The Dynamics of Skill to Job Matching Across Generations: A Theoretical & Empirical Analysis[1]

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Abstract

This paper develops an overlapping generations household economy model to explore the impact of adults' skill-to-job matching on the human capital formation and skill-to-job matching outcomes for their children. The model assumes that even educated individuals may fail to secure skilled-sector jobs and instead may be absorbed into the unskilled sector, where labor demand is infinitely elastic. Adults form expectations about their offspring's probability of obtaining a skilled-sector job after education and use this expectation to decide whether to invest a fixed, lump-sum amount in their child's education. This decision shapes the supply of educated labor in the next period. In the skilled sector, firms post job vacancies proportional to the surplus generated in the previous period, determining the demand for skilled labor. The probability of matching to a skilled-sector job is derived using a matching function, which connects skilled labor supply to demand. The model establishes a dynamic relationship between the probability of skilled-sector matching for the parental generation and that of the offspring generation. An empirical investigation further examines the association between the skill-to-job matching of the first generation and the skill levels of the second generation. The study also provides insights into the predicted intergenerational probabilities of skill-to-job matching in the skilled sector, revealing patterns of continuity or change across generations.

Keyword: Skill-to-Job Matching, Skill Labour & unskilled Labour, Skilled & Unskilled Sector, skill mobility

1 Introduction

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In this paper, we analyze the impact of skill-to-job matching at skilled sector across generations. The major motivation for studying the relationship of skill-to-job matching between generations is that in underdeveloped countries there are many individuals who are skilled but do not find appropriate match at the skilled sector. Statistics show that there is a pool of skilled individuals who do not find suitable jobs at the skilled sectors, and get absorbed in the unskilled sectors, which may demotivate parents to invest in their child's education or encourage the latter to acquire skill with the hope of better placement. Based on unit level periodic labour force survey data on Employment and Unemployment situation in India conducted and published by National Sample Survey Organization (NSSO), we observe from our analysis that in the year 2022-23, the proportion of the skilled population increased between generations by 43.26%, whereas only 8.58% among them are appropriately matched at the skilled sector job and around 33% are either absorbed in the low skilled jobs or are unemployed despite being skilled. This mismatches are very demotivating for the parents who are taking decisions regarding educational investment of their children and also for the future generation. The rest of this paper is organized as follows. In Section-2 we discuss the literature review, Section-3.1 describes the basic structure of the theoretical model, Section-3.2 Job Matching, Section-3.3 illustrates the wage determination in the factor market through bargaining power of the workers, Section-4 Matching Dynamics and illustration of Matching across generations, Section-5 Theoretical Findings, Section-6 presents the empirical analysis on the basis of NSSO data and Hypothesis Section-7 specifies the methodology, Section-8 presents the empirical results and graphical representation, Section- 9 Conclusion and Policy Prescription

2 Literature Review

Individuals with higher wealth tend to be more selective when choosing jobs, often preferring unemployment over accepting positions that do not align with their skill level or family status, as their wealth provides sufficient sustenance. Studies, such as Marjit et al. (2022) and Mazumder and Santra (2009), highlight a linkage between inheritance and unemployment. These studies illustrate how family wealth, human capital, and occupational status significantly influence descendants' skill levels and occupational choices.

In the model, parents form expectations about future skill-to-job matching in the skilled sector by observing current matching levels. If current matching is high, parents assume it will persist, believing their child will have a similar probability of matching upon entering the labor market. This type of expectation is referred to as myopic. However, under rational expectations, parents anticipate future matching based on the best available market information, ensuring that expected and actual future matching probabilities align.

Our analysis assumes parents have rational expectations regarding future job matching. These expectations drive their decision to invest in their child’s education. If parents anticipate a high probability of skill-to-job matching in the skilled sector, more parents are likely to invest in education, increasing the future skilled labor supply. However, this growth in skilled labor may not necessarily result in a proportional increase in skilled sector matching, potentially altering the future probability of matching.

Teulings (1995) highlights the connection between worker types and job characteristics, demonstrating that returns to skill are higher for more complex jobs. Similarly, Satinger (1993) and Rosen (1982) show that high-skilled workers hold both absolute and comparative advantages over low-skilled workers across all job types. This comparative advantage in performing complex tasks creates wage differentials, rewarding higher skill levels, as further elaborated by Satinger (1975).Numerous theoretical papers address skill-to-job matching, including Pissarides (1985), Albrecht and Vroman (2002), Yashiv (2007), Pissarides (2011), and Mortensen (2011). These models analyze both the labor supply (eligible workers) and the firm-side demand (employers seeking workers), framing the matching process between unemployed workers and job vacancies within a static framework.

To extend the theoretical framework across generations, this paper develops a simplified overlapping generations (OLG) model where altruistic parents make decisions to benefit their children. OLG models, widely studied in literature, analyze intergenerational interactions within an economy. In this model, individual utility depends on both present and future consumption. Following the structure of Galor and Zeira (1993), we examine a household economy with skilled and unskilled sectors. While the unskilled sector maintains full employment, the skilled sector experiences unemployment due to limited job opportunities. Unemployed skilled individuals are absorbed into the unskilled sector at a reservation wage, ensuring no overall unemployment.

All adults participate in the labor force to meet basic needs. Higher expectations of skilled-sector job matching increase the likelihood of parental investment in child education, leading to a rise in skilled children. The subsequent growth or decline in skill-to-job matching depends on the skilled sector's vacancy growth rate.

The actual skill-to-job matching in the skilled sector determines the probability of such matching. Under rational expectations, the expected probability equals the actual probability, establishing an equilibrium probability for skill-to-job matching. This equilibrium influences adults' decisions to invest in their child's education during the initial period of human capital formation, enabling the child to pursue skilled sector jobs in the future.

The paper models the intergenerational dynamics of skill-to-job matching theoretically and analyzes them empirically. A critical level of human capital in skilled adults exists, below which they do not invest in their child's education. This critical level depends on adults' expectations about future matching probabilities, affecting the future skilled labor force. The skilled labor force and job vacancies in the skilled sector jointly determine future matching probabilities.

The model establishes conditions for individual participation in the skilled sector and links investment decisions to their critical human capital threshold. Furthermore, the growth of the skilled labor force, in alignment with job vacancies, shapes intergenerational skill-to-job matching patterns.

This study examines the intergenerational transmission of skill-to-job matching, a topic under-researched despite extensive literature on skill mismatches, educational mobility, and occupational mobility. McGuinness et al. (2017) reviewed methods for measuring skill mismatches (primarily over- and under-education), identifying three common approaches: subjective self-assessment, empirical analysis (using mean or modal procedures to determine job requirements), and job evaluation (using occupation dictionaries). Our analysis employs the empirical method, specifically the modal procedure (Kiker et al., 1997), due to the mean method's sensitivity to data distribution (Verdugo & Verdugo, 1989).

Research on intergenerational educational mobility distinguishes between absolute (overall improvement in educational attainment) and relative mobility (the parent-child relationship in educational achievement). This study focuses on relative mobility, building upon work demonstrating significant upward mobility among certain groups in India (Majumder, 2010; Ray & Majumder, 2014; Kishan, 2018; Azam & Bhatt, 2015; Asher et al., 2021, using data such as the Indian Human Development Survey). Roy et al. (2022) further analyzed mobility across various social and demographic groups using regression techniques (Leone, 2021), a methodology we also utilize to assess matching mobility and generational changes.

While intergenerational occupational mobility is well-studied in developed nations (DeJong et al., 1971; Goyder & Curtis, 1975; Dearden et al., 1997; Long & Ferrie, 2013; Xie & Killewald, 2013; Javed & Irfan, 2014; Piraino, 2015; Ribeiro, 2017), research in developing countries like India is limited by data availability. Existing Indian studies often rely on the Indian National Classification of Occupations (NCO) and Altham statistics (Azam, 2013, 2015; Hnatkovska et al., 2013), or combine Altham statistics with multinomial logistic regression (Lodh et al., 2021).

This study uniquely focuses on the intergenerational dynamics of skill-to-job mismatches, a gap in existing research that primarily utilizes static models or examines educational and occupational mobility separately. We aim to fill this gap through a rigorous theoretical and empirical analysis.

3 The Model

We present an overlapping generations household economy model, where each household consists of one adult and one child. One person lives only for two periods. One period as a child and in the second period as an adult. The parent decides on the child's education based on family income and their human capital level. In the subsequent period, an educated (skilled) child may secure a job in the skilled sector. If unsuccessful, the child is absorbed into the unskilled sector. Following Chakraborty & Chakraborty (2018), the household derives utility from both current consumption and the child’s expected future earnings.

The model considers a labor-abundant developing economy, where a small skilled sector coexists with a significantly larger unskilled sector. The skilled sector has limited demand for labor and requires a minimum level of qualifications for employment, creating barriers for those who do not meet these criteria. Skilled individuals actively search for jobs in the skilled sector, but this search process is uncoordinated, resulting in a probabilistic matching outcome. In contrast, the unskilled sector has perfectly elastic labor demand, ensuring employment for all workers who seek it.

Skilled individuals are heterogeneous in their levels of human capital. Those who secure employment in the skilled sector earn wages proportional to their human capital, while those absorbed into the unskilled sector receive a fixed reservation wage. This framework introduces the concepts of *Ex-Post Segmentation* and *Cross-Skill Matching*, as defined by Albrecht & Vroman (2002). Ex-Post Segmentation occurs when skilled workers find employment in the skilled sector, and unskilled workers are employed in the unskilled sector. *Cross-Skill Matching* occurs when skilled workers are forced to accept unskilled jobs due to a lack of suitable matches. However, the model does not consider the reverse scenario, where unskilled workers find employment in the skilled sector.

Parents invest in their child’s education if their human capital level and expectations about job matching in the skilled sector justify the investment. Adult utility depends on household consumption and the child's expected future earnings. As the child transitions to adulthood, their job prospects in the skilled sector depend on the probabilistic nature of matching, influenced by current job market conditions.

The adult decides whether to invest in their child's education to maximize utility, subject to a budget constraint. When parents choose to invest in education, they allocate an amount ē (private investment in education, including tuition fees, skill development programs, programs, etc.) from their total income, while the remainder is used for consumption in the initial period. If the child attends government-aided schools or colleges, the education cost may also include supplemental private investments.

In the skilled sector, a skilled adult worker earns a wage $W_s h_t$ in period t, determined endogenously within the system. The skilled sector wage depends on the individual's level of human capital (h_t), as W_s is fixed in the skilled sector. In contrast, both skilled and unskilled workers absorbed into the unskilled sector earn a fixed return (W_u).

The human capital accumulation function for an individual in period t+1 is defined as:

$$h_{t+1} = \begin{cases} (\sigma h_t + \underline{h})a_{t+1} \text{When education cost of skilled parent is} & \bar{e} > 0 \\ (\sigma \underline{h} + \underline{h})a_{t+1} \text{ When education cost of unskilled parent is} & \bar{e} > 0 \\ \underline{h}\, a_{t+1} \qquad \text{When education cost of parent is} & \bar{e} = 0 \end{cases} \tag{1}$$

where h_t represents the parent's level of human capital, $\sigma>0$ is a positive constant representing the education technology parameter, $\underline{h}\, a_{t+1}$ denotes the minimum level of human capital attainable, and a represents the individual's ability. Ability (a) lies within $\overline{a} > \underline{a} > 0$ ensuring that $h_{t+1} > 0$ even when $\bar{e} = 0$.

As described by equation (1), parental human capital is assumed to positively enhance the child's acquired human capital level, emphasizing the intergenerational transmission of human capital. It is also assumed that population is constant over time and total population is assumed to have a mass of unity (1) in each period. We have not considered any unemployment in our model[5]. It is assumed that when an individual finds a job, they stop searching for better jobs while skilled or unskilled.

Assumptions

i) Population over the period is constant that is distribution of population is 1 in each period.

ii) We have not considered any unemployment in our model[6].

[5] Our model starts from the t^{th} period. In this model, parents are always assumed to be working because for the survival they need to earn and take care of the family. When child becomes adult in the next period, he/she must join work to fulfill the basic needs of the family. One person lives only for two periods. One period as a child and in the second period as an adult.

[6] Our model starts from the t^{th} period. Parents are here always at the job sector or working because for the survival they need to earn and take care of the family. When child becomes adult in the next period, he/she must join the work to fulfill the basic needs of the family. One person lives only for two periods. One period as a child and in the second period as an adult.

iii) It is assumed that when an individual finds a job, they stop searching for better jobs while skilled or unskilled.

At any point of time there are ‘Φ’ number of labourers (skilled and unskilled) in the economy who participate in the work-force. ‘$\delta\Phi$’ is the fraction of skilled workers in the economy who participate in the search friction. ‘$\Phi(1-\delta)$’ is the fraction of unskilled labour-force who get absorbed in the unskilled sector. Those who are skilled ($\delta\Phi$) but could not find appropriate match at the skilled sector they also get absorbed in the unskilled sector. 'u’ is the number of skilled workers who do not find their job match at the skilled sector, hence get absorbed in the unskilled sector.

3.1 Skilled labour supply

The utility function of an adult depends on household consumption and the expected future earnings of their child. When the child becomes an adult, they may or may not secure a job in the skilled sector despite being skilled. Adults form expectations about their child’s likelihood of obtaining skilled-sector employment and decide whether to invest in their education to maximize utility, subject to a budget constraint. Based on skill-to-job matching, three possible scenarios arise:

1. Skilled individuals are matched with skilled-sector jobs (Ex-Post Segmentation of Skilled Individuals)

2. Skilled individuals are not matched with skilled-sector jobs and are absorbed into the unskilled sector (Cross-Skill Matching of Skilled Individuals)

3. Unskilled individuals work in the unskilled sector (Ex-Post Segmentation of Unskilled Individuals

The utility function of a parent in each case is determined by whether they invest in their child’s education or not, leading to different outcomes for household consumption and the child’s future earnings. Consequently, the budget constraints vary for each case, as they depend on the parent’s earnings and spending decisions, which are influenced by the outcomes of skill-to-job matching and educational investment.

These cases provide a framework for analyzing parental utility functions and identifying the number of skilled individuals in the next period. Variations in skill-to-job matching and investment decisions across households will determine the dynamics of skill formation and labor market outcomes over time.

3.1.1 Expost-Segmentation of Parents

This is the utility function of those parents who are skilled and fortunate enough to be absorbed in the skilled sector. Parents earning is '$W_s h_t$' and they spend '$W_s h_t - \bar{e}$' for consumption purpose at the first (t^{th}) period. Hence, the budget constraint is:

$$C_t + \bar{e} = W_s h_t \tag{2}$$

When the parents decide to invest in their children's education ($\bar{e} > 0$), the expected probability of the parents for their children's skill to job matching in the future $(t+1)^{th}$ period is denoted as 'ρ^e_{t+1}'. The utility function of the parent will be given by as follows:

$$U_t = \alpha \ln(W_s h_t - \bar{e}) + (1-\alpha)\ln\left[\rho^e_{t+1} W_s\left(\sigma h_t + \underline{h}\right)a_{t+1} + (1-\rho^e_{t+1})W_u\right] \qquad \bar{e}>0$$

$$\bar{a} > \underline{a} > 0 \tag{3}$$

When parents who are working in the skilled sector do not invest in their children's education so, $\bar{e} = 0$ their budget constraint is $C_t = W_s h_t$ and the utility function is given by

$$U_t = \alpha \ln W_s h_t + (1-\alpha)\ln W_u\,, \qquad \bar{e} = 0\ , \bar{a} > \underline{a} > 0 \tag{4}$$

As parents do not invest in their children's education, at the first (t^{th}) period they only bear the consumption expenditure. In the second $(t+1)^{th}$ period when the children become adults, they join the unskilled sector and earn W_u.

Now, Comparing utility functions given by equation (3) and equation (4) we get the condition for which parents will prefer to invest in the education of their children. Parents would invest in children's education when (3) ≥ (4).

$$\Rightarrow \alpha \ln(W_s h_t - \bar{e}) + (1-\alpha)\ln\left[\rho^e_{t+1} W_s\left(\sigma h_t + \underline{h}\right)a_{t+1} + (1-\rho^e_{t+1})W_u\right] \geq \alpha \ln W_s h_t + (1-\alpha)\ln W_u \tag{5}$$

Taking First order & Second order differentiation of equation (3) with respect to h_t simultaneously, we have:

$$\frac{dU_t}{dh_t} = \frac{\alpha W_s}{W_s h_t - \bar{e}} + \frac{(1-\alpha)\rho^e_{t+1} W_s \sigma a_{t+1}}{\rho^e_{t+1} W_s(\sigma h_t + \underline{h})a_{t+1} + (1-\rho^e_{t+1})W_u} > 0 \tag{i}$$

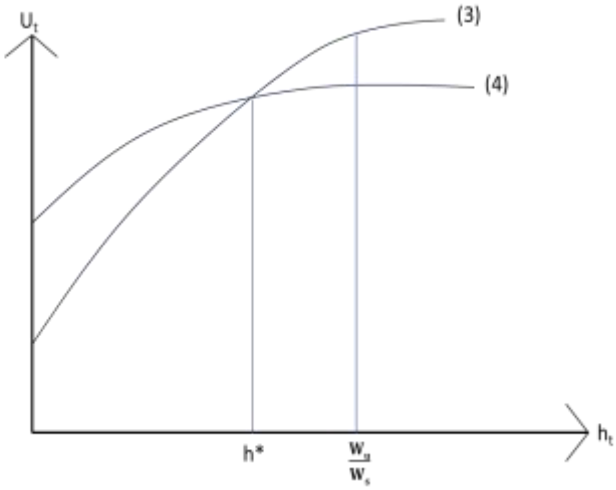
$$\frac{d^2U_t}{dh_t^2} = -\left[\frac{\alpha {W_s}^2}{(W_s h_t - \bar{e})^2} + \frac{(1-\alpha)(\rho^e_{t+1} W_s \sigma a_{t+1})^2}{\{\rho^e_{t+1} W_s\left(\sigma h_t + \underline{h}\right)a_{t+1} + \left(1-\rho^e_{t+1}\right)W_u\}^2}\right] < 0 \tag{ii}$$

Now taking the First order & Second order differentiation of equation (4) with respect to h_t simultaneously, we have :

$$\frac{dU_t}{dh_t} = \frac{\alpha}{W_s h_t} > 0 \qquad \text{(iii)}$$

$$\frac{d^2U_t}{dh_t^2} = = - \frac{\alpha}{W_s h_t^2} < 0$$

(iv)



[7]**Figure 1:** Optimal utility path for the skilled parents at skilled sector

Curve (3) is showing the optimal utility path of skilled sector parents who have invested in their offspring's education and curve (4) is showing the optimal utility path when education cost of skilled sector parents is zero.

h* is the critical level of human capital at which or beyond which equation (5) gets satisfied. h* is the human-capital level of parents at which or beyond which every parent, who is working in the skilled sector, invests in their child's education for given a_{t+1}. The incentive condition to join the skilled sector for skilled individual is $W_s h_t \geq W_u$.

Parents in the skilled sector must have met this incentive condition, and it is reasonable to assume that they desire their child to meet this condition in the future. Therefore, they are assumed to invest in their child's education. Hence, we posit that $\frac{W_u}{W_s}$ always lies to the right of h* for parents in the skilled sector, investing in their child's education is the optimal choice to maximize their utility.

3.1.2 Cross-Skill Matching of Parents

[7] Both the curves are upward rising concave. By comparing equation (i) and (iii) we can see when, h_t is zero, (i) < (iii). Therefore, the curve which is given by equation (i) will start below the curve, which is given by equation (iii). Now, if h_t increases then (iii) will decrease at a higher rate than (i). Hence, they cut each other at some level of parental human capital (say h*) at which parents would indifferent between investing or not investing in their children's education.

Now, we consider the parents who are skilled but do not get jobs at the skilled sector and therefore join the unskilled sector.

$U_t = \alpha\ln(W_u - \bar{e}) + (1-\alpha)\ln\left[\rho^e_{t+1}W_s(\sigma h_t + \underline{h})a_{t+1} + (1-\rho^e_{t+1})W_u\right]$

$\bar{e}>0,\ \bar{a} > \underline{a} > 0$ (6)

This is the utility function of parents who invest in their children's education forming an expectation regarding the future job matching of their children. Though these individuals are skilled but as they are absorbed in the unskilled sector, they earn only reservation wage (W_u). Therefore, the budget constraint of cross-skill matching parents here is:

$C_t + \bar{e} = W_u$ (7)

When a representative parent who is skilled but fails to get job in skilled sector and is absorbed in unskilled sector (cross-skill matching), does not invest in their children's education her utility is given by

$U_t = \alpha\ln W_u + (1-\alpha)\ln W_u \qquad \bar{e} = 0,$ (8)

In this case, as parents do not invest in their children's education, in the second period, when the children become adults, they join the unskilled sector and earn reservation wage. The budget constraint of the parent here is:

$C_t = W_u$ (9)

To find out the condition for which cross-skill matching parents would like to invest in their children's education we compare the equation (6) and (8) below:

$$\ln(W_u - \bar{e})^{\alpha} + \ln\left[\rho^e_{t+1}W_s(\sigma h_t + \underline{h})a_{t+1} + (1-\rho^e_{t+1})W_u\right]^{(1-\alpha)} \geq \ln(W_u)^{\alpha} + \ln(W_u)^{(1-\alpha)}$$

$$\Rightarrow\ \rho^e_{t+1}W_s(\sigma h_t + \underline{h})a_{t+1} \geq W_u\left[\left(\frac{W_u}{W_u - \bar{e}}\right)^{\frac{\alpha}{1-\alpha}} - (1-\rho^e_{t+1})\right]$$

$$\Rightarrow\ h_t \geq \frac{W_u}{\rho^e_{t+1}\sigma W_s a_{t+1}}\left[\left(\frac{W_u}{W_u - \bar{e}}\right)^{\frac{\alpha}{1-\alpha}} - (1-\rho^e_{t+1})\right] - \frac{\underline{h}}{\sigma} = k \qquad (10)$$

From the above derivation it is observed that parents who are working in the unskilled sector, they invest in their child's education when $h_t \geq k$. Here, k is a function of 'ρ^e_{t+1}' and 'a_{t+1}'. Differentiating 'k' w.r.t 'ρ^e_{t+1}' we have

$$\frac{dk}{d\rho^e_{t+1}} = -\frac{W_u}{(\rho^e_{t+1})^2\,\sigma W_s a_{t+1}}\left[\left(\frac{W_u}{W_u - \bar{e}}\right)^{\frac{\alpha}{1-\alpha}} - (1-\rho^e_{t+1})\right] + \frac{W_u}{\rho^e_{t+1}\sigma W_s a_{t+1}} \qquad (11)$$

Note that as a_{t+1} increases k decreases. So, for children born with higher ability requires less parental skill level to satisfy this constraint. So, the cut off k is ability specific.

3.1.3 Expost Segmentation of unskilled-parents

When a representative parent who is unskilled and work at unskilled sector, invests in her child's education

$$U_t = \alpha(W_u - \bar{e}) + (1-\alpha)\ln\left[\rho^e_{t+1}W_s\underline{h}(1+\sigma)a_{t+1} + (1-\rho^e_{t+1})W_u\right] \qquad \bar{e} > 0, \bar{a} > \underline{a} > 0 \tag{12}$$

Here, unskilled parent's earning is spent in the consumption expenditure as well as in the education. Therefore, the budget constraint is:

$$C_t + \bar{e} = W_u \tag{13}$$

When a representative parent who is unskilled and work at unskilled sector and does not invest in their child's education

$$U_t = \alpha \ln W_u + (1-\alpha)\ln W_u \qquad \bar{e} = 0 \tag{14}$$

In this case, her budget constraint is:

$$C_t = W_u \tag{15}$$

Now, to find out the critical level of human-capital at which and beyond which unskilled parents would invest in their children's education we compare equation (12) with (14) and have:

$$\ln(W_u - \bar{e})^\alpha + \ln\left[\rho^e_{t+1}W_s\underline{h}(1+\sigma)a_{t+1} + (1-\rho^e_{t+1})W_u\right]^{(1-\alpha)} \geq \ln(W_u)^\alpha + \ln(W_u)^{(1-\alpha)}$$

$$\Rightarrow \rho^e_{t+1}W_s\underline{h}(1+\sigma)a_{t+1} + (1-\rho^e_{t+1})W_u \geq \left(\frac{W_u}{W_u - \bar{e}}\right)^{\frac{\alpha}{1-\alpha}} W_u$$

$$\Rightarrow a_{t+1} \geq \frac{W_u}{\rho^e_{t+1}W_s(1+\sigma)\underline{h}}\left[\left(\frac{W_u}{W_u - \bar{e}}\right)^{\frac{\alpha}{1-\alpha}} - (1-\rho^e_{t+1})\right] = F \tag{16}$$

'$\underline{h}$' is the minimum level of skill one can acquire, without having any formal training or education. 'F' is the required level of ability of child to incentivize an unskilled parent to invest in the education for his child. But, note that 'F' is dependent on a_{t+1} and it is a decreasing function of a_{t+1}. Uneducated parents who are working in the unskilled sector invest in the education of their child if $a_{t+1} \geq$ F, otherwise, they do not invest in their education.

$$\frac{df}{d\rho^e_{t+1}} = -\frac{W_u}{(\rho^e_{t+1})^2 W_s(1+\sigma)\underline{h}\, a_{t+1}}\left[\left(\frac{W_u}{W_u - \bar{e}}\right)^{\frac{\alpha}{1-\alpha}} - (1-\rho^e_{t+1})\right] + \frac{W_u}{\rho^e_{t+1}W_s(1+\sigma)\underline{h}\, a_{t+1}} \qquad \bar{e} < W_u \tag{17}$$

Note that as a_{t+1} increases F decreases, as ability is individual specific, therefore, as ability increases child would cross the threshold level easily.

3.3 Determination of skilled sector wage through Nash Bargaining

It is assumed that wage in the factor market is determined by the Nash Bargaining. In all the matching models. Bargaining power of the workers are commonly used to determine the wage of the labourers and firms' mark-up. Like Pissarides (2000) model, here also we assume that one firm creates one vacancy. After a successful matching vacancy is filled up. But, unlike Pissarides (2000) model, we assume once a job is created it is not dissolved. Since, there is no unemployment in the economy, we consider reservation wage (W_u) instead of unemployment benefit to calculate the total surplus of a worker, which help to determine the wage of the skilled labourers. This is the basic structural difference of our model from the traditional matching model.

In traditional Matching model wage is determined by using the following form of equation:

$$(W_s h_t - W_u)^{\boldsymbol{\beta}} \, (y_t^s(h_t) - W_s h_t)^{(\mathbf{1-\boldsymbol{\beta}})} \qquad \mathbf{0} < \beta < 1 \tag{22}$$

Where,

β is the worker's bargaining power

(1- β) is firm's bargaining power

Skilled worker's surplus : $W_s h_t - W_u$ **,** $\qquad W_s h_t \geq W_u$ (23)

'$W_s h_t$' is the t[th] period wage of one skilled worker whose acquired skill level is 'h_t'. If a skilled individual gets absorbed in the unskilled sector, then he/she would earn 'W_u', which is less than skilled sector wage. Hence**,** the surplus an individual gets while absorbed in the skilled sector is given by the equation (10).

'W_s' and 'W_u' both are constant but 'W_s' is determined within the system.

Firm's Surplus: $y_t^s(h_t) - W_s h_t$ (24)

'$y_t^s(h_t)$' is the output produced by one skilled individual, whose acquired skill level is h_t. Hence, firm's productivity is '$y_s(h_t)$' from one filled position and in return firm will pay '$W_s h_t$' wage to that skilled worker for the production. Therefore, firm's surplus can be written as equation (24).

β is the worker's bargaining power

(1- β) is firm's bargaining power

The total surplus at t[th] period from each filled position is the sum of firm's surplus and worker's surplus at the skilled sector. Hence, the total surplus is:

$$y_t^s(h_t) - W_u \tag{25}$$

It is assumed that worker's share in total surplus is 'β' [8] fraction of the total surplus,

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[8] In different studies workers' bargaining power & firms' mark-up are simultaneously determined when product and labour markets are imperfectly competitive. In India Pal & Rathore (2016) estimate WBP and FMU

Hence, worker's share in the total surplus is : $\beta[y_t^s(h_t) - W_u]$ (26)

Therefore,

$W_s h_t - W_u = \beta[y_t^s(h_t) - W_u]$

$$W_s h_t = \beta[y_t^s(h_t)] + W_u(1 - \beta) \tag{27}$$

Here, '$W_s h_t$' is the skilled sector wage of a worker, who acquired a skill level (h_t).[9]

'$W_s h_t$' is dependent on the productivity ($y_t^s(h_t)$) of the skilled worker, the reservation wage, bargaining strength of the workers' (β). '$W_s h_t$' is directly related to worker's productivity $y_t^s(h_t)$) and the reservation wage (W_u).

Incentive constraint for a skilled individual to join the skilled sector is $W_s h_t \geq W_u$. Here, we have assumed that positive investment in education ensures that $h_t \geq \frac{Wu}{Ws}$. This condition must be satisfied for all the individuals when education expenditure is positive irrespective of their parents' skill level, that in turn implies $h_{t+1} \geq \frac{Wu}{Ws}$.

4. **Dynamics of Matching**

The output produced by a skilled worker is assumed to be a function of her human capital. In the skilled sector total output produced at t^{th} period, from all filled position is suppose Y_t. Therefore, Total output is dependent on total skill-to-job matching at the skilled sector, and the level of human capital of each individual who gets absorbed in the skilled sector at the particular time point. Hence,

$$Y_t = \sum_{i=1}^{\rho_t \Phi_t \delta_t} y_t^s(h_i) \tag{28}$$

Here we are assuming firms post vacancies in the next period on the basis of total employers' surplus generated in the previous period. So, the number of vacancies in second period is a $'(1-\beta)'$ fraction of total surplus. Hence, vacancy of the second period that is $(t+1)^{th}$ period is following:

$$V_{t+1} = \mu(1-\beta)(Y_t - \rho_t \delta_t \Phi_t W_u) \qquad \mu>0 \ , \ (Y_t - \rho_t \delta_t \Phi_t W_u) > 0 \tag{29}$$

Therefore, we can write probability of matching at the second period by substituting equation (29) in equation (20) in the following:

---

simultaneously using WBP. Then average level of WBP in 1981- 1985 was 0.0666 and reduced to 0.0194 during 2000-2007. It has decreased due to the discontentment amongst workers.

[9] $y_t^s(h_t)$ is a increasing function of h_t, in such a way that W_s is constant.

Here, $y_t^s(h_t) = \frac{kh_t - W_u(1-\beta)}{\beta}$, where $k = \frac{\beta y_t^s(h_t) + W_u(1-\beta)}{h_t}$

As, WBP(workers' bargaining power) increases firm's mark-up would decrease and it incentivizes the worker to produce more at given level of human capital (h_t).

$$\boldsymbol{\rho_{t+1}} = \frac{[\mu(1-\beta)\,(Y_t - \rho_t\delta_t\Phi_t W_u)]^{(1-\theta)}}{(\delta\Phi)_{t+1}^{(1-\theta)}} \tag{30}$$

This is the dynamic equation of the model. In the subsequent section of the model, we will determine the skilled labour-force in the second period which, in turn will ascertain the probability of matching at the skilled sector in the second period or (t+1)th period.

Therefore, the total fraction of skilled labour at (t+1)th period is following:

$$\delta_{t+1}\Phi_{t+1} = \rho_t\delta_t\Phi_t + (1-\rho_t)\delta_t\Phi_t\left[\int_{\underline{a}}^{\overline{a}}\int_{k(a_{t+1},\rho_{t+1})}^{\infty} f(h)j(a)dhda\right] + \left(\frac{\overline{a}-F(\rho_{t+1})}{\overline{a}-\underline{a}}\right)\Phi_t(1-\delta_t) \tag{31}$$

where:

'$\rho_t\delta_t\Phi_t$' refers to all the skilled sector parents who invested in their child's education. This means children of all skilled sector parents are included as skilled individuals in the second period.

$\int_{\underline{a}}^{\overline{a}}\int_{k(a_{t+1},\rho_{t+1})}^{\infty} f(h)j(a)dhda$ represents the children whose parents are skilled but employed in the unskilled sector jobs and parents' skill level is 'k' or more than 'k' and ability of the children lie between the range $\underline{a} > \underline{a} > 0$.

'$\left(\frac{\overline{a}- F(\rho_{t+1})}{\overline{a}-\underline{a}}\right)\Phi_t(1-\delta_t)$' represents those children, who have ability $a_{t+1} \geq$ F but their parents are unskilled and employed in the unskilled sector at the initial period.

Here, human capital is assumed to follow Pareto distribution with parameter of minimum human capital m and inequality parameter g. The probability density function of human capital is given as follows;

$$f(h) = \left(\frac{m}{k}\right)^g$$

Ability is assumed to follow uniform with minimum value $\underline{a}$ and maximum value $\overline{a}$ The probability density function of ability is given as follows:

$$j(a) = \frac{1}{\overline{a}-\underline{a}}$$

We assume that f(h) follows the pareto distribution.

Therefore, the number of individuals having human capital level above 'k' is given by,

$$\int_k^{\infty}\frac{gm^g}{h^{g+1}}dh \qquad h \geq m$$

$$= gm^g\left[\frac{h^{-g}}{-g}\right]_k^{\infty}$$

$$= \left(\frac{m}{k}\right)^g \tag{32}$$

Here,

g = inequality parameter

m = minimum level of human-capital. It is a parameter

Substituting $\delta_{t+1}\Phi_{t+1}$ given by equation (31) into equation (30) the dynamic relation of skill-to-job matching across generations is obtained. The numerator represents the number of job vacancies in the $(t+1)^{th}$ period, which is a fraction (μ) of the total surplus generated by employers/firms in the t^{th} period. The denominator corresponds to the total skilled labor force in the $(t+1)^{th}$ period, as derived from equation (31). The relation also dependent on elasticity of substitution of vacancy $(1 - \boldsymbol{\theta})$.

5. Theoretical Findings:

Skilled parents employed in the skilled sector consistently invest in their child's education. In contrast, for individuals who are despite of being skilled employed in the unskilled sector, make investment decisions based on their own level of human capital. The threshold level of human capital at which these parents choose to invest depends on the expected probability of their child securing a skilled-sector job in the future and the child's inherent ability. However, for unskilled parents, the decision hinges on whether the child's ability exceeds the critical threshold. This creates a unique intergenerational relationship between skill-to-job matching probabilities.

Implicit Relationship: The equation depicting the dynamic relationship between ρ_t involves ρ_{t+1} is a nonlinear complicated equation and we illustrate the relation empirically in next section.

6. Empirical Analysis

This study provides a focused analysis of intergenerational skill-to-job matching within India's formal, informal and regular salaried/wage employment sector, using data from the 2022-23 Periodic Labour Force Survey (PLFS). By concentrating on this specific segment—a substantial and economically significant portion of the Indian workforce—we aim to provide a rigorous and in-depth examination of the dynamics of skill transmission and matching. While this approach limits the generalizability of findings to the entire Indian labour market, it enables a more detailed analysis of skill-to-job matching within this crucial sector, revealing patterns that might be masked in broader, less homogeneous samples. Future research should investigate the extent to which these patterns extend to female-dominated sectors.

Based on the theoretical model, which posits that parental expectations about children's future skill-to-job matching probabilities influence educational investment decisions and consequently shape intergenerational skill and employment outcomes, we formulate the following testable hypotheses:

Hypothesis 1: Intergenerational Skill Transmission through Parental Human Capital and Expectations

We hypothesize a positive association between parental human capital (as proxied by parental skill level) and offspring skill levels, controlling for other factors influencing a child's skill acquisition. This relationship reflects the transmission of human capital across generations and the indirect influence of parental expectations about the returns to skilled labor on their investment in children's education.

Hypothesis 2: Intergenerational Skill-to-Job Matching and Parental Experience

We hypothesize a positive association between parental skill-to-job matching outcomes and the likelihood that their children will experience similar (appropriate) skill-to-job matches, controlling for other factors. This hypothesis reflects the model's prediction that parental experiences (including successful skill-to-job matching) influence their expectations and investment decisions, shaping their children's probability of obtaining a comparable job match. However, we expect this association to be moderated by the availability of jobs in the skilled sector; a large number of skilled workers in relation to the number of suitable jobs may attenuate this effect. We anticipate a non-linear relationship, with the positive association potentially weakening or even reversing at high levels of skilled employment in the parental generation. This is because high parental success in the skilled sector does not automatically translate into a similar likelihood for children if the number of skilled jobs does not match the growing skilled workforce.

7. Data and Methodology:

The analysis utilizes unit-level data from the PLFS (2022-23), a nationally representative survey of the Indian workforce. The sample includes 14,006 observations of male workers in regular salaried/wage employment, self-employed and casual labourers aged 35-65 for the first generation and 15-47 for the second generation. A minimum age gap of 18 years was used to define the generations. Using the data, we explore the intergenerational dynamics of skill-to-job matching and skill mobility across various matching types.

The PLFS employs a rotational panel sampling technique in urban areas and a cross-sectional approach in rural regions. Urban households are revisited four times for data collection, while independent quarterly estimates are generated for rural areas.

Skill Level: Skill levels are categorized into four levels: Unskilled (0), Low-skilled (0.25/1), Medium-skilled (2/2.5), and High-skilled (3/4), following the skill definitions detailed in Table A1 of the Appendix. This operationalization is based on the Empirical Method (EM) as proposed by Kiker et al. (1997). We employed the EM because skill levels defined by ISCO-2008 and NCO-2015 correspond to broad occupational divisions, which might not capture the wide range of skills within each division. The EM, using the modal skill level for each 3-digit occupational group, addresses this limitation. The specific criteria for each skill level based on education, vocational training, and work experience are detailed in Table A1 in the Appendix. Potential measurement error in skill levels is acknowledged, and we discuss the limitations this introduces.

Skill-to-Job Matching: Skill-to-job matches are categorized into five types: SS (appropriate match), LH (low skill in high-skill job), HL (high skill in low-skill job), UU (unskilled in unskilled job), and SU (skilled in unskilled job). These categories are further grouped into Skilled and Unskilled sector matches for the subsequent analysis.

Control Variables: To control for potential confounding factors, the analysis includes individual-level variables such as son age, son age-square, father age, father age-square, son's social security benefit dummy, son's paid leave dummy, son's enterprise size dummy, father's matching category dummy, Table A6 in the Appendix), and household-level variables, such as caste dummies, religion dummies, sector of residence dummy.

Focusing exclusively on the working population within the age range of 15–65 years, our study analyses all occupational categories as outlined in the National Classification of Occupations (NCO). Given the low female labour force participation rate in India, our sample is restricted to males to mitigate selection bias concerns. To capture the current activity status of an individual here we have considered usual principal activity status of each house-hold member. The principal activity status (PS) is the activity that a person spent the most time during the 365 days prior to the survey date. Here to select the working group in the total population Principal activity status of the population has been considered.

We analysed data for individuals categorized as regular salaried or wage employees and casual labourers further dividing them into three sub-groups:

- Regular Salaried Persons
- Self-Employed Individuals
- Casual labourers with daily or weekly earning

Our analysis excluded unemployed population such as non-paid house-help, students, pensioners, begging etc. In the following table we have tabulated our sample data set briefly.

Table-1: **Construction of Son-Father Sample**

Total Number of Population Surveyed in 2022-23 in PLFS	4,19,512
Unemployed Population	2,49,422
Male Working population in the age group 15-65	1,04,395
Identification of Father/1st Generation	69,991
a) Individual is head of the house-hold and male	69,531
b) Individual is Spouse of the head of the house-hold and male	460
Identification of Son/ 2nd Generation	30,424
a) Married child of the head of the house-hold and male	16,686
b) Unmarried child of the head of the house-hold and male	13,738
Father Age between 35- 65	54,695
Son Age between 15-47	29,062
Final sample size of Father-Son Pair at same house-hold and age difference 18 years	**14,006**
Number of Fathers in the final Sample	11,367
Number of Sons in the final Sample	14,006

Source: author's own calculation

Skill-to-Job Matching: Skill-to-job matches were categorized using the Empirical Method (EM). Skill levels were derived from education, vocational training, and years of schooling; required skill levels were determined using the modal skill level for each 3-digit occupation group. This modal approach (Kiker et al., 1997) addresses potential biases from skewed skill distributions within broader occupational categories, unlike the mean method and the limitations of using ISCO-2008/NCO-2015 1-digit classifications. Matches were classified into five categories ('SS', 'LH', 'HL', 'UU', 'SU'), then grouped into four skill levels ('Unskilled', 'Low-skilled', 'Medium-skilled', 'High-skilled').

Intergenerational Analysis: Two generations were defined by household relationships: Generation-1 (family head/spouse, 35-65 years) and Generation-2 (children, 15-47 years), maintaining a minimum 18-year age gap. The intergenerational transmission of skill-to-job matching was analyzed using:

1. Distributional Analysis: Table 2 below presents the distribution of skill-to-job matching categories across generations, revealing patterns in intergenerational mobility.

2. Multinomial Logistic Regression: To investigate intergenerational associations in skill levels and skill-to-job matching mobility, we used multinomial logistic regression.

Model 1: Intergenerational Skill Level Association: This model assessed the association between parental (Generation-1) and offspring (Generation-2) skill levels. The model is specified as:

$$\ln(P_i/P_u) = \beta_0 + \beta X_i + u_i$$

Where:

a) P_i is the probability of Generation-2 achieving skill level i.

b) P_u is the probability of Generation-2 achieving the unskilled skill level (reference category).

c) (P_i/P_u) it measures the ratio of the probability that generation-2 will be achieved different level of skill than that of their generation-1 to the probability that both the generation will remain unskilled.

d) X_i represents predictor variables (Generation-1 skill level dummies, Generation-2 age, Generation-2 age², caste dummies, sector of residency dummies, enterprise size dummies, religion dummies).

e) β_0, β are model coefficients.

f) u_i is the error term.

Model 2: Intergenerational Skill-to-Job Matching:

Intergenerational Skill-to-Job Matching Mobility: A second multinomial logistic regression assessed the mobility of skill-to-job matching categories across generations:

$$\ln(\pi_j(x_i)/\pi_k(x_i)) = a_1 + aZ_i + u_i$$

Where:

a) $\pi_j(x_i)$ is the probability of a son achieving skill-to-job matching category j.

b) $\pi_k(x_i)$ is the probability of a son in the unskilled (UU) category (reference).

c) $\pi_j(x_i)/\pi_k(x_i)$ it is showing the odds of 2nd generation being in the skilled sector or unskilled sector while skilled to the odds of being in the unskilled sector while unskilled like the 1st generation.

d) Z_i includes socio-economic and individual factors (son's age, son's age^2, caste dummies, sector of residency dummies, enterprise size dummies, religion dummies).

e) a_1, a are coefficients.

f) u_i is the error term.

This model examined the predictive power of parental skill-to-job matching on offspring skill-to-job matching. The model structure mirrors Model 1, but the dependent variable is Generation-2's skill-to-job matching category (with 'UU' as the reference category), and X_i includes Generation-1's skill-to-job matching category, along with the control variables.

Model 3: Predicted Probability of Skilled Matches: A separate multinomial logistic regression predicted the probability of skilled individuals achieving appropriate skill-to-job matches ('SS' category) within the skilled sector for each generation. This model also uses similar predictors to Model 1 and Model 2.

The results from these models were visualized using scatter plots to illustrate the intergenerational relationships between the probabilities.

8. Results

This section presents the empirical findings, examining the intergenerational transmission of skill and skill-to-job matching, and relating them to the theoretical model's predictions. The analysis uses three models: Model 1 assesses intergenerational skill level mobility, Model 2 examines the intergenerational transmission of skill-to-job matching, and Model 3 predicts the probability of skilled matches for each generation.

8.1 Skill Mismatch in the Skilled Sector

Our analysis revealed a significant discrepancy between theoretical expectations and empirical observations regarding skill-to-job matching in skilled sectors. While the theoretical model predicted "ex-post segmentation" (skilled workers in skilled sectors), our findings indicate a substantial portion of skilled workers are employed in jobs mismatched to their skill levels. To capture this, we categorized skilled sector matches into three groups:

1. SS: Appropriate match (acquired and required skills align).
2. LH: Low skill-high skill mismatch (acquired skills below job requirements).
3. HL: High skill-low skill mismatch (acquired skills exceed job requirements).

The 'SS' category represents the ideal match or ex-post segmentation. However, a substantial number of individuals fell into the 'LH' and 'HL' categories, indicating significant skill mismatches within the skilled sector.

8.2. Intergenerational Skill-to-Job Matching:

Table 2 shows the distribution of skill-to-job matching categories across two generations. Several key patterns emerge:

The overall proportion of skilled individuals (SS, LH, HL, SU combined) increased significantly between generations (43.26% increase), while the proportion of unskilled individuals (UU) decreased by 43.26%. This finding supports the model's overall prediction of an increasing skilled labor force.

Despite the overall increase in skilled employment, this growth is significantly driven by skill mismatches in the LH (2.83% increase) and particularly HL (32.53% increase) categories. The proportion of those with appropriate matches (SS) increased by only 8.58%, suggesting that improvements in skill levels are not necessarily translating into a commensurate rise in appropriate skill-to-job matches. More than half of the increase in skilled individuals are employed in mismatched jobs. This mismatch underscores a crucial limitation of solely focusing on skill development without addressing the corresponding need for job creation in the appropriate sectors.

Examination of the individual cells in Table 2 shows a clear pattern of intergenerational transmission of skill-to-job matching types. For example, a high proportion of individuals from UU households in the first generation continue to be in UU in the second generation (25.07%). Similarly, a high proportion of those in the HL category in the first generation see their offspring in the HL category (14.34%). This suggests that skill mismatches persist across generations, highlighting the need for proactive policy interventions.

Table 2: Intergenerational Skill-to-Job Matching in India (2022-23)

	2ND GENERATION'S MATCHING					
1ST GENERATION'S MATCHING	UU	SS	LH	HL	SU	Total
UU	25.07%	5.24%	3.30%	36.86%	1.14%	71.61%
SS	0.13%	0.84%	0.10%	0.86%	0.01%	1.94%
LH	0.16%	0.67%	0.27%	1.36%	0.04%	2.49%
HL	2.53%	3.38%	1.48%	14.34%	0.14%	21.85%
SU	0.47%	0.39%	0.17%	0.96%	0.11%	2.11%
TOTAL	28.35%	10.52%	5.32%	54.38%	1.44%	100.00%

Source: author's own calculation

8.3 Intergenerational Skill Level Association:

Table 3 illustrates intergenerational skill mobility. For example, having a father with low skills (instead of being unskilled) reduces a son's likelihood of remaining unskilled by 21.5%, while increasing the probabilities of attaining low-skill, medium-skill, and high-skill levels by 11.3%, 5.3%, and 5%, respectively. If the father is medium-skilled rather than low-skilled, the son's likelihood of remaining medium-skilled rises by 7.9%, and the probability of attaining high-skill increases by 21%. Sons of high-skilled fathers are most likely to be high-skilled, with a 41.5% probability. This highlights notable skill mobility across generations.

Table 3: Marginal Effects of Parental Skill Level on Son's Skill Level

Observations-13747	*2nd Generation Skill level*			
Pseudo $R^2 = 0.1045$				
1st Generation Skill Level	Marginal Probabilities(SE)			
	Unskilled	Low-Skilled	Medium Skilled	High Skilled
Low Skilled	-0.215***(0.008)	0.113***(0.011)	0.053***(0.010)	0.050***(0.008)
Medium Skilled	-0.215***(0.008)	-0.067***(0.019)	0.079***(0.020)	0.210***(0.018)
High Skilled	-0.209***(0.020)	-0.178***(0.019)	-0.029(0.020)	0.415***(0.022)

***1% level of significance, ** 5% level of significance, *10% level of significance

Source: author's own calculation

8.4 Intergenerational Skill-to-Job Matching Mobility:

Table 4 presents the results of Model 2 and examines the marginal effects of parental skill-to-job matching on sons' skill-to-job matching, relating to Hypothesis 2. The reference category is "UU". The results indicate a significant association between parental skill-to-job matching and their sons' outcomes. The probability of a son achieving an appropriate match (SS) is highest when the father also had an appropriate match (19.1%). However, parental mismatches (LH and HL) significantly influence sons' probabilities of ending up in similar or even worse mismatches. For instance, fathers with LH matches significantly increase the probability of their sons ending up in LH and HL matches (8.9% and 12%, respectively). Similarly, fathers with HL matches significantly increase the probability that their sons will also have HL matches (16.7%).

Table 4: Marginal Effects of Parental Skill-to-Job Matching on Son's Skill-to-Job Matching

Observations-10,346	*2nd Generation Matching*
Pseudo $R^2 = 0.1466$	

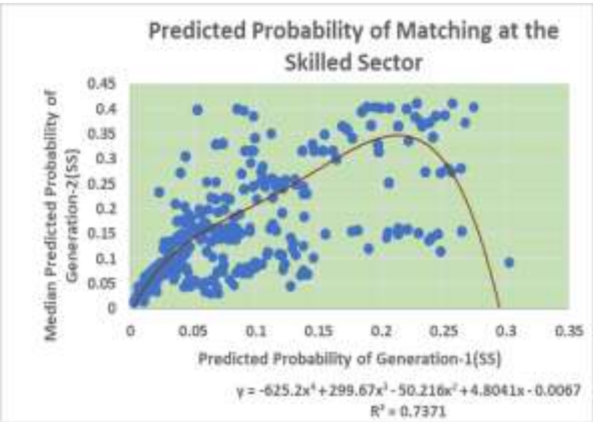
1st Generation Matching	Marginal Probabilities(SE)				
	UU	SS	LH	HL	SU
SS	-0.179***(0.038)	0.191***(0.027)	-0.006(0.015)	0.003(0.042)	-0.008(0.008)
LH	-0.258***(0.022)	0.089***(0.021)	0.055***(0.019)	0.120***(0.033)	-0.006(0.007)
HL	-0.207***(0.009)	0.036***(0.007)	0.013**(0.006)	0.167***(0.011)	-0.010***(0.002)
SU	-0.065**(0.030)	0.048**(0.020)	0.020(0.016)	-0.035(0.034)	0.033**(0.015)

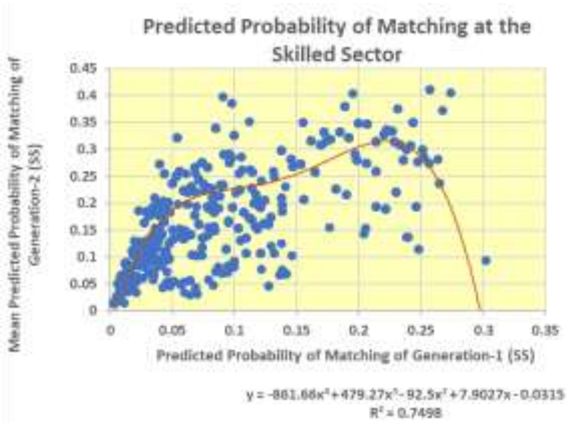
***1% level of significance, ** 5% level of significance, *10% level of significance
Source: Author's own calculation

8.5 Predicted Probability of Skilled Matches:

Finally, we predicted the probability of skilled individuals achieving appropriate skilled sector matches ('SS' category) using separate multinomial logistic regressions for each generation. The results are presented graphically in Figures 1 and 2, indicating an inverted-U relationship between the predicted probabilities of 'SS' matching for fathers and sons. The relationship demonstrates that while higher skill-to-job matching probabilities for fathers initially increase a son's 'SS' matching likelihood, the effect eventually diminishes as higher skilled father proportions increase the rate of skilled job applicants outpacing the job supply.

Figures 1 & 2: Predicted Probability of Skilled Matches





In Figure-1 median value of predicted probability of skilled sector matching of generation-2 (SS category) is plotted graphically against corresponding predicted probability of matching of first generation(SS category). In Figure-2 average value of predicted probability of skilled sector matching of generation-2(SS category) is plotted against corresponding to the predicted probability of matching of first generation(SS category). The shape of the curve is non-linear concave. It suggests that initially, when a father is matched in the ‘SS’ category, the predicted probability of the second generation being matched in the same category increases. However, beyond a certain point, as the predicted probability of the father’s matching under the ‘SS’ category continues to rise—leading to an increase in the number of skilled individuals in the next generation (shown in the Table:A5 in the Appendix) and the probability of the son obtaining an appropriate match in the skilled sector decreases. This can happen when the number of vacant positions in the skilled sector fails to match the growth in the skilled population. As a result, many skilled individuals are unable to secure suitable matches in the skilled sector. This indicates that when the rate of job vacancy growth outpaces the rate of growth in skilled individuals, the probability of skill-to-job matching improves across generations, and vice-versa.

9. Conclusion and Policy Prescriptions:

This paper presents an overlapping generations household economy model to examine the effects of a growing skilled labor force and intergenerational job matching. The model assumes that children’s human capital accumulation is influenced by parental investment, which contributes to the future skilled labor force and job matching. Job matching depends on the availability of vacancies, determined by the previous period’s firm surplus. The empirical analysis captures this skill-to-job matching mechanism and its intergenerational transmission. Key theoretical and empirical findings are summarized below.

Theoretical Findings:

Skilled parents working in the skilled sector consistently invest in their child’s education, while those in the unskilled sector base their decision on their human capital level and the child’s ability. Parental investment in education influences the future skilled labor force and affects job-matching probabilities in subsequent generations. However, for unskilled parents, the decision hinges on whether the child’s ability exceeds the critical threshold. This creates a unique intergenerational relationship between skill-to-job matching probabilities.

Empirical Results:

When parents are well-matched to skilled-sector jobs, a higher percentage of individuals in the next generation become skilled (Appendix, Table A5). Initially, an increase in the first generation’s matching probability leads to an increase in the next generation’s probability at the skilled sector. However, beyond a certain point, the relationship becomes nonlinear and concave. This implies that when the growth of the skilled labor force outpaces the growth of skilled-sector vacancies, the probability of matching for future generations declines.

The findings emphasize that the core issue lies in the creation of skilled-sector jobs. Increasing skill development alone will not address unemployment or underemployment. Job creation for various skill levels must accompany efforts to enhance skills. Skilled parents consistently aim to educate their children with the expectation that they will secure skilled-sector jobs in the future. However, for sustainable economic progress, the rate of job creation must align with the rate of skill development.

The government should focus on fostering a business-friendly environment to expand skill-intensive industries. This alignment will ensure that jobs are available at levels corresponding to the skills of the labor force, enhancing employment outcomes and economic growth.

Our empirical findings, while partially supporting the model's predictions, reveal significant non-linear effects and underscore the prevalence of skill mismatches. Although intergenerational continuity in skill and job matching is evident, the tight correlation between parental skill and offspring outcomes is significantly moderated by the state of the skilled labor market. The substantial number of skill mismatches in the second generation emphasizes the crucial need to complement skill development initiatives with policies aimed at creating adequate skilled-sector jobs.

The results expose a key imbalance in the Indian labour market: a widening gap between a burgeoning supply of skilled workers and insufficient demand. Simply increasing skill development without a commensurate rise in high-skill job opportunities will likely exacerbate unemployment and underemployment, particularly given the considerable investment made by skilled parents in their children's education.

To achieve sustainable economic growth and mitigate skill mismatches, a concerted policy response is required, focusing on:

Individuals should strive to attain at least a medium skill level, as this can significantly raise the overall skill level of the economy. When public education expenditure complements private investment in education, it ensures that skill development within the economy becomes sustainable over the long term. Proactive policies must stimulate job creation in skilled sectors through industry-specific incentives, infrastructure improvements, and support for innovation. Careful labour market forecasting is crucial for directing investment towards sectors with the highest absorption capacity for skilled workers. This approach ensures that increased skill supply is met with sufficient demand. Beyond job creation, active labour market policies are essential: improving job matching efficiency through enhanced placement services and career counselling; providing retraining and upskilling opportunities to address skill mismatches; and facilitating smoother intersectoral transitions to alleviate underemployment among skilled individuals in low-skill jobs. A supportive regulatory framework that encourages investment and entrepreneurship, particularly in skill-intensive industries, is vital. This requires streamlining regulations, reducing bureaucratic obstacles, and improving access to finance. The education system should adapt to evolving labour market demands. Curricula should reflect current and projected skill requirements, ensuring that educational investments translate effectively into marketable skills.

This integrated approach—combining strategic skill development with targeted job creation and robust active labour market policies—is paramount for India's sustainable economic progress. Ignoring the need for a balanced increase in both skilled workers and skilled jobs risks perpetuating skill mismatches and hindering overall economic development.

There are few limitations in the theoretical part of the model. It assumes uniform job-matching probabilities, but it does not account for the comparative advantage of high-skilled individuals in the job sector. Education expenditure considered to be lump-sum for the simplicity of the analysis.

In the empirical part this study is limited by its focus on male workers, potentially introducing gender bias and affecting the generalizability of findings to the entire Indian population. Additionally, the skill classification, while employing the Empirical Method, may not fully capture the multifaceted nature of skills across all sectors due to limitations in occupational categorizations. Future research should utilize more representative data encompassing female workers and a broader range of occupations to overcome these limitations and further illuminate the complex dynamics of intergenerational skill transmission and job matching in India.

Appendix

Table A1: Skill Level Definitions Based on Education, Training, and Experience

Skill Definitions-

Skill Code	Code specification
Unskilled(skill-level=0)	Education below Secondary level or no formal vocational training received
Skill level =0.25	Below Secondary level but have some formal vocational training
Skill Level =1	Secondary level of education with or without formal vocational training
Skill Level =2	Higher Secondary level or diploma certificate in technical education and 11-12years of schooling with or without vocational training
Skill Level = 2.5	Diploma certificate in technical education and schooling years more than 12 years but less than 15 years with or without vocational certificate
Skill Level = 3	Graduation Level with or without formal vocational Training
Skill Level = 4	Post Graduation and above with or without formal vocational training

Table A2: Skill-to-Job Matching Category Codes and Definitions

Skill-to-job Matching Codes	
Matching Code	Code Name
UU	Unskilled labour force at Unskilled sector
SU	Skilled workers at unskilled sector job
SS	Skilled Labour at skilled Sector
LH	Low skilled labour at high skilled occupation or acquired skill is less than required skill level
HL	High Skilled workers at low skilled Occupation or acquired skill is more than required skill level

Table A3: NCO (2015) Occupational Classification: Skill Level Codes and Modal Skill Levels (2022-2023)

NCO (2015 Classification)				2022-2023
Occupation Group	Occupation Code (Group)	Occupation Division	Required Skill (Division-	Modal Skill

			wise specified)	
Legislators & Senior Officials	111	1	not Defined	3
Managing Directors & Chief Executives	112	1	not Defined	0
Business Services & Administration Managers	121	1	not Defined	3
Sales Marketing & Development Managers	122	1	not Defined	3
Production Managers in Agriculture, Forestry & Fisheries	131	1	not Defined	0
Manufacturing Mining, Construction & Distribution Managers	132	1	not Defined	3
Information & Communication Technology Services Manager	133	1	not Defined	3
Professional Services Managers	134	1	not Defined	3
Hotel & Restaurant Managers	141	1	not Defined	2
Retail & Wholesale Trade Managers	142	1	not Defined	0
Other Services Managers	143	1	not Defined	3
Physical & Earth Science Professionals	211	2	4	3
Mathematicians, Actuaries & Statisticians	212	2	4	3
Life Science Professionals	213	2	4	4
Engineering Professionals (Excluding Electrotechnology)	214	2	4	3
Electrotechnology Engineers	215	2	4	3
Architects, Planners, Surveyors & Designer	216	2	4	3
Medical Doctors	221	2	4	4
Nursing & Midwifery Professionals	222	2	4	3
Traditional & Complementary Medicine	223	2	4	3
Paramedical Practitioners	224	2	4	3
Veterinarians	225	2	4	3
Other Health Professionals	226	2	4	3
University & Higher Education Teachers	231	2	4	4
Vocational Education Teachers	232	2	4	3
Secondary Education	233	2	4	3
Primary School & Early Childhood Teachers	234	2	4	3

Other Teaching Professionals	235	2	4	3
Finance Professionals	241	2	4	3
Administration Professionals	242	2	4	3
Sales , Marketing & Public Relations Professionals	243	2	4	3
Software & Application Developers, & Analyst	251	2	4	3
Database & Network Professionals	252	2	4	3
Legal Professionals	261	2	4	3
Librarians, Archivists & Curators	262	2	4	4
Social & Religious Professionals	263	2	4	0
Authors & Journalist & Linguist	264	2	4	3
Creative & Performing Artists	265	2	4	0
Physical & Engineering Science Technicians	311	3	3	3
Mining, Manufacturing & Construction Supervisors	312	3	3	3
Process Control Technicians	313	3	3	0
Life Science Technicians & Related Associate Professionals	314	3	3	3
Ship & Aircraft Controllers, & Technicians	315	3	3	3
Medical & Pharmaceutical Technicians	321	3	3	3
Nursing & Midwifery Associate Professionals	322	3	3	2
Traditional & Complementary Medicine Associate Professionals	323	3	3	3
Veterinary Technicians & Assistants	324	3	3	3
Other Health Associate professionals	325	3	3	3
Financial & Mathematical Associate Professionals	331	3	3	3
Sales & Purchasing Agents & Brokers	332	3	3	3
Business Service Agents	333	3	3	3
Administrative & Specialized Secretaries	334	3	3	3
Government Regulatory Associate Professionals	335	3	3	3

Legal, Social & Religious Associate Professionals	341	3	3	3
Sports & Fitness Workers	342	3	3	3
Administrative Associate Professionals	343	3	3	3
Information & Communication Technology User Support Technicians	351	3	3	3
Telecommunication & Broadcasting Technicians	352	3	3	3
General office Clerks	411	4	2	3
Secretaries	412	4	2	3
Keyboard Operators	413	4	2	3
Tellers, Money Collectors & Related Clerks	421	4	2	3
Client Information Workers	422	4	2	3
Numerical Clerks	431	4	2	3
Material Recording & Transport Clerks	432	4	2	3
Other Clerical Support Workers	441	4	2	0
Travel Attendants, Conductors & Guides	511	5	2	2
Cooks	512	5	2	0
Waiters & Bartenders	513	5	2	0
Hairdressers, Beauticians & Related Workers	514	5	2	0
Building & Housekeeping Supervisors	515	5	2	0
Other Personal Services Workers	516	5	2	0
Street & Market Salespersons	521	5	2	0
Shop Salespersons	522	5	2	0
Cashier & Ticket Clerks	523	5	2	3
Other Sales Workers	524	5	2	0
Child Care Workers & Teachers' Aides	531	5	2	3
Personal Care Workers in Health Services	532	5	2	1
Protective Service Workers	541	5	2	0
Market Oriented Skilled Agricultural Workers	611	6	2	0
Animal Producers	612	6	2	0
Mixed Crop & Animal Workers	613	6	2	0

Forestry & Related Workers	621	6	2	0
Fishery Workers, Hunters & Trappers	622	6	2	0
Subsistence Crop Farmers	631	6	2	0
Subsistence Livestock Farmers	632	6	2	0
Subsistence Mixed Crop & Livestock Farmers	633	6	2	0
Subsistence Fishers, Hunters, Trappers & Gatherers	634	6	2	0
Building Frame & Related Trade Workers	711	7	2	0
Building Finishers & Related Trades Workers	712	7	2	0
Painters, Builders, Structure Cleaners & Related Trades Workers	713	7	2	0
Sheet & Structural Metal Workers, Moulders & Welders, & Related Workers	721	7	2	0.25
Blacksmiths, Tool Makers & Related Trades Workers	722	7	2	0
Machinery Mechanics & Repairer	723	7	2	0
Handcraft Workers	731	7	2	0
Printing Trades Workers	732	7	2	2
Electrical Equipment Installers & Repairers	741	7	2	2
Electronics & Telecommunication Installer & Repairer	742	7	2	2
Food Processing & Related Trade Workers	751	7	2	0
Wood Treaters, cabinet Makers & Related Trades Workers	752	7	2	0
Garment & Related Trades Workers	753	7	2	0
Other Craft & Related Workers	754	7	2	0
Mining & Mineral Processing Plant Operators	811	8	2	0
Metal Processing & Finishing Plant Operators	812	8	2	1
Chemical & Photographic Products Plant & Machine Operators	813	8	2	2
Rubber, Plastic & Paper Products Machine Operators	814	8	2	0

Textile, Fur & Leather Products Machine Operators	815	8	2	0
Food & Related Products Machine Operators	816	8	2	0
Wood Processing & Papermaking Plant Operators	817	8	2	0
Other Stationary Plant & Machine Operators	818	8	2	0.25
Assemblers	821	8	2	2
Locomotive Engine Drivers & Related Workers	831	8	2	3
Car, Taxi & Van Drivers	832	8	2	0
Heavy Truck & Bus Drivers	833	8	2	0
Mobile Plant Operators	834	8	2	0
Ships' Deck Crews & Related Workers	835	8	2	2
Domestic, Hotel & Office Cleaners & helpers	911	9	1	0
Vehicle, Window, Laundry & Other Hand Cleaners	912	9	1	0
Agricultural, Forestry & Fishery Labourers	921	9	1	0
Mining & Construction Labourers	931	9	1	0
Manufacturing Labourers	932	9	1	0
Transport & Storage Labourers	933	9	1	0
Food Preparation Assistants	941	9	1	0
Street & Related Service Workers	951	9	1	0
Street Vendors (Excluding Food)	952	9	1	0
Refuse Workers	961	9	1	0
Other Elementary Workers	962	9	1	0

Table A4: Skill Level Definitions

Skill Definitions	
Skill Code	Code specification
Unskilled (skill-level = 0)	Education below Secondary level and no formal vocational training received

Low skill (skill level =0.25 / 1)	Only up to Secondary level of education but no vocational or technical training or up to middle school plus formal /vocational training
Medium Skill (skill level =2 or 2.5)	Up to H.S. level of education or may have diploma certificate in technical education and schooling years 11-14.
High Skill (skill level =3 or 4)	Any degree which considers graduation and above level of education

Table A5: Skill Level Distribution by Generation and Skill-to-Job Matching Category

Skill-level of 2nd Generation					
1st Generation's Matching	Unskilled	Low-Skilled	Medium-Skilled	High-Skilled	Total
UU	26.21%	20.93%	14.28%	10.19%	71.61%
SS	0.14%	0.17%	0.34%	1.29%	1.94%
LH	0.19%	0.44%	0.69%	1.16%	2.49%
HL	2.66%	7.32%	5.37%	6.50%	21.85%
SU	0.58%	0.46%	0.47%	0.60%	2.11%
Total	29.79%	29.32%	21.15%	19.75%	100.00%

Table A6: Definition of Dummy Variables Used in Regression Analysis

List of Dummy variables used in the empirical Analysis-	
Religion dummy1	= 1, if Hinduism = 0, Otherwise
Religion dummy2	= 1, if Islam = 0, Otherwise
Religion dummy3	=1, if Christianity, Sikhism, Jainism, Buddhism, Zoroastrianism = 0, Otherwise
Sector dummy1	= 1, if Rural = 0, Otherwise
Sector dummy2	= 1, if Urban = 0, Otherwise
Enterprise Size1	= 1, if Number of workers less than 6 and 6 above but less than 10 = 0, Otherwise

Enterprise Size2	= 1, if Number of workers above 10 but less than 20 = 0, Otherwise,
Enterprise Size3	= 1, if Number of workers above 20 = 0, Otherwise
Caste1	= 1, if ST = 0, Otherwise,
Caste2	= 1, if SC = 0, Otherwise
Caste3	= 1, if OBC = 0, Otherwise
Caste4	= 1, if General = 0, Otherwise
Generation1	= 1, if Relation to head- Self or spouse of the head & Male = 0, Otherwise
Generation2	= 1, if Relation to head- child (married/ unmarried) & male = 0, Otherwise
Paid Leave dummy	= 1, if Eeligible for paid leave = 0, Otherwise
Social Security dummy	= 1, if Receive any kind = 0, Otherwise

Table A7: Summary Statistics of all Variables taken in the Analysis

Variables	Observations	Mean	Std. dev.	Min	Max
Father Age	11,367	54.22	6.32	35	65
Father Age^2	11,367	2980.18	678.44	1225	4225
Father Skill level	11,367	0.40	0.76	0	3
Father Matching	11,367	0.83	1.34	0	4
Father Sector	11,367	1.38	0.48	1	2
Father Enterprise size	11,244	1.22	0.59	1	3
Father Religion	11,367	1.34	0.63	1	3
Father Social Security Dummy	5,023	0.19	0.39	0	1
Father Paid-leave dummy	5,023	0.21	0.41	0	1
Father Caste	11,367	2.78	0.96	1	4
Son Age	14,006	26.00	5.25	15	47
Son Age^2	14,006	703.37	289.07	225	2209
Son Skill level	14,006	1.31	1.10	0	3
Son Matching	14,006	1.90	1.35	0	4
Son Sector	14,006	1.39	0.49	1	2

Son Enterprise size	13,747	1.41	0.76	1	3
Son Religion	14,006	1.34	0.63	1	3
Son Social Security	10,359	0.21	0.41	0	1
Son Paid-leave-dummy	10,359	0.26	0.44	0	1
Son Caste	14,006	2.78	0.96	1	4

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