a nationally representative survey that contains information on education, occupation, parental background etc. Respondents in the survey were asked about the principal occupation of their parents. The occupational data for Egypt is reported on a much detailed level and hence it is possible to map these occupations to the 4-digit ISCO structure.

Integrated Public Use Microdata Series, International (IPUMS-I): IPUMS-I project in engaged in costructing harmonized data across countries using the publicly available census samples. There are around 60 countries for which the IPUMS-I has occupational data coded on a ISCO-88 structure for at least an year in the last 20 year period. Out of these 60, 3-digit coding is available for 29 countries. The rest have occupations coded on a 1-digit level. Using the general 1-digit code together with the original occupation coding from the census, the occupations are mapped to the modified 2-digit structure for these countries. In some instances, the original classification is not narrow enough to construct such mapping. There are 16 countries for which such a mapping has been done. Hence, I am able to measure occupational persistence for 45 countries using the IPUMS-I data of which 10 also feature in the baseline dataset.

Table A.2: International Standard Classification of Occupations

| 1-digit code | 2-digit code | Occupation |
|---|---|---|
| **1** | | LEGISLATORS, SENIOR OFFICIALS AND MANAGERS |
| | 11 | Legislators and Senior Officials |
| | 12 | Corporate Managers |
| | 13 | General Managers |
| **2** | | PROFESSIONALS |
| | 21 | Physical, mathematical and engineering science professionals |
| | 22 | Life science and health professional |
| | 23 | Teaching professionals |
| | 24 | Other professionals |
| **3** | | TECHNICIANS AND ASSOCIATE PROFESSIONALS |
| | 31 | Physical and engineering science associate professionals |
| | 32 | Life science and health associate professionals |
| | 33 | Teaching associate professionals |
| | 34 | Other associate professionals |
| **4** | | CLERKS |
| | 41 | Office clerks |
| | 42 | Customer service clerks |
| **5** | | SERVICE WORKERS AND SHOP AND MARKET SALES WORKERS |
| | 51 | Personal and protective services workers |
| | 52 | Models, salespersons and demonstrators |

International Standard Classification of Occupations *(contd.)*

| 1-digit code | 2-digit code | Occupation |
|---|---|---|
| **6** | | Skilled Agricultural and Fishery Workers |
| | 61 | Market-oriented skilled agricultural and fishery workers |
| **7** | | Craft and related Trade Workers |
| | 71 | Extraction and building trade workers |
| | 72 | Metal, machinery and related trades workers |
| | 73 | Precision, handicraft, printing and related trades workers |
| | 74 | Other craft and related trades workers |
| **8** | | Plant and Machine Operators and Assemblers |
| | 81 | Stationary plant and related operators |
| | 82 | Machine operators and assemblers |
| | 83 | Drivers and mobile plant operators |
| **9** | | Elementary Occupations |
| | 91 | Sales and services elementary occupations |
| | 92 | Agricultural, fishery and related laborers |
| | 93 | Laborers in mining, construction, manufacturing and transport |
| **10** | | Armed Forces |

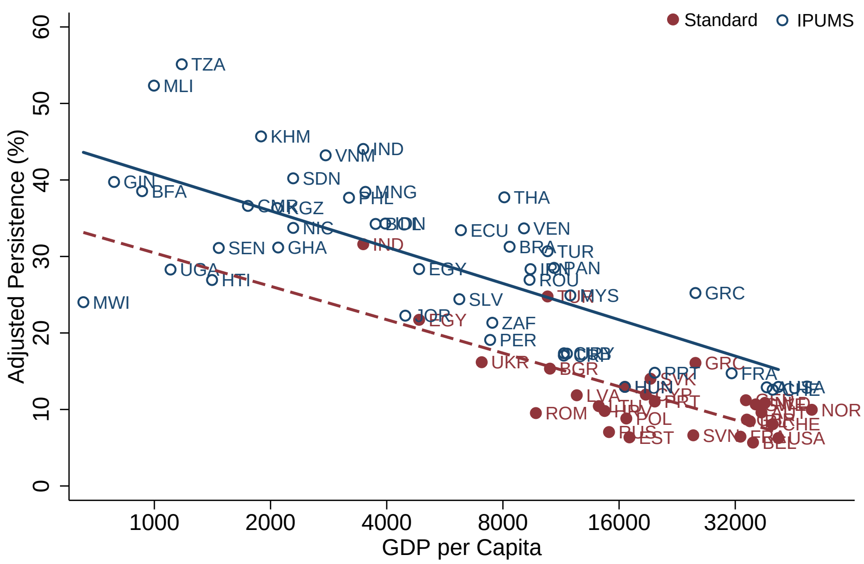
# APPENDIX B

# CHAPTER 1: ROBUSTNESS OF ESTIMATED OCCUPATIONAL PERSISTENCE

## B.1 Persistence Calculated From IPUMS-I Data

I used the mean bias in persistence for the 10 countries present in both datasets to correct for the measured persistence obtained from the IPUMS-I data. This adjustment was based on the fact that the bias was uncorrelated with incomes. A concern here is that the bias might be correlated with incomes at very low levels of income. I find that bias and income is uncorrelated even when the poorest countries of the IPUMS-I database are considered.

Figure B.1: Persistence Across Datasets




The red solid dots represent the adjusted persistence measured using representative sample of workers while the blue hollow dots correspond to persistence measured using IPUMS-I data. The similar slope of fitted lines across the two datasets imply that the bias from the IPUMS-I data is uncorrelated with income.

Adjusted persistence estimated from both datasets are shown together in figure B.1. The solid red dots correspond to persistence estimates from the representative dataset and the hollow blue dots show persistence calculated from the census data. The dashed red line and solid blue line shows the linear fit between persistence and incomes for the two datasets. The non-systematic bias in estimates from the two datasets is captured by the similar slopes of the two regression lines. This means that the upward bias present in the persistence calculated from the census data is approximately constant across the income distribution. This is consistent with the uncorrelated bias obtained across 10 countries shown earlier in the paper. Moreover, the difference in intercepts (8.7%) of the two regression lines is fairly close the mean bias (6.1%) obtained in the baseline adjustment.

## B.2 Persistence Across Occupations

Previously, I showed that the negative correlation between persistence and income was not driven by agriculture. The correlation was negative and significant even when persistence was calculated dropping the fathers practicing agriculture. However, the concern here is that high persistence in poor countries could be due to larger representation of workforce in implicitly more persistent occupations in general. To test for this, I do the same exercise for all the other 22 occupations and find that the correlation remains negative and significant at 1% level for all specifications. Moreover, the magnitude of the relationship is in close range to what is obtained with the complete data. Table B.1 shows the result of the exercise.

Table B.1: Correlations After Dropping Occupations

| Dropped Occupation | 2-digit code(s) | Naïve | Adjusted |
|---|---|---|---|
| Legislators and senior officials | 11 | -0.784 | -0.716 |
| Managers | 12,13 | -0.778 | -0.717 |
| Physical, mathematical and engineering science professionals | 21 | -0.767 | -0.675 |
| Life science and health professionals | 22 | -0.797 | -0.734 |
| Teaching professionals | 23 | -0.791 | -0.740 |
| Other professionals | 24 | -0.779 | -0.715 |
| Physical and engineering science associate professionals | 31 | -0.785 | -0.724 |
| Life science and health associate professionals | 32 | -0.776 | -0.711 |
| Teaching associate professionals | 33 | -0.787 | -0.730 |
| Other associate professionals | 34 | -0.788 | -0.729 |
| Clerks | 41,42 | -0.771 | -0.698 |
| Personal and protective services workers | 51 | -0.775 | -0.703 |
| Models, salespersons and demonstrators | 52 | -0.780 | -0.722 |
| Skilled agriculture and fishery workers | 61 | -0.783 | -0.723 |
| Extraction and building trade workers | 71 | -0.829 | -0.746 |
| Metal, machinery and related trades workers | 72 | -0.775 | -0.716 |
| Precision, handicraft, printing and related workers | 73 | -0.785 | -0.752 |
| Other craft and related trade workers | 74 | -0.783 | -0.723 |
| Machine operators | 81,82,83 | -0.787 | -0.732 |
| Sales and services elementary occupations | 91 | -0.710 | -0.701 |
| Agricultural, fishery and related laborers | 92 | -0.777 | -0.716 |
| Laborers in mining, construction, manufacturing and transport | 93 | -0.824 | -0.737 |
| Armed forces | 10 | -0.777 | -0.716 |

All correlations significant at 1% level of significance.

# APPENDIX C

## CHAPTER 1: PROOFS OF PROPOSITIONS

Proposition 1: Let the optimal choice of labor supplied $l$ by a worker with talent $\epsilon_j$ in occupation $j$, conditional on choosing that occupation be given by $l_j^C(\boldsymbol{\epsilon})$ when making repayment and by $l_j^R$ when reneging on the contract. From the first order conditions of the conditional optimization:

$$l_j^C(\boldsymbol{\epsilon}) = \frac{\gamma}{1+\gamma} + \frac{\bar{\xi}_j^{\,1-\eta}}{(1+\gamma)w\epsilon_j} \tag{C.1}$$

$$l_j^R = \frac{\gamma}{1+\gamma} \tag{C.2}$$

Incentive compatibility for a worker with talent $\epsilon_j$ fails if his utility from reneging is greater than his utility from making the repayment:

$$\begin{aligned}
&\tilde{U}_j^C(\boldsymbol{\epsilon}) < \tilde{U}_j^R(\boldsymbol{\epsilon})\\
\Rightarrow&\left[\frac{\gamma}{1+\gamma}w_j\epsilon_j\bar{\xi}_j^{\,\eta}\left(1-\frac{\bar{\xi}_j^{\,1-\eta}}{w_j\epsilon_j}\right)\right]^{\gamma}\left[\frac{1}{1+\gamma}\left(1-\frac{\bar{\xi}_j^{\,1-\eta}}{w_j\epsilon_j}\right)\right] < \left[\frac{\gamma}{1+\gamma}w_j\epsilon_j\bar{\xi}_j^{\,\eta}(1-\phi)\right]^{\gamma}\left[\frac{1}{1+\gamma}\right]\\
&\text{(using optimal conditions from C.1 and C.2)}\\
\Rightarrow&\left(1-\frac{\bar{\xi}_j^{\,1-\eta}}{w_h\epsilon_j}\right)^{\gamma}\left(1-\frac{\bar{\xi}_j^{\,1-\eta}}{w_j\epsilon_j}\right) < (1-\phi)^{\gamma}\\
\Rightarrow&\left(1-\frac{\bar{\xi}_j^{\,1-\eta}}{w_j\epsilon_j}\right)^{1+\gamma} < (1-\phi)^{\gamma}\\
\Rightarrow&\epsilon_j < \frac{\bar{\xi}_j^{\,1-\eta}}{w_j(1-h(\phi,\gamma))} \equiv \epsilon_{\phi j}^* \quad \left(\text{where } h(\phi,\gamma) = (1-\phi)^{\frac{\gamma}{1+\gamma}}\right).
\end{aligned}$$

Hence, a worker can obtain credit only is his talent in occupation $j$ is at least as much as the threshold talent $\epsilon_{\phi j}^*$. □

Proposition 2: $\epsilon_{\phi j}^*(h(\theta,\gamma)) = \dfrac{\bar{\xi}_j^{\,1-\eta}}{w_j(1-h(\phi,\beta))} \Rightarrow \dfrac{d\epsilon_{\phi j}^*}{d\phi} = \dfrac{\bar{\xi}_j^{\,1-\eta}}{w_j(1-h(\phi,\beta))^2}\dfrac{dh}{d\phi}$. $\dfrac{dh}{d\phi} < 0 \Rightarrow \dfrac{d\epsilon_{\phi j}^*}{d\phi} < 0$. This means that credit becomes available to increasingly lower talent levels as financial frictions are reduced. In the limiting case of no credit markets, $\epsilon_{\phi j}^* \to \infty$, which means no talent level is able to obtain funding for education. □

Proposition 3: Conditional on choosing his father's occupation $f$ and obtaining education using the home-based technology, the optimal time worked $l^H$ by a worker is given by:

$$l^H = \frac{\gamma}{1+\gamma} \tag{C.3}$$

It is optimal for a worker to choose home-based education technology instead of obtaining it outside through borrowing if:

$$
\begin{aligned}
&\tilde{U}_f^C(\boldsymbol{\epsilon}) < \hat{U}(\boldsymbol{\epsilon}, f)\\
\Rightarrow &\left[\frac{\gamma}{1+\gamma} w_f \epsilon_f \bar{\xi}_f^{\eta}\left(1-\frac{\bar{\xi}_f^{1-\eta}}{w_f\epsilon_f}\right)\right]^{\gamma}\left[\frac{1}{1+\gamma}\left(1-\frac{\bar{\xi}_f^{1-\eta}}{w_f\epsilon_f}\right)\right] < \left[\frac{\gamma}{1+\gamma} w_f\epsilon_f(\alpha\bar{\xi}_f)^{\eta}\right]^{\gamma}\left[\frac{1}{1+\gamma}\right]\\
&\hfill \text{(using optimal condition from C.3)}\\
\Rightarrow &\left(1-\frac{\bar{\xi}_f^{1-\eta}}{w_f\epsilon_f}\right)^{1+\gamma} < \alpha^{\eta\gamma}\\
\Rightarrow &\epsilon_f < \frac{\bar{\xi}_f^{1-\eta}}{w_f(1-\alpha^{\frac{\eta\gamma}{1+\gamma}})}
\end{aligned}
$$

Hence, there exists a $\epsilon_f^*$ such that conditional on choosing his father's occupation $f$, it is optimal for a worker with talent $\epsilon_f < \epsilon_f^*$ to use the home-based education technology. Note if $\alpha \geq 1 \Rightarrow \epsilon_f^* < 0$, this means that it is always better to use the home-based technology as talent is always positive ($\epsilon_f > 0$). □

Corollary: First, consider the decision to choose the father's occupation. At $\phi = 1$, $h(1,\gamma) = 0$. This implies that the threshold level of talent that a worker must have in his father's occupation to get credit is given by $\epsilon^*_{f(\phi=1)} = \frac{\bar{\xi}_f^{1-\eta}}{w_f}$. If $\alpha \in [0,1)$, then the threshold talent below which it is optimal to use home-based technology $\epsilon_f^* = \frac{\bar{\xi}_f^{1-\eta}}{w_f(1-\alpha^{\frac{\eta\gamma}{1+\gamma}})} > \frac{\bar{\xi}_f^{1-\eta}}{w_f}$. Hence, conditional on joining father's occupation, it is always optimal for a worker to use home-based technology if he doesn't has access to credit. Of course, no workers at any level of $\phi$ are contrained if $\alpha \geq 1$.

For any other occupation $j$, consumption condition of choosing that occupation is given by (using C.1)

$$
\begin{aligned}
c^*(\boldsymbol{\epsilon}, f|j) &= w_j\epsilon_j\bar{\xi}_j^{\;\eta}\left(\frac{\gamma}{1+\gamma} + \frac{\bar{\xi}_j^{\;1-\eta}}{(1+\gamma)w\epsilon_j}\right) - \bar{\xi}_j\\
&= \frac{\gamma\bar{\xi}_j^{\eta}}{1+\gamma}\left(w_j\epsilon_j - \bar{\xi}_j^{1-\eta}\right)
\end{aligned}
$$

$c^*(\boldsymbol{\epsilon}, f|j) > 0 \Rightarrow w_j\epsilon_j - \bar{\xi}_j^{1-\eta} \Rightarrow \epsilon_j > \frac{\bar{\xi}_j^{1-\eta}}{w_j} = \frac{\bar{\xi}_j^{1-\eta}}{w_j(1-h(1,\gamma))} = \epsilon^*_{j(\phi=1)}$ (using $h(1,\gamma) =$ 1). □

# APPENDIX D

## CHAPTER 1: SUPPLEMENTARY RESULTS

### D.1 Productivity Gap Explained

The baseline results in table 1.2 reported the loss in productivity for Tanzania and India. The next natural question is what fraction of the total productivity gap can be explained by the model. I compute this by comparing the model generated output per worker to output per worker reported in Penn World Tables (Heston *et al.* (2012)). Column 3 in table D.1 shows the model's strength in explaining the productivity gaps between the US and the two countries.

Table D.1: Productivity Gap Explained

| | Relative $Y$ | | |
|---|---|---|---|
| | Model (1) | Data (2) | **Gap Explained** (3) |
| Tanzania | 0.03 | 0.32 | 70% |
| India | 0.11 | 0.77 | 26% |

Column 1 shows output per worker relative to US as predicted by the model. Column 2 reports output per worker relative to US (Source: Penn World Tables).

I find that the model is able to account for about 70% of the productivity gap between Tanzania and US. The decomposition exercise implies that 54% of the gap between the two countries can be explained by the presence of financial frictions alone. The gap explained by the model for India is significantly less compared to Tanzania but still sizable.

### D.2 No Credit Markets

The counterfactual economies considered in the baseline results were some distance away from an economy with no credit markets. Furthermore, the direct estimates of frictions suggest that financial frictions could be higher in poor countries as compared to the level of frictions used in the previous exercises. As such, I consider the extreme case of no credit markets in this exercise. In this experiment too, I use the country-specific distribution of fathers together with a single value of $\phi = 0$ for all distributions. Table D.1 reports the results of the exercise.

Column 1 reports output of an economy with a country-specific distribution of fathers' occupations with no credit markets relative to US under perfect credit markets. Column 2 reports the analogous estimates for output per hour worked. Productivity drops by a factor of 14–17 for Tanzania and by a factor of 7–8 for India. The exercise also reports significant loss in productivity for US. The model predicts that labor productivity would drop by about a factor of 3 in US if workers are unable to borrow in order to fund their education. However, productivity for US in absence of credit markets is still multiples greater than productivity for the other countries in absence

Table D.1: Productivity Relative to US

| | Relative $Y$ (1) | Relative $Y/H$ (2) |
|---|---|---|
| Tanzania | 0.06 | 0.07 |
| India | 0.12 | 0.13 |
| United States | 0.34 | 0.35 |

of credit markets. Naïve persistence is always equal to one in absence of credit markets as all workers are restricted in their fathers' occupations. The much higher level of productivity in US in absence of credit markets implies that the fathers in US are employed in more productive occupations as compared to other countries.

## D.3 Sensitivity to Parameter Values

The value of the elasticity of human capital with respect to education spending $\eta$ is taken to be 0.400 based on Erosa *et al.* (2010) and Manuelli and Seshadri (2014). Table D.2 shows the sensitivity of results when alternative values of $\eta$ are considered. Output drops less at a higher level of $\eta$. With an increase in the elasticty $\eta$, the relative importance of talent in producing human capital decreases and the effects of misallocation gets somewhat muted. The productivity loss is always within 1% of the loss reported by the benchmark model for both the measures.

Table D.2: Estimates at Different Levels of $\eta$

| | $\eta = 0.3$ | | | **Baseline** $\eta = 0.4$ | | | $\eta = 0.5$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\phi$ | $Y$ | $Y/H$ | $\phi$ | $Y$ | $Y/H$ | $\phi$ | $Y$ | $Y/H$ |
| Tanzania | 0.12 | 0.32 | 0.33 | 0.12 | 0.32 | 0.33 | 0.12 | 0.33 | 0.33 |
| India | 0.26 | 0.76 | 0.79 | 0.26 | 0.77 | 0.79 | 0.26 | 0.77 | 0.79 |

The two estimates of productivity vary over a closer range when larger values of elasticity is considered. This happens because the relative importance of hours worked in producing human capital declines with an increase in $\eta$. Overall, relative output and relative output per worker vary over a small range when different values of $\eta$ are considered.

The value of elasticity of substitution parameter $\rho$ has been set to 2/3 following Hsieh *et al.* (2014). Table D.3 reports the sensitivity of results with respect to $\rho$. It becomes easier to substitute among occupational labor inputs with an increase in $\rho$ which compensates for some of the talent misallocation. This is reflected in higher relative output obtained when $\rho$ is changed to 4/5. In absence of credit markets output drops four percentage points more at $\rho = 1/2$ and one percentage point

Table D.3: Estimates at Different Levels of $\rho$

| | $\rho = 1/2$ | | | **Baseline** $\rho = 2/3$ | | | $\rho = 4/5$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\phi$ | $Y$ | $Y/H$ | $\phi$ | $Y$ | $Y/H$ | $\phi$ | $Y$ | $Y/H$ |
| Tanzania | 0.13 | 0.29 | 0.34 | 0.12 | 0.32 | 0.33 | 0.11 | 0.33 | 0.33 |
| India | 0.28 | 0.73 | 0.80 | 0.26 | 0.77 | 0.79 | 0.24 | 0.78 | 0.79 |

less at $\rho = 4/5$ compared to the output produced under perfect credit markets. Both measures of productivity drop by a factor of 16 in absence of credit markets at $\rho = 4/5$ compared to 25 times drop seen in the baseline case when all fathers are placed in agriculture. However, the loss in productivity calculated at considered levels of $\rho$ do not deviate from each other by more than 5 percentage points. Similar to higher values of $\eta$, higher values of $\rho$ imply higher substitutibility between occupational labor inputs which limit the relative importance of hours worked in human capital creation leading to a convergence in the two measures of productivity.

Based on above discussion, I conclude that the baseline results of the model do not change much to alternative choices of these two parameters.

# APPENDIX E

## CHAPTER 1: SUPPLEMENTARY FIGURES AND TABLES

Figure E.1: Naïve Persistence Across Data Sources

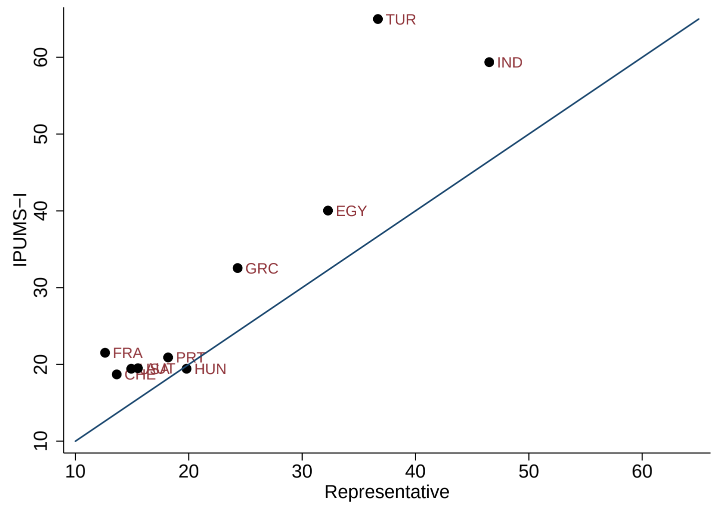



Figure E.2: Bias in Naïve Persistence vs. GDP per Capita

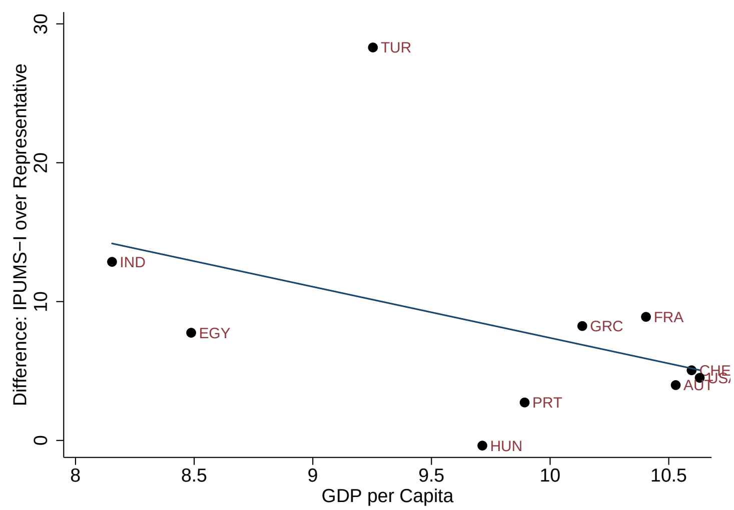


Table E.1: Productivity Relative to US

| | $\phi$ (1) | Relative $Y$ (2) | Relative $Y/H$ (3) |
|---|---|---|---|
| Austria | 0.37 | 0.97 | 0.97 |
| Belgium | 1.00 | 1.00 | 1.00 |
| Bulgaria | 0.32 | 0.92 | 0.93 |
| Croatia | 0.36 | 0.96 | 0.96 |
| Czech Republic | 0.38 | 0.97 | 0.97 |
| Egypt | 0.28 | 0.83 | 0.85 |
| Estonia | 0.45 | 0.99 | 0.99 |
| France | 0.42 | 0.99 | 0.99 |
| Germany | 0.36 | 0.96 | 0.96 |
| Greece | 0.31 | 0.91 | 0.92 |
| Hungary | 0.34 | 0.94 | 0.95 |
| India | 0.25 | 0.77 | 0.79 |
| Ireland | 0.37 | 0.96 | 0.97 |
| Latvia | 0.34 | 0.94 | 0.95 |
| Lithuania | 0.35 | 0.95 | 0.96 |
| Netherlands | 0.36 | 0.95 | 0.96 |
| Norway | 0.37 | 0.97 | 0.97 |
| Poland | 0.36 | 0.96 | 0.97 |
| Portugal | 0.34 | 0.94 | 0.95 |
| Romania | 0.36 | 0.96 | 0.97 |
| Russia | 0.40 | 0.98 | 0.98 |
| Slovakia | 0.34 | 0.94 | 0.95 |
| Slovenia | 0.41 | 0.98 | 0.98 |
| Sweden | 0.36 | 0.96 | 0.96 |
| Switzerland | 0.39 | 0.98 | 0.98 |
| Turkey | 0.27 | 0.82 | 0.84 |
| Ukraine | 0.33 | 0.93 | 0.94 |
| United Kingdom | 0.42 | 0.98 | 0.98 |

The table reports productivity relative to US when the country-specific distribution of fathers is used together with a value of $\phi$ that pins down the adjusted persistence for the country.

Table E.2: Productivity Relative to US: IPUMS-I Sample

| | $\phi$ (1) | Relative $Y$ (2) | Relative $Y/H$ (3) |
|---|---|---|---|
| Bolivia | 0.27 | 0.83 | 0.85 |
| Brazil | 0.29 | 0.87 | 0.89 |
| Burkina Faso | 0.08 | 0.18 | 0.19 |
| Cambodia | 0.20 | 0.61 | 0.63 |
| Cameroon | 0.21 | 0.63 | 0.65 |
| Costa Rica | 0.35 | 0.95 | 0.96 |
| Cuba | 0.37 | 0.97 | 0.97 |
| Ecuador | 0.28 | 0.85 | 0.87 |
| El Salvador | 0.31 | 0.91 | 0.92 |
| Ghana | 0.26 | 0.79 | 0.81 |
| Guinea | 0.19 | 0.56 | 0.58 |
| Haiti | 0.25 | 0.76 | 0.78 |
| Indonesia | 0.26 | 0.80 | 0.81 |
| Iran | 0.29 | 0.87 | 0.88 |
| Jordan | 0.33 | 0.93 | 0.94 |
| Kyrgyzstan | 0.27 | 0.82 | 0.83 |
| Malawi | 0.29 | 0.87 | 0.88 |
| Malaysia | 0.31 | 0.91 | 0.92 |
| Mali | 0.16 | 0.47 | 0.49 |
| Mongolia | 0.24 | 0.74 | 0.76 |
| Nicaragua | 0.28 | 0.84 | 0.85 |
| Panama | 0.30 | 0.89 | 0.90 |
| Peru | 0.34 | 0.94 | 0.95 |
| Philippines | 0.26 | 0.79 | 0.81 |
| Senegal | 0.26 | 0.80 | 0.82 |
| South Africa | 0.34 | 0.94 | 0.95 |
| Sudan | 0.26 | 0.80 | 0.82 |
| Tanzania | 0.12 | 0.31 | 0.32 |
| Thailand | 0.27 | 0.82 | 0.84 |
| Uganda | 0.22 | 0.68 | 0.70 |
| Uruguay | 0.36 | 0.96 | 0.96 |
| Venezuela | 0.29 | 0.87 | 0.89 |
| Vietnam | 0.23 | 0.66 | 0.68 |

The table reports productivity relative to US when the country-specific distribution of fathers is used together with a value of $\phi$ that pins down the adjusted persistence for the country.

Table E.3: Productivity Relative to US: No Credit Markets

| | Relative $Y$ (1) | Relative $Y/H$ (2) |
|---|---|---|
| Austria | 0.29 | 0.30 |
| Belgium | 0.30 | 0.31 |
| Bulgaria | 0.26 | 0.27 |
| Croatia | 0.27 | 0.28 |
| Czech Republic | 0.29 | 0.30 |
| Egypt | 0.19 | 0.20 |
| Estonia | 0.30 | 0.32 |
| France | 0.28 | 0.29 |
| Germany | 0.30 | 0.32 |
| Greece | 0.23 | 0.24 |
| Hungary | 0.29 | 0.30 |
| India | 0.12 | 0.13 |
| Ireland | 0.25 | 0.27 |
| Latvia | 0.29 | 0.30 |
| Lithuania | 0.27 | 0.28 |
| Netherlands | 0.30 | 0.32 |
| Norway | 0.31 | 0.33 |
| Poland | 0.25 | 0.26 |
| Portugal | 0.25 | 0.26 |
| Romania | 0.26 | 0.27 |
| Russia | 0.29 | 0.30 |
| Slovakia | 0.31 | 0.32 |
| Slovenia | 0.29 | 0.30 |
| Sweden | 0.30 | 0.32 |
| Switzerland | 0.29 | 0.31 |
| Turkey | 0.16 | 0.17 |
| Ukraine | 0.30 | 0.32 |
| United Kingdom | 0.32 | 0.34 |
| United States | 0.34 | 0.36 |

The table reports productivity relative to US when the country-specific distribution of fathers is used in absence of credit markets.

Table E.4: Productivity Relative to US: : No Credit Markets (IPUMS-I Sample)

| | Relative $Y$ (1) | Relative $Y/H$ (2) |
|---|---|---|
| Bolivia | 0.19 | 0.19 |
| Brazil | 0.23 | 0.25 |
| Burkina Faso | 0.04 | 0.04 |
| Cambodia | 0.10 | 0.10 |
| Cameroon | 0.09 | 0.10 |
| Costa Rica | 0.22 | 0.23 |
| Cuba | 0.29 | 0.31 |
| Ecuador | 0.19 | 0.20 |
| Egypt | 0.21 | 0.22 |
| El Salvador | 0.22 | 0.23 |
| Ghana | 0.12 | 0.13 |
| Guinea | 0.08 | 0.08 |
| Haiti | 0.09 | 0.10 |
| Indonesia | 0.12 | 0.13 |
| Iran | 0.19 | 0.20 |
| Jordan | 0.29 | 0.30 |
| Kyrgyzstan | 0.16 | 0.17 |
| Malawi | 0.13 | 0.13 |
| Malaysia | 0.26 | 0.27 |
| Mali | 0.08 | 0.09 |
| Mongolia | 0.15 | 0.16 |
| Nicaragua | 0.19 | 0.20 |
| Panama | 0.24 | 0.25 |
| Peru | 0.23 | 0.24 |
| Philippines | 0.17 | 0.18 |
| Senegal | 0.13 | 0.14 |
| South Africa | 0.31 | 0.32 |
| Sudan | 0.16 | 0.17 |
| Tanzania | 0.06 | 0.06 |
| Thailand | 0.19 | 0.20 |
| Uganda | 0.08 | 0.08 |
| Uruguay | 0.26 | 0.27 |
| Venezuela | 0.28 | 0.29 |
| Vietnam | 0.09 | 0.09 |

The table reports productivity relative to US when the country-specific distribution of fathers is used in absence of credit markets.

Table E.5: Productivity Gap Explained

| | Relative $Y$ | | |
|---|---|---|---|
| | Model (1) | Data (2) | **Gap Explained** (3) |
| Austria | 0.97 | 0.92 | 38% |
| Belgium | 1.00 | 0.96 | 0% |
| Bulgaria | 0.92 | 0.28 | 11% |
| Croatia | 0.96 | 0.40 | 7% |
| Czech Republic | 0.97 | 0.57 | 7% |
| Egypt | 0.83 | 0.18 | 21% |
| Estonia | 0.99 | 0.40 | 2% |
| France | 0.99 | 0.83 | 6% |
| Germany | 0.96 | 0.81 | 21% |
| Greece | 0.91 | 0.69 | 29% |
| Hungary | 0.94 | 0.47 | 11% |
| India | 0.77 | 0.11 | 26% |
| Ireland | 0.96 | 0.88 | 33% |
| Latvia | 0.94 | 0.29 | 8% |
| Lithuania | 0.95 | 0.35 | 8% |
| Netherlands | 0.95 | 0.88 | 42% |
| Norway | 0.97 | 1.15 | -20% |
| Poland | 0.96 | 0.44 | 7% |
| Portugal | 0.94 | 0.46 | 11% |
| Romania | 0.96 | 0.24 | 5% |
| Russia | 0.98 | 0.34 | 3% |
| Slovakia | 0.94 | 0.47 | 11% |
| Slovenia | 0.98 | 0.60 | 5% |
| Sweden | 0.96 | 0.83 | 24% |
| Switzerland | 0.98 | 0.79 | 10% |
| Turkey | 0.82 | 0.41 | 31% |
| Ukraine | 0.93 | 0.17 | 8% |
| United Kingdom | 0.98 | 0.81 | 11% |

Column 1 shows output per worker relative to US as predicted by the model. Column 2 reports output per worker relative to US (Source: Penn World Tables).

Table E.6: Productivity Gap Explained: IPUMS-I Sample

| | Relative $Y$ | | |
|---|---|---|---|
| | Model (1) | Data (2) | **Gap Explained** (3) |
| Bolivia | 0.83 | 0.10 | 19% |
| Brazil | 0.87 | 0.19 | 16% |
| Burkina Faso | 0.18 | 0.02 | 84% |
| Cambodia | 0.61 | 0.04 | 41% |
| Cameroon | 0.79 | 0.05 | 22% |
| Costa Rica | 0.95 | 0.30 | 7% |
| Cuba | 0.30 | 0.97 | 4% |
| Ecuador | 0.85 | 0.16 | 18% |
| El Salvador | 0.91 | 0.18 | 11% |
| Ghana | 0.79 | 0.06 | 22% |
| Guinea | 0.56 | 0.02 | 45% |
| Haiti | 0.76 | 0.04 | 25% |
| Indonesia | 0.10 | 0.80 | 22% |
| Iran | 0.87 | 0.34 | 20% |
| Jordan | 0.93 | 0.21 | 9% |
| Kyrgyzstan | 0.82 | 0.05 | 19% |
| Malawi | 0.87 | 0.02 | 13% |
| Malaysia | 0.91 | 0.34 | 14% |
| Mali | 0.47 | 0.04 | 55% |
| Mongolia | 0.74 | 0.10 | 29% |
| Nicaragua | 0.84 | 0.07 | 17% |
| Panama | 0.89 | 0.28 | 15% |
| Peru | 0.94 | 0.17 | 7% |
| Philippines | 0.79 | 0.09 | 23% |
| Senegal | 0.80 | 0.04 | 21% |
| South Africa | 0.94 | 0.25 | 8% |
| Sudan | 0.80 | 0.09 | 22% |
| Tanzania | 0.32 | 0.03 | 70% |
| Thailand | 0.82 | 0.17 | 22% |
| Uganda | 0.68 | 0.03 | 33% |
| Uruguay | 0.96 | 0.28 | 6% |
| Venezuela | 0.87 | 0.24 | 17% |
| Vietnam | 0.66 | 0.06 | 36% |

Column 1 shows output per worker relative to US as predicted by the model. Column 2 reports output per worker relative to US (Source: Penn World Tables).

Table E.7: Output Relative to US: All Models

| | $\phi$ (1) | Relative $Y$ (2) | $\phi$ (3) | Relative $Y$ (4) | $\phi$ (5) | Relative $Y$ (6) | $\phi$ (7) | Relative $Y$ (8) |
|---|---|---|---|---|---|---|---|---|
| Tanzania | 0.12 | 0.32 | 0.12 | 0.33 | 0.09 | 0.20 | 0.13 | 0.35 |
| India | 0.26 | 0.77 | 0.26 | 0.78 | 0.13 | 0.67 | 0.27 | 0.80 |
| Labor Supply | Elastic | | Inelastic | | Inelastic | | Elastic | |
| Bequests | No | | No | | Yes | | No | |
| Talent Adjustment | No | | No | | No | | Yes | |

The table reports productivity relative to US when the country-specific distribution of fathers is used together with a value of $\phi$ that pins down the adjusted persistence for the country.

Table E.8: Output per Hour Worked Relative to US: All Models

| | $\phi$ (1) | Relative $Y/H$ (2) | $\phi$ (3) | Relative $Y/H$ (4) | $\phi$ (5) | Relative $Y/H$ (6) | $\phi$ (7) | Relative $Y/H$ (8) |
|---|---|---|---|---|---|---|---|---|
| Tanzania | 0.12 | 0.33 | 0.12 | 0.33 | 0.09 | 0.20 | 0.13 | 0.37 |
| India | 0.26 | 0.79 | 0.26 | 0.78 | 0.13 | 0.67 | 0.27 | 0.82 |
| Labor Supply | Elastic | | Inelastic | | Inelastic | | Elastic | |
| Bequests | No | | No | | Yes | | No | |
| Talent Adjustment | No | | No | | No | | Yes | |

The table reports productivity relative to US when the country-specific distribution of fathers is used together with a value of $\phi$ that pins down the adjusted persistence for the country.

Table E.9: Distribution of Workers Across Occupations

| | 1-digit ISCO Occupation | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | N |
| Austria | 8.46 | 14.67 | 21.57 | 8.47 | 11.33 | 8.62 | 15.99 | 4.19 | 5.20 | 1.56 | 611 |
| Belgium | 17.73 | 15.12 | 15.3 | 8.77 | 3.36 | 2.06 | 18.48 | 11.20 | 7.09 | 0.94 | 536 |
| Bulgaria | 12.99 | 7.16 | 9.47 | 2.37 | 9.74 | 2.49 | 20.96 | 19.81 | 13.83 | 1.24 | 735 |
| Croatia | 5.62 | 11.49 | 14.60 | 7.52 | 12.29 | 3.29 | 24.76 | 15.48 | 5.00 | 0.00 | 338 |
| Czech Republic | 5.19 | 8.94 | 11.59 | 7.18 | 7.48 | 1.00 | 30.61 | 19.30 | 8.71 | 0.06 | 855 |
| Egypt | 5.80 | 3.69 | 4.34 | 1.44 | 6.52 | 45.65 | 12.80 | 8.32 | 11.43 | 0.00 | 13,723 |
| Estonia | 18.92 | 9.33 | 4.67 | 1.30 | 4.15 | 3.89 | 30.57 | 18.14 | 8.30 | 0.78 | 386 |
| France | 21.26 | 13.98 | 20.98 | 4.45 | 4.62 | 2.66 | 15.62 | 9.66 | 6.10 | 0.73 | 426 |
| Germany | 9.86 | 22.91 | 16.33 | 7.68 | 4.07 | 3.45 | 21.36 | 9.67 | 3.81 | 0.90 | 949 |
| Greece | 13.79 | 9.00 | 5.39 | 5.83 | 11.47 | 12.60 | 23.97 | 10.73 | 7.27 | 0.00 | 923 |
| Hungary | 6.02 | 9.72 | 7.10 | 7.45 | 8.34 | 3.88 | 27.18 | 13.48 | 15.99 | 0.89 | 446 |
| India | 6.24 | 4.20 | 0.76 | 4.01 | 12.71 | 31.32 | 13.09 | 4.93 | 22.79 | 0.00 | 26,834 |
| Ireland | 14.26 | 14.83 | 3.83 | 2.45 | 11.49 | 1.72 | 16.71 | 9.78 | 24.24 | 0.74 | 617 |
| Latvia | 10.00 | 7.53 | 8.87 | 1.77 | 7.82 | 3.62 | 25.25 | 24.38 | 9.44 | 1.37 | 410 |
| Lithuania | 15.85 | 9.16 | 12.44 | 0.83 | 3.92 | 0.42 | 32.75 | 13.64 | 11.03 | 0.00 | 286 |
| Netherlands | 20.73 | 20.73 | 17.57 | 9.02 | 6.10 | 2.69 | 12.90 | 7.20 | 3.09 | 0.00 | 651 |
| Norway | 12.73 | 18.61 | 19.40 | 5.60 | 9.40 | 4.87 | 13.83 | 11.96 | 3.49 | 0.15 | 588 |
| Poland | 13.14 | 4.15 | 8.70 | 2.17 | 5.69 | 9.44 | 28.10 | 18.39 | 9.50 | 0.76 | 514 |
| Portugal | 2.43 | 4.77 | 9.60 | 7.03 | 13.45 | 5.42 | 30.76 | 17.41 | 8.47 | 0.70 | 685 |
| Romania | 9.30 | 11.03 | 8.60 | 2.77 | 9.75 | 0.45 | 27.10 | 15.78 | 14.96 | 0.30 | 356 |
| Russia | 9.63 | 9.80 | 8.15 | 1.25 | 5.00 | 2.70 | 30.45 | 25.96 | 5.97 | 1.14 | 588 |
| Slovakia | 17.92 | 15.97 | 7.04 | 6.97 | 5.58 | 1.34 | 24.92 | 13.61 | 5.83 | 0.89 | 413 |
| Slovenia | 12.04 | 11.50 | 15.25 | 5.35 | 10.70 | 1.88 | 26.74 | 12.04 | 4.28 | 0.27 | 374 |
| Sweden | 10.60 | 20.55 | 20.07 | 4.18 | 5.94 | 4.34 | 17.66 | 14.29 | 2.41 | 0.00 | 623 |
| Switzerland | 8.79 | 18.14 | 20.00 | 6.36 | 8.23 | 6.36 | 21.31 | 5.43 | 5.43 | 0.00 | 535 |
| Turkey | 6.25 | 9.19 | 2.78 | 6.61 | 7.08 | 22.73 | 22.45 | 6.11 | 16.83 | 0.00 | 356 |
| Ukraine | 16.68 | 12.57 | 7.49 | 4.08 | 6.76 | 0.65 | 25.90 | 19.97 | 5.13 | 0.82 | 358 |
| United Kingdom | 22.26 | 13.14 | 8.33 | 5.61 | 6.41 | 1.85 | 14.42 | 14.18 | 13.06 | 0.81 | 677 |
| United States | 10.45 | 14.34 | 10.55 | 5.28 | 6.80 | 2.91 | 18.43 | 18.72 | 12.52 | 0.05 | 2,030 |

Figure in all columns except the last are in percentages. The last column represents the number of observations.

Table E.10: Distribution of Fathers Across Occupations

| | 1-digit ISCO Occupation | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | N |
| Austria | 11.33 | 11.25 | 8.16 | 5.20 | 5.75 | 18.85 | 27.55 | 4.03 | 7.53 | 0.39 | 611 |
| Belgium | 16.80 | 9.89 | 9.71 | 5.79 | 4.11 | 9.89 | 28.36 | 7.84 | 5.79 | 1.87 | 536 |
| Bulgaria | 7.92 | 5.84 | 5.89 | 1.60 | 4.33 | 19.66 | 21.37 | 14.92 | 16.71 | 1.82 | 735 |
| Croatia | 8.70 | 5.45 | 5.17 | 4.67 | 3.91 | 18.89 | 36.34 | 7.90 | 7.95 | 1.07 | 338 |
| Czech Republic | 4.44 | 6.05 | 7.10 | 6.02 | 3.06 | 7.62 | 40.57 | 16.49 | 7.47 | 1.22 | 855 |
| Egypt | 0.71 | 7.33 | 3.55 | 2.00 | 10.16 | 41.04 | 22.12 | 7.40 | 5.67 | 0.00 | 13,723 |
| Estonia | 13.22 | 7.52 | 2.60 | 1.30 | 3.63 | 11.92 | 25.65 | 24.62 | 8.04 | 1.56 | 386 |
| France | 10.49 | 9.92 | 12.22 | 2.52 | 5.23 | 20.76 | 25.54 | 6.80 | 5.43 | 1.15 | 426 |
| Germany | 6.05 | 14.13 | 9.58 | 6.86 | 3.11 | 9.90 | 31.7 | 11.38 | 6.11 | 1.24 | 949 |
| Greece | 9.00 | 2.48 | 1.54 | 3.36 | 5.79 | 41.26 | 18.58 | 6.58 | 11.47 | 0.00 | 923 |
| Hungary | 8.00 | 7.09 | 4.65 | 1.59 | 4.23 | 9.03 | 30.97 | 17.83 | 15.56 | 1.12 | 446 |
| India | 1.05 | 2.92 | 1.40 | 2.30 | 8.14 | 50.99 | 8.30 | 1.34 | 23.60 | 0 | 26,834 |
| Ireland | 12.14 | 7.09 | 5.06 | 2.77 | 4.16 | 33.53 | 16.30 | 9.94 | 6.69 | 2.37 | 617 |
| Latvia | 5.11 | 8.81 | 2.41 | 1.53 | 1.82 | 6.36 | 22.29 | 25.42 | 24.23 | 2.07 | 410 |
| Lithuania | 11.63 | 15.01 | 5.30 | 0.03 | 2.86 | 12.55 | 25.90 | 14.41 | 11.25 | 1.11 | 286 |
| Netherlands | 15.91 | 13.22 | 9.34 | 9.10 | 5.62 | 12.11 | 22.16 | 7.28 | 5.31 | 0.00 | 651 |
| Norway | 16.3 | 17.27 | 9.31 | 1.56 | 4.84 | 13.71 | 21.90 | 6.23 | 7.57 | 1.34 | 588 |
| Poland | 9.71 | 0.45 | 7.46 | 2.68 | 1.32 | 31.05 | 23.52 | 12.72 | 9.88 | 1.27 | 514 |
| Portugal | 5.06 | 1.41 | 2.56 | 2.29 | 6.52 | 28.49 | 28.37 | 14.34 | 10.32 | 0.70 | 685 |
| Romania | 10.12 | 4.91 | 3.82 | 0.65 | 2.21 | 2.84 | 32.29 | 13.54 | 28.53 | 1.13 | 356 |
| Russia | 4.98 | 5.83 | 6.95 | 0.64 | 1.51 | 3.44 | 31.14 | 27.29 | 15.9 | 2.37 | 588 |
| Slovakia | 13.94 | 15.79 | 3.41 | 4.59 | 4.37 | 8.11 | 26.2 | 13.17 | 9.25 | 1.22 | 413 |
| Slovenia | 5.62 | 4.82 | 8.29 | 6.42 | 6.42 | 7.22 | 37.71 | 10.43 | 12.57 | 0.54 | 374 |
| Sweden | 7.87 | 12.69 | 7.39 | 3.54 | 5.14 | 16.06 | 27.45 | 15.57 | 4.34 | 0.00 | 623 |
| Switzerland | 13.84 | 15.71 | 8.04 | 2.25 | 4.30 | 17.01 | 24.86 | 6.17 | 7.29 | 0.57 | 535 |
| Turkey | 5.16 | 5.74 | 0.42 | 0.06 | 5.57 | 60.85 | 11.32 | 4.57 | 6.35 | 0.02 | 356 |
| Ukraine | 13.86 | 10.28 | 2.36 | 1.70 | 0.64 | 5.81 | 32.46 | 24.06 | 7.61 | 1.27 | 358 |
| United Kingdom | 19.30 | 13.22 | 5.53 | 4.01 | 5.93 | 6.73 | 24.18 | 12.17 | 6.65 | 2.33 | 677 |
| United States | 9.86 | 9.91 | 7.15 | 3.90 | 5.03 | 4.73 | 20.15 | 24.88 | 14.44 | 0.01 | 2,030 |

Figure in all columns except the last are in percentages. The last column represents the number of observations.

Figure E.3: Naïve Persistence Across Countries: World Map

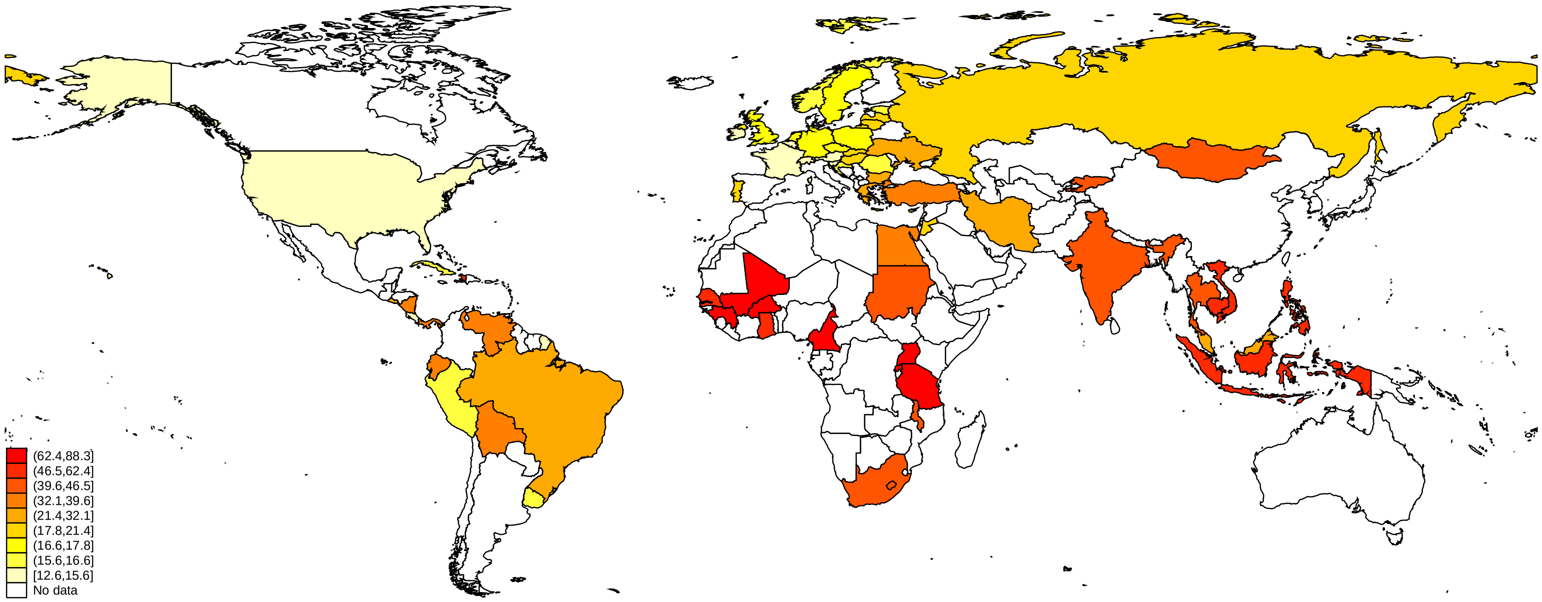
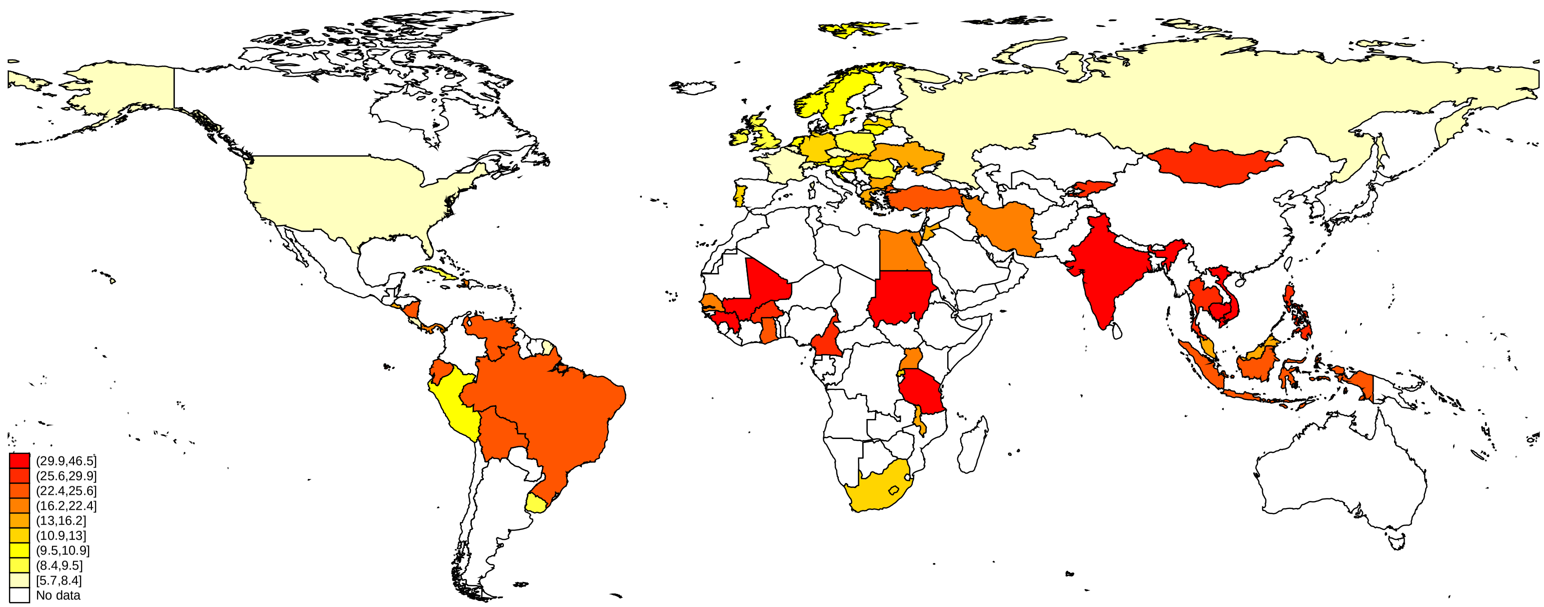


Figure E.4: Adjusted Persistence Across Countries: World Map



# APPENDIX F

# CHAPTER 2: ESTIMATES OF INTERGENERATIONAL OCCUPATIONAL MOBILITY

Table F.1: Intergenerational Occupational Elasticity

| Country | Absolute Scale | | Adjusted Scale | |
|---|---|---|---|---|
| | Sons | Daughters | Sons | Daughters |
| Austria | 0.234*** | 0.396*** | 0.241*** | 0.520*** |
| Belgium | 0.392*** | 0.412** | 0.348*** | 0.373* |
| Bolivia | 0.306*** | 0.365*** | 0.293*** | 0.364*** |
| Bulgaria | 0.430*** | 0.336*** | 0.260*** | 0.204*** |
| Cambodia | 0.429*** | 0.385*** | 0.419*** | 0.380*** |
| Cameroon | 0.240*** | 0.249*** | 0.232*** | 0.244*** |
| Costa Rica | 0.216*** | 0.230*** | 0.166*** | 0.176*** |
| Croatia | 0.229** | 0.216* | 0.199** | 0.099 |
| Cuba | 0.203*** | 0.150*** | 0.198*** | 0.145*** |
| Czech Republic | 0.286*** | 0.249*** | 0.226*** | 0.204*** |
| Ecuador | 0.312*** | 0.262*** | 0.293*** | 0.251*** |
| Egypt | 0.371*** | 0.325*** | 0.367*** | 0.314*** |
| Estonia | 0.336*** | 0.190*** | 0.323*** | 0.160*** |
| France | 0.248*** | 0.258*** | 0.196*** | 0.224*** |
| Germany | 0.318*** | 0.356*** | 0.271*** | 0.313*** |
| Ghana | 0.205*** | 0.164*** | 0.224*** | 0.179*** |
| Greece | 0.338*** | 0.281*** | 0.417*** | 0.334*** |
| Guinea | 0.281*** | 0.243*** | 0.285*** | 0.262*** |
| Hungary | 0.301*** | 0.236*** | 0.301*** | 0.216*** |
| India | 0.357*** | 0.384*** | 0.362*** | 0.406*** |
| Iran | 0.226*** | 0.058** | 0.224*** | 0.056*** |
| Ireland | 0.224*** | 0.363*** | 0.167** | 0.310*** |
| Jordan | 0.437*** | 0.375*** | 0.379*** | 0.347*** |
| Latvia | 0.234*** | 0.259*** | 0.183*** | 0.252*** |
| Lithuania | 0.323*** | 0.276** | 0.351*** | 0.362** |

***Significant at 1%. **Significant at 5%. *Significant at 10%.

Intergenerational Occupational Elasticity *(contd.)*

| Country | Absolute Scale | | Adjusted Scale | |
|---|---|---|---|---|
| | Sons | Daughters | Sons | Daughters |
| Malaysia | 0.212*** | 0.184*** | 0.202*** | 0.167*** |
| Mali | 0.348*** | 0.191*** | 0.379*** | 0.182*** |
| Mongolia | 0.261*** | 0.343*** | 0.258*** | 0.379*** |
| Netherlands | 0.343*** | 0.191*** | 0.332*** | 0.205*** |
| Nicaragua | 0.283*** | 0.328*** | 0.269*** | 0.320*** |
| Panama | 0.243*** | 0.280*** | 0.138*** | 0.173*** |
| Philippines | 0.430*** | 0.403*** | 0.418*** | 0.394*** |
| Poland | 0.249*** | 0.443*** | 0.207*** | 0.439*** |
| Romania | 0.439*** | 0.470*** | 0.427*** | 0.459*** |
| Russia | 0.223*** | 0.246*** | 0.162*** | 0.173*** |
| Senegal | 0.238*** | 0.228*** | 0.238*** | 0.225*** |
| Slovakia | 0.195*** | 0.271*** | 0.097*** | 0.135*** |
| Slovenia | 0.280*** | 0.364*** | 0.261*** | 0.400*** |
| South Africa | 0.339*** | 0.324*** | 0.342*** | 0.325*** |
| Sudan | 0.429*** | 0.518*** | 0.415*** | 0.469*** |
| Switzerland | 0.290*** | 0.238*** | 0.255*** | 0.224*** |
| Thailand | 0.387*** | 0.369*** | 0.399*** | 0.367*** |
| Turkey | 0.179** | 0.201 | 0.204** | 0.213 |
| Uganda | 0.275*** | 0.177*** | 0.276*** | 0.146*** |
| Ukraine | 0.289*** | 0.262*** | 0.211*** | 0.217** |
| United Kingdom | 0.354*** | 0.225*** | 0.358*** | 0.246*** |
| United States | 0.189*** | 0.149*** | 0.189*** | 0.149*** |
| Uruguay | 0.225*** | 0.246*** | 0.215*** | 0.236*** |
| Venezuela | 0.312*** | 0.269*** | 0.268*** | 0.243*** |
| Vietnam | 0.391*** | 0.365*** | 0.370*** | 0.349*** |

***Significant at 1%. **Significant at 5%. *Significant at 10%.

Table F.2: Propensity to Move Relative to Father's Position

| Country | Sons | | Daughters | |
|---|---|---|---|---|
| | Upwards | Downwards | Upwards | Downwards |
| | (1) | (2) | (3) | (4) |
| Austria | 54.59 | 40.56 | 43.34 | 55.29 |
| Belgium | 46.84 | 49.50 | 36.61 | 60.71 |
| Bolivia | 43.52 | 31.90 | 51.01 | 40.82 |
| Bulgaria | 47.14 | 45.14 | 48.41 | 50.40 |
| Cambodia | 24.70 | 25.73 | 25.85 | 28.83 |
| Cameroon | 31.54 | 36.76 | 33.09 | 45.13 |
| Costa Rica | 35.45 | 43.07 | 49.96 | 45.35 |
| Croatia | 45.36 | 48.63 | 46.21 | 51.52 |
| Cuba | 39.65 | 40.07 | 59.34 | 35.76 |
| Czech Republic | 46.03 | 45.26 | 44.76 | 53.02 |
| Ecuador | 35.80 | 26.00 | 50.47 | 33.29 |
| Egypt | 35.52 | 27.29 | 56.47 | 33.68 |
| Estonia | 57.83 | 37.75 | 62.67 | 34.93 |
| France | 39.01 | 46.40 | 43.79 | 51.21 |
| Germany | 50.46 | 42.88 | 46.20 | 50.76 |
| Ghana | 37.05 | 41.78 | 23.70 | 64.89 |
| Greece | 39.78 | 35.86 | 53.82 | 38.23 |
| Guinea | 28.14 | 23.46 | 35.46 | 43.26 |
| Hungary | 46.79 | 47.55 | 48.75 | 50.53 |
| India | 26.13 | 52.16 | 22.25 | 54.68 |
| Iran | 36.19 | 27.60 | 66.20 | 19.25 |
| Ireland | 42.30 | 50.98 | 53.50 | 45.50 |
| Jordan | 49.03 | 28.54 | 65.87 | 24.25 |
| Latvia | 55.02 | 38.41 | 57.10 | 41.39 |
| Lithuania | 52.38 | 42.86 | 59.60 | 39.07 |

†The table reports the fraction of sons and daughters that moved up (columns 1 and 3) or down (columns 2 and 4) relative to their fathers' occupational score. All figures in percentages.

Propensity to Move Relative to Father's Position *(contd.)*

| Country | Sons | | Daughters | |
|---|---|---|---|---|
| | Upwards | Downwards | Upwards | Downwards |
| | (1) | (2) | (3) | (4) |
| Malaysia | 36.50 | 33.62 | 48.98 | 37.92 |
| Mali | 4.25 | 5.08 | 5.27 | 11.16 |
| Mongolia | 34.64 | 50.36 | 45.10 | 48.69 |
| Netherlands | 50.30 | 43.41 | 55.31 | 40.71 |
| Nicaragua | 27.62 | 29.62 | 44.47 | 48.57 |
| Panama | 34.14 | 29.19 | 49.29 | 44.16 |
| Philippines | 33.53 | 26.71 | 46.93 | 39.32 |
| Poland | 48.54 | 40.13 | 44.44 | 45.99 |
| Romania | 31.70 | 32.51 | 47.16 | 33.27 |
| Russia | 50.12 | 39.40 | 60.69 | 36.69 |
| Senegal | 20.37 | 26.08 | 19.01 | 46.00 |
| Slovakia | 46.22 | 49.00 | 50.19 | 47.86 |
| Slovenia | 57.02 | 36.40 | 56.15 | 38.93 |
| South Africa | 42.89 | 35.03 | 44.95 | 43.71 |
| Sudan | 22.65 | 26.42 | 35.93 | 21.32 |
| Switzerland | 42.22 | 42.50 | 50.23 | 46.33 |
| Thailand | 25.45 | 28.38 | 32.28 | 30.46 |
| Turkey | 41.82 | 43.27 | 40.00 | 60.00 |
| Uganda | 33.41 | 37.64 | 34.26 | 42.23 |
| Ukraine | 50.48 | 43.81 | 56.46 | 42.11 |
| United Kingdom | 46.59 | 49.86 | 41.44 | 57.21 |
| United States | 40.08 | 50.28 | 51.67 | 43.89 |
| Uruguay | 35.39 | 45.37 | 42.23 | 51.57 |
| Venezuela | 32.18 | 27.37 | 54.68 | 36.17 |
| Vietnam | 22.35 | 13.51 | 25.87 | 16.69 |

†The table reports the fraction of sons and daughters that moved up (columns 1 and 3) or down (columns 2 and 4) relative to their fathers' occupational score. All figures in percentages.

Table F.3: Transition Probabilities

| Country | Sons | | Daughters | |
|---|---|---|---|---|
| | Bottom to Top (1) | Top to Bottom (2) | Bottom to Top (3) | Top to Bottom (4) |
| Austria | 3.06 | 3.83 | 3.75 | 1.02 |
| Belgium | 3.99 | 2.99 | 5.36 | 4.46 |
| Bolivia | 6.29 | 3.90 | 6.38 | 4.56 |
| Bulgaria | 3.43 | 4.00 | 3.57 | 3.17 |
| Cambodia | 3.24 | 4.09 | 2.95 | 3.62 |
| Cameroon | 5.22 | 3.76 | 4.93 | 4.33 |
| Costa Rica | 6.74 | 4.16 | 7.07 | 3.46 |
| Croatia | 3.83 | 5.46 | 4.55 | 3.03 |
| Cuba | 5.84 | 5.20 | 5.47 | 5.00 |
| Czech Republic | 3.29 | 3.48 | 5.85 | 3.63 |
| Ecuador | 5.85 | 3.10 | 5.01 | 7.97 |
| Egypt | 5.32 | 5.20 | 2.32 | 5.82 |
| Estonia | 2.41 | 4.02 | 7.88 | 3.08 |
| France | 3.85 | 4.24 | 3.27 | 4.67 |
| Germany | 4.44 | 3.70 | 5.86 | 0.87 |
| Ghana | 4.62 | 4.91 | 7.44 | 9.58 |
| Greece | 5.39 | 2.85 | 4.65 | 2.73 |
| Guinea | 5.22 | 4.31 | 8.51 | 6.38 |
| Hungary | 4.15 | 5.66 | 7.12 | 3.91 |
| India | 5.96 | 14.76 | 17.83 | 14.59 |
| Iran | 6.29 | 5.99 | 8.68 | 4.06 |
| Ireland | 6.16 | 2.52 | 2.75 | 4.00 |
| Jordan | 2.53 | 2.02 | 6.29 | 2.54 |
| Latvia | 3.81 | 3.11 | 3.93 | 3.02 |
| Lithuania | 2.04 | 5.44 | 3.31 | 5.30 |

†Columns (1) and (3) report the fraction of sons and daughters from lowest quartile fathers that moved to the top quartile in their generation, while columns (2) and (4) report the fraction of sons and daughters from the highest quartile fathers that moved to the bottom quartile in their generation. All figures in percentages.

Transition Probabilities *(contd.)*

| Country | Sons | | Daughters | |
|---|---|---|---|---|
| | Bottom to Top (1) | Top to Bottom (2) | Bottom to Top (3) | Top to Bottom (4) |
| Malaysia | 6.90 | 11.52 | 5.66 | 9.01 |
| Mali | 2.58 | 3.77 | 3.20 | 8.16 |
| Mongolia | 2.86 | 6.43 | 3.27 | 2.61 |
| Netherlands | 4.49 | 2.99 | 4.20 | 4.42 |
| Nicaragua | 7.03 | 5.18 | 6.02 | 5.89 |
| Panama | 6.27 | 5.46 | 6.62 | 5.98 |
| Philippines | 4.64 | 2.75 | 5.64 | 3.25 |
| Poland | 5.83 | 4.53 | 4.32 | 5.25 |
| Romania | 4.49 | 7.24 | 2.58 | 6.79 |
| Russia | 5.74 | 3.99 | 4.44 | 4.23 |
| Senegal | 4.08 | 16.74 | 7.10 | 28.89 |
| Slovakia | 3.59 | 3.59 | 5.06 | 1.17 |
| Slovenia | 4.39 | 4.82 | 5.74 | 1.64 |
| South Africa | 2.65 | 3.93 | 4.19 | 5.91 |
| Sudan | 1.73 | 1.49 | 1.77 | 0.84 |
| Switzerland | 5.44 | 3.53 | 3.44 | 2.98 |
| Thailand | 5.60 | 3.75 | 5.77 | 9.63 |
| Turkey | 6.91 | 18.18 | 6.25 | 18.72 |
| Uganda | 2.00 | 4.68 | 2.39 | 4.38 |
| Ukraine | 7.62 | 4.76 | 11.00 | 0.96 |
| United Kingdom | 5.45 | 3.00 | 4.95 | 6.53 |
| United States | 5.20 | 5.95 | 5.22 | 5.47 |
| Uruguay | 4.92 | 10.60 | 5.26 | 7.85 |
| Venezuela | 6.50 | 2.81 | 8.50 | 2.73 |
| Vietnam | 12.63 | 5.29 | 6.73 | 5.31 |

†Columns (1) and (3) report the fraction of sons and daughters from lowest quartile fathers that moved to the top quartile in their generation, while columns (2) and (4) report the fraction of sons and daughters from the highest quartile fathers that moved to the bottom quartile in their generation. All figures in percentages.

# APPENDIX G

## CHAPTER 2: AVERAGE GAIN AND LOSS IN OCCUPATIONAL PRESTIGE (ABSOLUTE SCALE)

Figure G.1: Average Gain in Occupational Prestige (Absolute Scale)

(a) Sons (b) Daughters

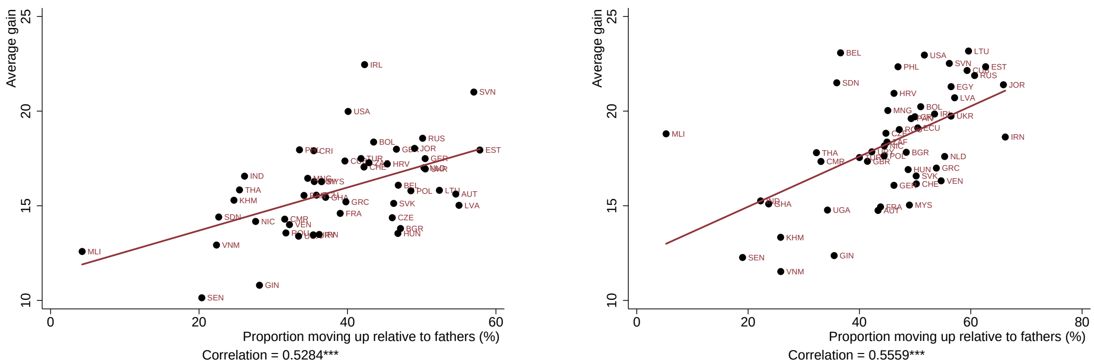
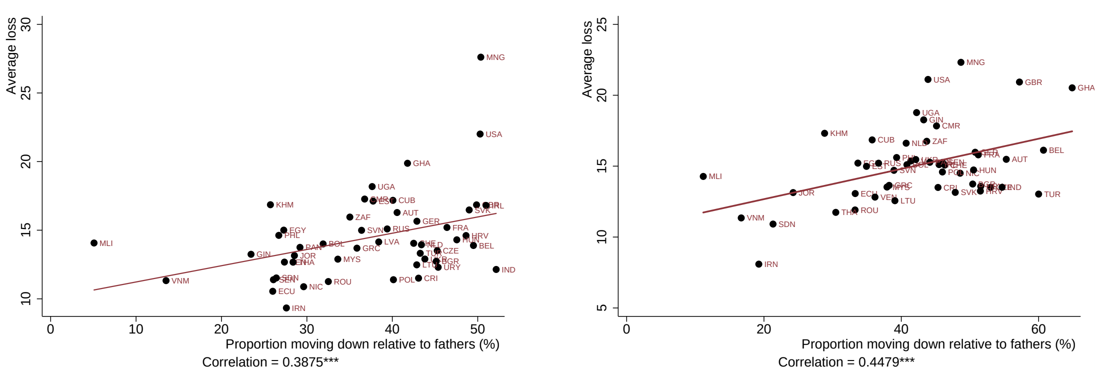



Figure G.2: Average Loss in Occupational Prestige (Absolute Scale)

(a) Sons (b) Daughters



# APPENDIX H

# CHAPTER 3: PROOFS OF PROPOSITIONS

PROPOSITION 1: Let $\bar{w}_{jg} = \dfrac{w_j \hat{\phi}_j^{\phi_j}(1-\hat{\phi}_j)\eta^\eta(1-\eta)^{1-\eta}}{(1+\tau^e_{jg})^\eta/(1-\tau^w_{jg})}$ where $\hat{\phi}_j = \dfrac{\phi_j}{1+\phi_j}$. Then, using equation 3.11 consumption conditional on choosing occupation $j$ can be written as $c^*_{jg}(\boldsymbol{\epsilon}|j) = (\bar{w}_{jg}\epsilon_j)^{\frac{1}{1-\eta}}$. A worker from group $g$ chooses an occupation $j$ if her consumption from choosing occupation $j$ is largest over all possible occupations. Hence,

$$
\begin{aligned}
p_{jg} &= \text{Prob}(c^*_{jg}(\boldsymbol{\epsilon}|j) > c^*_{sg}(\boldsymbol{\epsilon}|s)\ \forall s \neq j \\
&= \text{Prob}(\bar{w}_{jg}\epsilon_j > \bar{w}_{sg}\epsilon_s)\ \forall s \neq j \\
&= \int_0^\infty \left[\int_0^{\alpha_{1g}\epsilon_j} \dots \int_0^{\alpha_{Jg}\epsilon_j} \theta T_{1g} e^{-T_{1g}\epsilon_1^{-\theta}} \dots \theta T_{Jg} e^{-T_{Jg}\epsilon_J^{-\theta}} d\epsilon_1 \dots d\epsilon_J\right] \theta T_{jg} e^{-T_{jg}\epsilon_1^{-\theta}} d\epsilon_j \\
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (\text{where } \alpha_{sg} = \bar{w}_{jg}/\bar{w}_{sg}) \\
&= \int_0^\infty \prod_{s\neq j} e^{-T_{sg}\alpha_{sg}^{-\theta}\epsilon_j^{-\theta}} \theta T_{jg} e^{-T_{jg}\epsilon_1^{-\theta}} d\epsilon_j \\
&= \int_0^\infty \frac{\sum_{s\neq j} T_{sg}\alpha_{sg}^{-\theta}}{\sum_{s\neq j} T_{sg}\alpha_{sg}^{-\theta}} \theta T_{jg} e^{-\sum_{s=1}^{J}(T_{sg}\alpha_{sg}^{-\theta})\epsilon_j^{-\theta}} d\epsilon_j \\
&= \frac{T_{jg}}{\sum_{s=1}^{J} T_{sg}\alpha_{sg}^{-\theta}} \int_0^\infty \theta \sum_{s\neq j} T_{sg}\alpha_{sg}^{-\theta} e^{-\sum_{s=1}^{J}(T_{sg}\alpha_{sg}^{-\theta})\epsilon_j^{-\theta}} d\epsilon_j \\
&= \frac{T_{jg}}{\sum_{s=1}^{J} T_{sg}\alpha_{sg}^{-\theta}} \\
&= \frac{\bar{w}_{jg}^\theta T_{jg}}{\sum_{s=1}^{J} \bar{w}_{sg}^\theta T_{sg}} \qquad \square
\end{aligned}
$$

PROPOSITION 2: First, I find the expected talent of a worker from group $g$ given that she has chosen occupation $j$, i.e., $\text{E}(\epsilon^*_{jg}|\text{Worker chooses } j)$. Let $\bar{w}^*\epsilon^* \equiv \max_s\{\bar{w}_{sg}\epsilon_s\}$. Then,

$$
\begin{aligned}
G(x) = \text{Prob}(\epsilon^* < x) &= \text{Prob}(\bar{w}_{sg}\epsilon_s < \bar{w}^* x)\ \forall s \\
&= \text{Prob}\left(\epsilon_s < \frac{\bar{w}^* x}{\bar{w}_{sg}}\right) \\
&= \prod_{s=1}^{J} e^{[-T_{sg}(\bar{w}_{sg}/\bar{w}^*)^\theta x^{-\theta}]} \\
&= e^{-[\sum(T_{sg}(\bar{w}_{sg}/\bar{w}^*)^\theta)x^{-\theta}]}
\end{aligned}
$$

The above result shows that the expected talent of a worker from group $g$ also follows Fréchet with the same shape parameter $\theta$ and an adjusted mean parameter given by $\sum(T_{sg}(\bar{w}_{sg}/\bar{w}^*)^{\theta})$.

Define $T^* = \sum(T_{sg}(\bar{w}_{sg}/\bar{w}^*)^{\theta})$ and let $\lambda$ be any positive number. Then,

$$\begin{aligned}
\mathrm{E}(\epsilon_j^{\lambda}) &= \int_0^{\infty} \epsilon^{\lambda} dG(\epsilon) \\
&= \int_0^{\infty} \theta T^* \epsilon^{-(\theta+1-\lambda)} e^{-T^*\epsilon^{-\theta}} d\epsilon \\
&= T^{*\lambda/\theta} \int_0^{\infty} y^{-\frac{\lambda}{\theta}} e^{-x} dy \\
& \qquad \text{(where } y = T^*\epsilon^{-\theta}\text{)} \\
&= T^{*\lambda/\theta}\Gamma\left(1 - \frac{\lambda}{\theta}\right)
\end{aligned}$$

where $\Gamma(.)$ is the gamma function. Using the above result and the expression of $p_{jg}$ from proposition 1, I get

$$\mathrm{E}\left(\epsilon_j^{\frac{1}{1-\eta}} \middle| \text{Worker chooses } j\right) = T^{*1/\theta(1-\eta)}\Gamma\left(1 - \frac{1}{\theta(1-\eta)}\right) = \left(\frac{T_{jg}}{p_{jg}}\right)^{\frac{1}{\theta(1-\eta)}} \Gamma\left(1 - \frac{1}{\theta(1-\eta)}\right) \tag{H.1}$$

Next, I find the expression for the expected efficiency labor provided by any group $g$ in any occupation $j$ which is given by

$$\mathrm{E}\left(e_{jg}^{*\eta}\epsilon_j s_j^{*\phi_j}(1-s_j^*)\right) = \gamma\left[\eta^{\eta} s_j^{*\phi_j}(1-s_j^*)\left(\frac{w_j(1-\tau_{jg}^w)}{1+\tau_{jg}^e}\right)^{\eta}\right]^{\frac{1}{1-\eta}} \left(\frac{T_{jg}}{p_{jg}}\right)^{\frac{1}{\theta(1-\eta)}} \tag{H.2}$$

Now, the expected wage income of workers in group $g$ working in an occupation $j$ can be written as

$$\begin{aligned}
\overline{\mathrm{inc}}_{jg} &= (1-\tau_{jg}^w)w_j \mathrm{E}\left(e_{jg}^{*\eta}\epsilon_j s_j^{*\phi_j}(1-s_j^*)\right) \\
\Rightarrow \frac{\overline{\mathrm{inc}}_{jg}}{\overline{\mathrm{inc}}_{j,hm}} &= \left[\frac{\sum_{s=0}^{J} \bar{w}_{sg}^{\theta} T_{sg}}{\sum_{s=0}^{J} \bar{w}_{s,hm}^{\theta} T_{s,hm}}\right]^{\frac{1}{\theta(1-\eta)}}
\end{aligned}$$

Hence, the wage gap across any two groups is same across all occupations and are independent of the occupation-specific frictions $\tau_{jg}^w$ and $\tau_{jg}^e$. □

# APPENDIX I

## CHAPTER 3: ESTIMATES OF GROSS FRICTIONS

Table I.1: Estimated Gross Frictions: High-caste Women

| | $\theta(1-\eta) = 2.96$ | | | $\theta(1-\eta) = 3.44$ | | |
|---|---|---|---|---|---|---|
| | 1983 | 1993 | 2004 | 1983 | 1993 | 2004 |
| Engineers | 3.12 | 1.76 | 1.39 | 2.87 | 1.65 | 1.30 |
| Engineering technicians | 70.58 | 1.99 | 1.94 | 65.17 | 1.85 | 1.84 |
| Aircraft and ship officers | 3.21 | 49.85 | - | 3.04 | 46.46 | - |
| Life scientists | 1.45 | 1.73 | - | 1.43 | 1.64 | - |
| Life science technicians | - | 1.09 | 2.12 | - | 1.03 | 2.00 |
| Physicians and surgeons | 0.89 | 1.03 | 1.00 | 0.89 | 1.02 | 1.00 |
| Medical Technicians | 0.64 | 0.76 | 0.76 | 0.67 | 0.79 | 0.80 |
| Technicians NEC | 2.20 | 1.09 | - | 2.11 | 1.09 | - |
| Mathematicians | 3.72 | 1.20 | 1.73 | 3.52 | 1.17 | 1.64 |
| Social Scientists | 1.20 | 1.60 | 1.58 | 1.16 | 1.54 | 1.55 |
| Law professionals | 1.37 | 1.27 | 2.41 | 1.32 | 1.22 | 2.30 |
| Teachers | 0.87 | 0.95 | 1.03 | 0.90 | 0.98 | 1.06 |
| Authors, artists and atheletes | 1.12 | 1.30 | 1.04 | 1.08 | 1.25 | 0.99 |
| Professionals NEC | 1.07 | 1.03 | 1.28 | 1.08 | 1.05 | 1.25 |
| Administrative, executive and managerial | 28.56 | 1.58 | 1.57 | 26.74 | 1.51 | 1.51 |
| Clerical supervisors | 1.40 | 1.28 | 1.27 | 1.34 | 1.25 | 1.24 |
| Typists | 1.07 | 0.89 | 0.97 | 1.07 | 0.92 | 0.97 |
| Bookkeepers | 1.41 | 1.16 | 1.18 | 1.36 | 1.13 | 1.16 |
| Clerks NEC | 1.16 | 1.07 | 1.11 | 1.14 | 1.05 | 1.10 |
| Customer service clerks | 25.94 | 1.52 | 1.48 | 24.97 | 1.48 | 1.45 |
| Transport supervisors | 165.41 | 2.03 | 1.59 | 156.96 | 1.92 | 1.54 |
| Transport conductors and guards | 5.77 | 5.39 | 1.95 | 5.21 | 4.70 | 1.73 |
| Mail distributors | 2.36 | 2.05 | 1.43 | 2.15 | 1.90 | 1.33 |
| Telephone and telegraph operators | 1.00 | 0.97 | 1.00 | 1.00 | 0.96 | 1.00 |
| Merchants and sales technicians | 98.92 | 1.99 | 2.15 | 95.2 | 1.92 | 1.99 |
| Salesmen and sales agents | 1.97 | 1.93 | 1.90 | 1.86 | 1.81 | 1.77 |
| Hotel and house keepers | 1.09 | 2.11 | 1.50 | 1.11 | 2.11 | 1.51 |
| Cooks and waiters | 1.53 | 1.85 | 1.79 | 1.52 | 1.83 | 1.80 |

The table reports the gross level of frictions faced by high-caste women over time. The first three column gives the baseline estimates while the next three columns correspond to the case when $\theta(1-\eta)$ is fixed at that considered in Hsieh *et al.* (2014). *(contd.)*

Estimated Gross Frictions: High-caste Women

| | $\theta(1-\eta) = 2.96$ | | | $\theta(1-\eta) = 3.44$ | | |
|---|---|---|---|---|---|---|
| | 1983 | 1993 | 2004 | 1983 | 1993 | 2004 |
| Housekeeping services and building care | 0.8 | 0.89 | 0.84 | 0.87 | 0.96 | 0.93 |
| Launderers | 1.58 | 2.25 | 2.16 | 1.62 | 2.33 | 2.22 |
| Hairdressers and barbers | 1.57 | 0.8 | 1.09 | 1.53 | 0.78 | 1.08 |
| Protective service workers | 2.59 | 1.97 | 1.93 | 2.32 | 1.81 | 1.77 |
| Service workers NEC | 1.35 | 1.85 | 1.88 | 1.33 | 1.85 | 1.89 |
| Farm managers and supervisors | - | 3.33 | 4.19 | - | 3.11 | 4.01 |
| Cultivators | 0.27 | 1.72 | 1.78 | 0.27 | 1.73 | 1.78 |
| Animal and Vegetable Growers | 473.89 | 1.44 | 2.44 | 479.62 | 1.47 | 2.45 |
| Agricultural labourers | 0.34 | 1.21 | 1.19 | 0.35 | 1.24 | 1.23 |
| Plantation labourers | 1.1 | 1.07 | 1.09 | 1.14 | 1.09 | 1.11 |
| Farm workers NEC | 1.78 | 1.61 | 2.05 | 1.69 | 1.56 | 1.98 |
| Loggers | 2.17 | 2.51 | 1.59 | 2.11 | 2.46 | 1.58 |
| Hunters and trappers | - | - | 5.7 | - | - | 5.59 |
| Fishermen | 3.82 | 1.8 | 0.86 | 3.56 | 1.72 | 0.8 |
| Agricultural workers NEC | - | 1.76 | - | - | 1.69 | - |
| Miners and quarrymen | 0 | 2.56 | 4.86 | 0 | 2.46 | 4.58 |
| Metal processors | 8.1 | 2.32 | 4.92 | 7.15 | 2.12 | 4.34 |
| Wood and paper workers | 2.63 | 2.36 | 1.36 | 2.45 | 2.26 | 1.32 |
| Chemical processors | 2.85 | 2.08 | 2.19 | 2.7 | 1.96 | 2.11 |
| Spinners and weavers | 52.15 | 1.94 | 2.05 | 51.27 | 1.93 | 2.04 |
| Fellmongers and pelt dressers | - | 2.21 | 2.09 | - | 2.28 | 2.04 |
| Food and beverage processors | 1.71 | 2.23 | 1.55 | 1.69 | 2.22 | 1.55 |

The table reports the gross level of frictions faced by high-caste women over time. The first three column gives the baseline estimates while the next three columns correspond to the case when $\theta(1-\eta)$ is fixed at that considered in Hsieh *et al.* (2014). *(contd.)*

Estimated Gross Frictions: High-caste Women

| | $\theta(1-\eta)=2.96$ | | | $\theta(1-\eta)=3.44$ | | |
|---|---|---|---|---|---|---|
| | 1983 | 1993 | 2004 | 1983 | 1993 | 2004 |
| Tobacco preparers | 0.86 | 0.86 | 1.13 | 0.92 | 0.93 | 1.21 |
| Tailors and dressmakers | 1.43 | 1.34 | 1.5 | 1.42 | 1.34 | 1.5 |
| Leather workers | 3.01 | 1.90 | 2.83 | 2.83 | 1.83 | 2.74 |
| Carpenters and cabinet makers | 2.25 | 2.41 | 2.37 | 2.03 | 2.16 | 2.06 |
| Stone cutters and carvers | 1.39 | 1.72 | 1.67 | 1.39 | 1.71 | 1.65 |
| Blacksmiths and toolmakers | 2.35 | 3.05 | 3.77 | 2.15 | 2.77 | 3.53 |
| Machinery fitters and assemblers | 95.45 | 3.07 | 2.76 | 83.62 | 2.77 | 2.46 |
| Electrical fitters | 1.98 | 1.95 | 2.69 | 1.79 | 1.78 | 2.45 |
| Communications equipment operators | - | - | 0.64 | - | - | 0.61 |
| Plumbers and welders | 2.10 | 3.51 | 9.84 | 1.84 | 3.11 | 8.58 |
| Precious metal workers | 5.01 | 2.76 | 2.94 | 4.53 | 2.59 | 2.70 |
| Glass formers and potters | 1.27 | 2.57 | 2.32 | 1.28 | 2.55 | 2.28 |
| Rubber and plastics product makers | 1.29 | 2.73 | 4.20 | 1.24 | 2.65 | 4.00 |
| Paper and paper product makers | 2.48 | 4.42 | 3.44 | 2.45 | 4.25 | 3.33 |
| Printers | 2.15 | 2.27 | 2.76 | 2.07 | 2.18 | 2.64 |
| Painters | 1.55 | 1.78 | 4.36 | 1.44 | 1.65 | 4 |
| Production workers NEC | 2.13 | 3.49 | 2.34 | 2.12 | 3.53 | 2.34 |
| Construction workers | 1.88 | 2.04 | 1.82 | 1.86 | 2.00 | 1.78 |
| Stationary engine operators | - | 4.27 | 1.35 | - | 3.87 | 1.27 |
| Material handling equipment operators | 1.83 | 2.02 | 2.23 | 1.78 | 1.94 | 2.13 |
| Transport equipment operators | 3.90 | 2.92 | 3.53 | 3.44 | 2.53 | 3.07 |
| Laborers NEC | 1.82 | 1.73 | 1.65 | 1.81 | 1.71 | 1.62 |

The table reports the gross level of frictions faced by high-caste women over time. The first three column gives the baseline estimates while the next three columns correspond to the case when $\theta(1-\eta)$ is fixed at that considered in Hsieh *et al.* (2014).

Table I.2: Estimated Gross Frictions: Low-caste Men

| | $\theta(1-\eta) = 2.96$ | | | $\theta(1-\eta) = 3.44$ | | |
|---|---|---|---|---|---|---|
| | 1983 | 1993 | 2004 | 1983 | 1993 | 2004 |
| Engineers | 1.96 | 1.75 | 1.51 | 1.84 | 1.65 | 1.47 |
| Engineering technicians | 57.26 | 1.62 | 1.41 | 54.00 | 1.55 | 1.37 |
| Aircraft and ship officers | 1.61 | 5.90 | - | 1.54 | 5.41 | - |
| Life scientists | 2.02 | 1.16 | - | 1.93 | 1.14 | - |
| Life science technicians | - | 0.96 | 1.26 | - | 0.94 | 1.21 |
| Physicians and surgeons | 1.91 | 1.78 | 1.15 | 1.83 | 1.70 | 1.13 |
| Medical Technicians | 1.19 | 1.08 | 1.00 | 1.17 | 1.06 | 1.00 |
| Technicians NEC | 1.98 | - | - | 1.91 | - | - |
| Mathematicians | 1.11 | 1.68 | 1.21 | 1.09 | 1.60 | 1.17 |
| Social Scientists | 1.70 | 1.68 | 1.28 | 1.62 | 1.60 | 1.25 |
| Law professionals | 0.76 | 1.73 | 1.31 | 0.69 | 1.65 | 1.26 |
| Teachers | 1.44 | 1.27 | 1.03 | 1.40 | 1.24 | 1.03 |
| Authors, artists and atheletes | 1.18 | 1.82 | 0.98 | 1.15 | 1.77 | 0.96 |
| Professionals NEC | 2.11 | 1.99 | 1.03 | 2.11 | 1.95 | 1.00 |
| Administrative, executive and managerial | 35.12 | 1.59 | 1.50 | 33.27 | 1.52 | 1.45 |
| Clerical supervisors | 1.49 | 1.32 | 1.13 | 1.45 | 1.29 | 1.12 |
| Typists | 1.76 | 1.38 | 1.23 | 1.65 | 1.32 | 1.20 |
| Bookkeepers | 1.62 | 1.28 | 1.16 | 1.53 | 1.22 | 1.11 |
| Clerks NEC | 1.47 | 1.27 | 1.08 | 1.40 | 1.23 | 1.06 |
| Customer service clerks | 21.61 | 1.13 | 0.98 | 21.42 | 1.12 | 0.99 |
| Transport supervisors | 123.42 | 1.29 | 1.26 | 116.73 | 1.25 | 1.22 |
| Transport conductors and guards | 1.17 | 1.18 | 1.14 | 1.15 | 1.15 | 1.12 |
| Mail distributors | 1.35 | 1.12 | 1.13 | 1.34 | 1.11 | 1.12 |
| Telephone and telegraph operators | 1.52 | 1.19 | 0.99 | 1.48 | 1.16 | 0.99 |
| Merchants and sales technicians | 46.33 | 1.58 | 1.76 | 43.57 | 1.55 | 1.68 |
| Salesmen and sales agents | 1.63 | 1.77 | 1.56 | 1.55 | 1.68 | 1.49 |
| Hotel and house keepers | 0.93 | 0.79 | 1.71 | 0.91 | 0.78 | 1.67 |
| Cooks and waiters | 1.27 | 1.27 | 1.32 | 1.22 | 1.23 | 1.28 |

The table reports the gross level of frictions faced by low-caste men over time. The first three column gives the baseline estimates while the next three columns correspond to the case when $\theta(1-\eta)$ is fixed at that considered in Hsieh *et al.* (2014). *(contd.)*

Estimated Gross Frictions: Low-caste Men

| | $\theta(1-\eta) = 2.96$ | | | $\theta(1-\eta) = 3.44$ | | |
|---|---|---|---|---|---|---|
| | 1983 | 1993 | 2004 | 1983 | 1993 | 2004 |
| Housekeeping services and building care | 0.72 | 0.61 | 0.61 | 0.75 | 0.64 | 0.63 |
| Launderers | 1.01 | 1.24 | 0.92 | 1.03 | 1.24 | 0.92 |
| Hairdressers and barbers | 1.63 | 0.8 | 0.93 | 1.56 | 0.78 | 0.89 |
| Protective service workers | 1.11 | 1.13 | 1.03 | 1.10 | 1.12 | 1.03 |
| Service workers NEC | 1.03 | 1.04 | 1.44 | 1.02 | 1.04 | 1.42 |
| Farm managers and supervisors | - | 1.49 | 0.81 | - | 1.45 | 0.80 |
| Cultivators | 0.53 | 0.85 | 0.94 | 0.55 | 0.87 | 0.95 |
| Animal and Vegetable Growers | 306.39 | 1.37 | 1.30 | 307.73 | 1.38 | 1.29 |
| Agricultural labourers | 19.54 | 0.82 | 0.88 | 20.13 | 0.85 | 0.90 |
| Plantation labourers | 1.32 | 1.10 | 0.94 | 1.32 | 1.10 | 0.94 |
| Farm workers NEC | 0.81 | 1.21 | 0.98 | 0.82 | 1.21 | 0.98 |
| Loggers | 0.95 | 0.83 | 1.04 | 0.97 | 0.86 | 1.06 |
| Hunters and trappers | - | 1.21 | 2.10 | - | 1.21 | 2.07 |
| Fishermen | 1.00 | 1.24 | 1.05 | 1.00 | 1.23 | 1.04 |
| Agricultural workers NEC | 1.08 | 2.99 | - | 1.07 | 2.84 | - |
| Miners and quarrymen | 0.83 | 0.89 | 1.30 | 0.85 | 0.90 | 1.31 |
| Metal processors | 1.65 | 1.27 | 1.26 | 1.61 | 1.24 | 1.23 |
| Wood and paper workers | 0.74 | 1.34 | 1.52 | 0.73 | 1.31 | 1.49 |
| Chemical processors | 2.10 | 1.49 | 1.54 | 2.02 | 1.46 | 1.50 |
| Spinners and weavers | 30.43 | 1.22 | 1.25 | 29.84 | 1.19 | 1.23 |
| Fellmongers and pelt dressers | - | 1.71 | 0.89 | - | 1.77 | 0.91 |
| Food and beverage processors | 1.42 | 1.22 | 1.36 | 1.38 | 1.19 | 1.33 |

The table reports the gross level of frictions faced by low-caste men over time. The first three column gives the baseline estimates while the next three columns correspond to the case when $\theta(1-\eta)$ is fixed at that considered in Hsieh *et al.* (2014). *(contd.)*

Estimated Gross Frictions: Low-caste Men

| | $\theta(1-\eta)=2.96$ 1983 | 1993 | 2004 | $\theta(1-\eta)=3.44$ 1983 | 1993 | 2004 |
|---|---|---|---|---|---|---|
| Tobacco preparers | 1.24 | 1.32 | 1.79 | 1.23 | 1.29 | 1.79 |
| Tailors and dressmakers | 1.48 | 1.29 | 1.37 | 1.43 | 1.25 | 1.33 |
| Leather workers | 0.97 | 1.36 | 0.86 | 1.00 | 1.37 | 0.88 |
| Carpenters and cabinet makers | 1.29 | 1.17 | 0.96 | 1.26 | 1.15 | 0.95 |
| Stone cutters and carvers | 0.88 | 1.13 | 1.03 | 0.90 | 1.14 | 1.04 |
| Blacksmiths and toolmakers | 1.55 | 1.33 | 1.40 | 1.50 | 1.28 | 1.37 |
| Machinery fitters and assemblers | 36.22 | 1.27 | 1.26 | 35.11 | 1.24 | 1.23 |
| Electrical fitters | 1.38 | 1.31 | 1.16 | 1.34 | 1.29 | 1.15 |
| Communications equipment operators | 1.55 | 0.91 | 0.50 | 1.51 | 0.88 | 0.49 |
| Plumbers and welders | 1.08 | 1.33 | 1.16 | 1.06 | 1.29 | 1.14 |
| Precious metal workers | 1.64 | 1.44 | 1.99 | 1.56 | 1.37 | 1.86 |
| Glass formers and potters | 0.94 | 1.17 | 1.23 | 0.95 | 1.18 | 1.24 |
| Rubber and plastics product makers | 1.43 | 1.65 | 1.92 | 1.41 | 1.64 | 1.87 |
| Paper and paper product makers | 1.28 | 1.45 | 0.97 | 1.27 | 1.34 | 0.95 |
| Printers | 1.37 | 2.25 | 1.21 | 1.31 | 2.15 | 1.18 |
| Painters | 1.06 | 0.92 | 1.05 | 1.06 | 0.91 | 1.04 |
| Production workers NEC | 1.09 | 1.5 | 1.34 | 1.09 | 1.49 | 1.32 |
| Construction workers | 0.99 | 1.02 | 1.03 | 1.00 | 1.04 | 1.04 |
| Stationary engine operators | - | 1.13 | 1.05 | - | 1.12 | 1.04 |
| Material handling equipment operators | 1.14 | 1.17 | 1.12 | 1.15 | 1.16 | 1.11 |
| Transport equipment operators | 1.22 | 1.19 | 1.08 | 1.20 | 1.17 | 1.06 |
| Laborers NEC | 0.03 | 0.96 | 0.95 | 0.03 | 0.98 | 0.96 |

The table reports the gross level of frictions faced by low-caste men over time. The first three column gives the baseline estimates while the next three columns correspond to the case when $\theta(1-\eta)$ is fixed at that considered in Hsieh *et al.* (2014).

Table I.3: Estimated Gross Frictions: Low-caste Women

| | $\theta(1-\eta) = 2.96$ | | | $\theta(1-\eta) = 3.44$ | | |
|---|---|---|---|---|---|---|
| | 1983 | 1993 | 2004 | 1983 | 1993 | 2004 |
| Engineers | - | 3.23 | 2.66 | - | 2.81 | 2.41 |
| Engineering technicians | 111.79 | 2.17 | 2.75 | 98.55 | 1.99 | 2.53 |
| Aircraft and ship officers | - | - | - | - | - | - |
| Life scientists | - | - | - | - | - | - |
| Life science technicians | - | - | - | - | - | - |
| Physicians and surgeons | 1.81 | 1.55 | 1.45 | 1.67 | 1.44 | 1.39 |
| Medical Technicians | 0.99 | 0.90 | 0.79 | 1.00 | 0.91 | 0.81 |
| Technicians NEC | - | - | - | - | - | - |
| Mathematicians | 1.83 | - | 1.00 | 1.83 | - | 0.94 |
| Social Scientists | 2.58 | 2.29 | 2.85 | 2.41 | 2.13 | 2.78 |
| Law professionals | - | - | - | - | - | - |
| Teachers | 1.45 | 1.46 | 1.23 | 1.42 | 1.43 | 1.24 |
| Authors, artists and atheletes | - | 7.34 | 2.39 | - | 6.55 | 2.18 |
| Professionals NEC | 2.20 | - | - | 2.21 | - | - |
| Administrative, executive and managerial | 76.24 | 6.71 | 2.98 | 69.83 | 6.04 | 2.76 |
| Clerical supervisors | 1.74 | 1.56 | 1.35 | 1.64 | 1.48 | 1.30 |
| Typists | 1.60 | 1.44 | 1.06 | 1.53 | 1.39 | 1.06 |
| Bookkeepers | 2.30 | 2.35 | 2.37 | 2.07 | 2.15 | 2.20 |
| Clerks NEC | 1.65 | 1.37 | 1.24 | 1.54 | 1.30 | 1.20 |
| Customer service clerks | 35.7 | 1.71 | 1.36 | 33.31 | 1.64 | 1.33 |
| Transport supervisors | 433.94 | 2.33 | 3.13 | 393.13 | 2.08 | 2.88 |
| Transport conductors and guards | - | - | 4.75 | - | - | 4.16 |
| Mail distributors | - | - | 1.22 | - | - | 1.14 |
| Telephone and telegraph operators | - | 1.23 | 1.48 | - | 1.15 | 1.36 |
| Merchants and sales technicians | 103.13 | 1.65 | 6.20 | 99.39 | 1.61 | 5.79 |
| Salesmen and sales agents | 3.48 | 2.45 | 2.97 | 3.16 | 2.23 | 2.66 |
| Hotel and house keepers | 1.26 | 1.64 | 1.41 | 1.27 | 1.63 | 1.38 |
| Cooks and waiters | 2.20 | 2.18 | 2.23 | 2.11 | 2.12 | 2.19 |

The table reports the gross level of frictions faced by low-caste women over time. The first three column gives the baseline estimates while the next three columns correspond to the case when $\theta(1-\eta)$ is fixed at that considered in Hsieh *et al.* (2014). *(contd.)*

Estimated Gross Frictions: Low-caste Women

| | $\theta(1-\eta) = 2.96$ | | | $\theta(1-\eta) = 3.44$ | | |
|---|---|---|---|---|---|---|
| | 1983 | 1993 | 2004 | 1983 | 1993 | 2004 |
| Housekeeping services and building care | 0.70 | 0.76 | 0.78 | 0.76 | 0.83 | 0.86 |
| Launderers | 0.84 | 1.37 | 1.14 | 0.87 | 1.38 | 1.16 |
| Hairdressers and barbers | - | 36.51 | 0.81 | - | 33.68 | 0.78 |
| Protective service workers | 2.60 | 2.38 | 2.04 | 2.35 | 2.13 | 1.88 |
| Service workers NEC | 4.00 | 2.04 | 4.63 | 3.68 | 2.00 | 4.39 |
| Farm managers and supervisors | - | - | 1.12 | - | - | 1.05 |
| Cultivators | 92.91 | 1.06 | 1.38 | 97.35 | 1.08 | 1.39 |
| Animal and Vegetable Growers | 256.54 | 1.72 | 1.56 | 259.6 | 1.75 | 1.61 |
| Agricultural labourers | 19.22 | 1.00 | 1.07 | 20.00 | 1.05 | 1.11 |
| Plantation labourers | 1.15 | 1.17 | 1.08 | 1.18 | 1.18 | 1.10 |
| Farm workers NEC | 2.46 | 1.71 | 1.87 | 2.37 | 1.71 | 1.82 |
| Loggers | 1.45 | 1.84 | 1.28 | 1.42 | 1.82 | 1.26 |
| Hunters and trappers | - | - | - | - | - | - |
| Fishermen | 1.63 | 2.30 | 4.14 | 1.54 | 2.23 | 3.89 |
| Agricultural workers NEC | 2.08 | 4.02 | - | 2.09 | 3.84 | - |
| Miners and quarrymen | 0.00 | 1.96 | 3.43 | 0.00 | 1.94 | 3.38 |
| Metal processors | 1.87 | - | 3.26 | 1.72 | - | 3.06 |
| Wood and paper workers | 3.93 | 5.08 | 2.79 | 3.63 | 4.58 | 2.65 |
| Chemical processors | - | - | 2.10 | - | - | 2.04 |
| Spinners and weavers | 70.10 | 2.78 | 1.68 | 65.79 | 2.65 | 1.61 |
| Fellmongers and pelt dressers | - | 2.64 | - | - | 2.70 | - |
| Food and beverage processors | 2.37 | 2.26 | 2.31 | 2.29 | 2.17 | 2.25 |

The table reports the gross level of frictions faced by low-caste women over time. The first three column gives the baseline estimates while the next three columns correspond to the case when $\theta(1-\eta)$ is fixed at that considered in Hsieh *et al.* (2014). *(contd.)*

Estimated Gross Frictions: Low-caste Women

| | $\theta(1-\eta) = 2.96$ | | | $\theta(1-\eta) = 3.44$ | | |
|---|---|---|---|---|---|---|
| | 1983 | 1993 | 2004 | 1983 | 1993 | 2004 |
| Tobacco preparers | 1.18 | 1.32 | 1.41 | 1.22 | 1.36 | 1.50 |
| Tailors and dressmakers | 2.78 | 2.10 | 2.49 | 2.61 | 1.98 | 2.38 |
| Leather workers | 2.90 | 4.57 | 1.63 | 2.77 | 4.26 | 1.65 |
| Carpenters and cabinet makers | - | 3.45 | 2.98 | - | 3.00 | 2.56 |
| Stone cutters and carvers | 1.09 | 1.87 | 1.94 | 1.13 | 1.85 | 1.93 |
| Blacksmiths and toolmakers | - | 2.13 | 8.44 | - | 1.84 | 7.53 |
| Machinery fitters and assemblers | - | - | 6.09 | - | - | 5.40 |
| Electrical fitters | 2.85 | 8.87 | 11.55 | 2.51 | 7.49 | 9.95 |
| Communications equipment operators | 0.67 | - | - | 0.67 | - | - |
| Plumbers and welders | 4.37 | - | - | 3.90 | - | - |
| Precious metal workers | - | 4.00 | 2.07 | - | 3.52 | 1.86 |
| Glass formers and potters | 1.54 | 2.68 | 1.61 | 1.55 | 2.66 | 1.62 |
| Rubber and plastics product makers | 1.42 | 1.70 | 2.84 | 1.37 | 1.64 | 2.75 |
| Paper and paper product makers | - | 3.05 | 6.92 | - | 2.91 | 6.64 |
| Printers | 4.10 | 1.92 | 1.90 | 3.70 | 1.79 | 1.78 |
| Painters | - | 1.61 | 8.92 | - | 1.49 | 7.99 |
| Production workers NEC | 1.84 | 2.52 | 2.52 | 1.82 | 2.57 | 2.49 |
| Construction workers | 1.78 | 1.78 | 1.68 | 1.78 | 1.77 | 1.66 |
| Stationary engine operators | - | 3.41 | 1.96 | - | 3.10 | 1.75 |
| Material handling equipment operators | 1.84 | 2.17 | 2.22 | 1.73 | 2.07 | 2.09 |
| Transport equipment operators | 6.22 | 7.97 | 3.06 | 5.21 | 6.87 | 2.65 |
| Laborers NEC | 1.63 | 1.53 | 1.61 | 1.64 | 1.53 | 1.59 |

The table reports the gross level of frictions faced by low-caste women over time. The first three column gives the baseline estimates while the next three columns correspond to the case when $\theta(1-\eta)$ is fixed at that considered in Hsieh *et al.* (2014).

# APPENDIX J

# CHAPTER 3: LIST OF BRAWNY OCCUPATIONS

Table J.1: List of Brawny Occupations

| | Nature of Work | |
|---|---|---|
| Agricultural | Construction and Metal | Unskilled Strength-based |
| Cultivators | Miners and quarrymen | Construction workers |
| Animal and Vegetable Growers | Metal processors | Laborers NEC |
| Agricultural labourers | Carpenters and cabinet makers | |
| Plantation labourers | Stone cutters and carvers | |
| Farm workers NEC | Blacksmiths and toolmakers | |
| Loggers | Machinery fitters and assemblers | |
| Hunters and trappers | Plumbers and welders | |
| Fishermen | | |
| Agricultural workers NEC | | |

NEC: Not elsewhere classified.

## BIOGRAPHICAL SKETCH

Rishabh Sinha is from Patna, India. He earned a bachelor's degree in Economics from the Shri Ram College of Commerce, University of Delhi in 2005 and a master's degree in Economics from the Indian Statistical Institute, Kolkata in 2007. From 2007 through 2010, he worked in the private sector as an Equity Research Analyst and Strategist.

During his stay in the graduate school at the Arizona State University, Rishabh served as a Research Assistant to Professors Alejandro Manelli and Gustavo Ventura. He did his Dissertation Intership at the Federal Reserve Bank of Kansas City during the summer of 2014. He was honored to receive the Prescott Award for summer research support, the Rondthaler Award for outstanding dissertation research and the Graduate Fellowship for outstanding academic performance. He also earned a master's degree in economics from the university in 2012.

Starting in the Fall of 2015, Rishabh will serve as an Economist in the Development Research Group of the World Bank at Washington D.C.