Labor Markets in India: Measurement in Times of Structural Change[1]

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Abstract: We analyze the evolution of India's labor market, with a focus on female labor force participation (FLFPR) from 1983-84 to 2022-23. Utilizing both Indian and international databases that include unit-level surveys and time use data, we address issues of data quality, labor market definitions, and measurement challenges and make necessary adjustments for accuracy. Additionally, by applying a structural microeconometric model, we evaluate the roles of both the labor market and the household sector in female labor participation. Our findings indicate that India's labor market is undergoing a structural transformation driven by rising educational attainments and declining fertility rates. After appropriate adjustments to data and definitions, we obtain six key results: (a) no significant decline in FLFPR between 1999-00 and 2022-23; (b) FLFPR in 2022-23 is comparable to international standards; (c) India requires 7-9 million jobs annually over the next five years, contrary to the widely believed 10 million per year; (d) education shows a U-shaped relationship with FLFPR due to its non-linear relationship with earnings; (e) India's gender wage gap is comparable to that of its peers; and (f) Indian women spend more time on child care, a crucial investment for childhood skill development, than women in OECD countries. These findings challenge assumptions of a sharp decline in FLFPR, significantly lower FLFPR compared to other countries, and slow job creation during 1999-00 to 2022-23.

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Introduction

An important determinant of the aggregate level of GDP is the total amount of labor employed in production. Differences in GDP across countries are often influenced by the total labor employed, while differences in per-capita GDP are influenced by factor productivities. This makes the study of labor market important, particularly for fast-growing transition economies such as India.

Transition economies – or emerging markets – typically witness a rapid period of economic growth that has implications for the predominant sectors of employment, nature of value added across different sectors and more importantly, the decisions undertaken by individual agents such as the number of hours to work. Such a Lewisian transformation has been observed for all major economies that went through such a transition from having a low per-capita incomes to the levels commiserate with advanced economies.

Not surprisingly, labor markets in India have been the subject of several studies in recent years. Some have focused on important labor market statistics such as unemployment rates and demographic trends underlying such statistics while others have attempted to explain the gap in labor force participation rates for different demographic groups. India is one of the few large economies with a sizeable and expanding potential labor force. In this globalized world, what happens in India is important both for Indian workers – and markets worldwide. Job creation issues are important due to several debates about India squandering its demographic advantage.

The reasons for extensive debate and discussions are not hard to find. India is one of the few large economies with a sizeable and expanding potential labor force. In this globalized world, what happens in India is important both for Indian workers – and markets worldwide. This report is an attempt to distil all the information available on the Indian labor market - and with particular reference to what has happened to female work and female labor force participation rate.

The title of this report *Labor Markets in India: **Measurement** in Times of **Structural Change*** says it all. The Report covers a period characterized by major structural changes: rapid advances in education, especially for women; large increases in living standards; rapid reduction in extreme poverty; and sustained levels of high economic growth. In particular, we focus on the female labor force participation, which is arguably lower in India than many countries in Asia (and contradicts the generation of sustained economic growth). An inherent difficulty in measurement of labor market status in transition economies stems from the presence of large household enterprises. Household enterprises often employ family members as unpaid workers compounding the challenge for statistical authorities to adequately measure labor force status. Further, the period of our analysis coincides with a general increase in educational attainment for both men and women. Consistent with the experience of other countries, there is a decline in fertility rates in India. Individual choices about attaining additional years of education or decisions to have children have implications for participation in the labor market.

This paper makes important contributions to a large and growing literature focused on the study of labor markets. The first focuses on outlining the importance of definitions and their application in emerging markets. The second focuses on accounting for "measurement. For example, ILO considers the PLFS surveys for 2018-19 and 2019-20 surveys to be unfit for use due to data quality issues. Including these surveys in analysis can, and does lead to policy mistakes and policy misunderstanding.

An additional contribution of our paper is in terms of imposing a structure on the individual decision of economic agents with regards to their participation in the labor force. Roy (1950) model of selectivity enables the separation of work between home production and labor market as two separate sectors of the economy. Economic agents therefore have to decide whether to participate in one of these two sectors. In particular, the decision to participate in either of the sectors is non-random and there is an element of self-selectivity which is exploited to draw inferences on the unobserved wage and productivity levels under a general set of identification assumptions.

The structure of the paper is as follows. Section 2 outlines the data used for our analysis. The analysis of employment-unemployment surveys from 1983 to 2022/23 allows us to construct a comparable series of labor market statistics such as employment levels and labor force participation rates. These data are useful to adequately understand the effect of economic transitions on India's labor markets and its implication for labor market outcomes. In addition, we discuss importance of definitions for analysis of labor market dynamics in India. We discuss the "usual status" definition which is more suited for economies with a larger share of workers in agriculture. The "current weekly status" definition which is generally better suited for developed economies can impose seasonality on labor market data due to agricultural patterns in India.

Section 3 focuses on labor force participation rates in India, especially in a male-female cross-country perspective. The section offers a method of assessing whether India's (or any other country's) labor market indicator is different than what cross-country data says it "should" be. India's aggregate (male plus female) LFPR in 2022 is very close to the international average for the usual status of work.

Section 4 extends this discussion by evaluating important labor market indicators for three distinct age cohorts: 15 to 24, 25-64 and 15-64. In addition, we evaluate the trends for each of these cohorts by gender. The first cohort corresponds to the years where young workers opt to attain education. Increase in compulsory schooling rules, societal norms with more individuals choosing to attain higher education has implications for labor force in this group. A substantial decline in the labor force participation rate is observed within this age cohort.

Unlike several advanced countries, in India there is a very small proportion of workers who simultaneously attend college and undertake in employment activities. College education in India is largely funded through parental earnings (and wealth) and this marks a different social norm relative to many other countries. In addition, the latter part of the first cohort and early part of the second cohort often corresponds to decisions to have children that has implications for female labor force participation rates. Decomposition of the underlying trends into these categories allows for a better evaluation of the dynamics that are largely driven by labor supply decisions.

In section 5, we use a consistent set of definitions to construct a series of total employed workers from India's labor market statistics. India does not have a consistent time-series from establishment surveys to capture employment generation. However, as with other countries, household surveys can be used to construct both the total size of the workforce and employed individuals. The time-series data on employed workers also allows inference based on job creation. We find that the period of the fastest GDP growth in India – 2004/5 to 2011/12 was also the period of the lowest job creation. Further, that 1999/00 to 2004/5, and 2019/20 to 2022/23, two periods with large infrastructure investment, also generated the highest employment growth. Finally, looking forward, in the next decade India will need no more than 10 million jobs a year in order to keep unemployment rates low and stable.

This is followed by a discussion of the Roy model (Section 6) and its application in the context of Indian workers who have the option of working either in the home production or in the formal labor market. Such a formulation is particularly appealing to study female labor force participation as it provides a comprehensive framework for modelling individual decision. We find that education is valued differently across both these sectors and consequently education attainment plays an important role in determining the participation decision across different sectors. A modest increase in years of education from a low base has a greater effect on productivity levels in home sector than compared to labor market, and thus, it reduces the female labor force participation rates. However, at higher education levels, increased years of education enhance greater value in the labor market than in household work resulting in an increase in FLPR. This structural approach yields a U-shaped FLPR curve, as seen in Goldin (1995) and provides an alternative mechanism that shapes this relationship.

In section 7 we focus on the gender wage gaps that are prevalent through advanced and emerging markets. These gaps exist even after controlling education attainment, experience and other demographic variables. Discrimination against women in the labor market can have suppressing effects on FLPR, thereby making it an important variable to study along with FLPR. We find the gender wage gap to be higher for countries that had a higher proportion of their workforce with college degrees. In addition, this finding is particularly pronounced for high-income and upper-middle income countries relative to lower middle income and low-income countries. However, the results for the same exercise with those with intermediate educational attainment are mixed. While for high-income, low-income and upper-middle income countries, a higher share of proportion of workforce with intermediate education results in a higher gender pay gap. The result reverses for lower-middle income countries. We report the gender pay gap for a select set of countries by educational attainment and by occupation choice.

Section 8 uses time-use data to infer the decision of women to participate in the labor force. Standard labor-supply models assume that a household determines their decision to participate in the labor force and the number of hours to supply as a part of an optimization routine. Time use surveys allows us to better understand the actual allocation of time by male and female members. This actual allocation could be interpreted as revealed preferences under the strict assumption of availability of outside work options to all individuals. Two key conclusions emerge from such an analysis. The first is that there is a gender difference in allocation of time across different activities and that this difference is not unique to India. However, Indian women spend the highest amount of time on childcare when compared to other countries for which time-use data is available. Using the time allocated to childcare, and the female labor force participation rates, we examine the underlying linear relationship across different countries. Countries where women allocate greater time to childcare have a lower labor force participation rate. This is consistent with theory as a higher time allocated for childcare leaves relatively lesser amount of time for market wage labor. Section 9 concludes.

Section II: Data, Definitions and Measurement

2.1 – Employment and Unemployment Surveys

In a "normal" research report, the section on "data and definitions" is a pro-forma section meant to briefly describe their use for the study. But what happens when the "*relative* accuracy" of the data is a large part of the story, a large part of the controversy surrounding the data and its interpretation? That is the case with the Indian "story" about what has happened in Indian labor markets over the last twenty-five years.

Employment surveys in India -referred to as NSS/PLFS to accommodate the name change from NSS "Employment and Unemployment Situation" to PLFS "Periodic Labor Force Survey"- contain estimates for several important aspects of the labor force. For the all-important employment and unemployment subject, two important definitions of employment are provided. The first is the ILO near universal definition of employment– current weekly status (CWS) or "did you work at least 1 hour in the preceding week".[2] The second definition maybe unique to India: usual status (US). It is based on principal status i.e. what was your main job (more than six months in the preceding year) and secondary status. The secondary status is asked of those respondents who were unemployed or not in the labor force in the preceding year and were employed for at least 30 days. The combination of these two is usual status (US).

2.2 Working Age Population (WAP)

Employment Surveys in India report data in the form of *ratios* (e.g. labor force participation rate (LFPR) of an age or sex group) rather than in the form of *levels* (e.g. total employment.) For policy purposes, both ratios and levels are important; hence, it is hoped that future editions of statistical reports in India will report national level estimates.

In order to obtain estimates of levels, one needs an estimate of the national population in a particular year e.g. Census. The UN provides updates and estimates of population through the UN World Population Prospects 2022 edition. Estimates of *levels* are obtained via a blow-up of survey population weights to census (or equivalent) population data. The years covered by the UN document are 1950 to 2100 for all the countries in the world (obviously, post the last census of

[2] In advanced countries like the US, the question is phrased as "Did you work at least 1-day last week".

2011 all estimates are projections based on estimates of fertility change – low, medium, and high variants). These population estimates are the "gold standard" and are used by international institutions and researchers worldwide. The national level estimates reported in different data bases (e.g. Penn World Tables, KLEMS (RBI) data base etc.) all use the UN estimates for population when census data are not available. Note that survey based level estimates can be inaccurate and misleading since the survey estimate of total population is often 5 to 20 percentage points *lower* than the national estimate.

2.3 Usual status (US) or Current Weekly Status (CWS) of Employment

For emerging economies with a large fraction of workforce engaged in crop-agriculture, usual status is a more appropriate indicator of employment. [3] This for the simple reason that a longer horizon of work better reflects the season-specific nature of agricultural employment. The ratios can be different; for example female labor force participation rates for usual status are typically around 4 to 6 percentage points (ppt) *higher* than the corresponding estimates for weekly status; for men, usual status LFPRs are about 2 ppt higher than CWS; for all workers, US LFPR's are about 4 ppt higher than those estimated by CWS.

We will report both estimates when appropriate, but the discussion, and preference, is for the usual status indicator. For discussions about Indian labor market, usual status *is* the preferred indicator for employment and unemployment by almost all authors working on Indian labor markets (e.g. Kapsos(2014), Desai-Doshi(2019), KLEMS-RBI, Penn World Tables (PWT)). As the country develops, it is likely that India will eventually move (perhaps over the course of the next decade) to the conventional weekly status for measuring labor demand and supply; for now, at least for the next 5 to 10 years, the usual status indicator of labor supply (and demand) is likely to be preferred.

2.4 India, and ILO, and "Work" definitions – A Review

Labor force estimates follow directly from the definition of work and unemployment. The sum of the two (working and not working but available for work) is how the labor force is defined. But what is *work*?

[3] See Desai & Joshi (2019).

India conducted its first Employment and Unemployment survey in 1983. Just a year earlier, the ILO (13th International Conference of Labor Statisticians ICLS) had met and drafted the guidelines for collection and dissemination of labor market data for its member countries. That conference offered guidelines for what should be considered work in the labor market as distinct from work as defined by other organizations or by the UN System of National Accounts. In particular, work was defined as that undertaken for "pay or profit", a definition that holds true today as well.

2.5 Home Production of home services

However, over the last forty years our understanding of work has undergone substantial revisions and improvements. It has been a collective cultural and social and gender effort aided by the availability of "time-use" data. These data have shown that men and women spend approximately the same time at work, except that men indulge in more market work (for wages) while women spend more time at work at home e.g. home production of services and goods. Home production of services (especially cooking, feeding, cleaning etc.) has never been considered as work for employment. Work for the market (whether paid or unpaid) has always been considered as work.

Home production of goods for home *consumption* (e.g. subsistence production, collecting water, fetching firewood, animal husbandry) has alternated between work for pay or profit or not. Indeed, a large part of the definitional problems with Indian female labor force participation (FLFPR) have occurred because the statistical authority MOSPI (NSS between 1983 and 2011/12 and now PLFS (agricultural years >=2017/18)), has not been consistent in the definition of work. Section 2.8 discusses the MOSPI inconsistency in some detail, particularly with respect to the 2004/5 and 2011/12 presumed outlier years.

However, the suggestions for "reform of work definitions" contained in the 19th ICLS, are beginning to be incorporated in national statistics and reporting by the ILO) acknowledge that home production of home services is work in every sense of the term – except that it is *not* employment-work. The 19th ICLS also concluded that women and men devote the same time to "work", with women likely spending more time. The primary difference was in the nature of work – men's work was often market work, and women's work was often "home oriented" work.

How does one classify work oriented towards human capital investment in children e.g. home tutoring and elderly care? Both these items of home production of services are often transformed into market production of services (e.g. tuition classes, homes for the elderly etc.) This is of particular relevance to the study of Indian FLFPR because Indian women spend considerably more time on human capital generation activities than women in most parts of the world. The *extra* time spent by Indian women on this "concerted cultivation" (human capital generation) accounts for around 3 to 5 percentage points of their lower than normal or "deficient" formal labor force participation. Section 8 documents in detail the near universal phenomenon of women spending three to five times more time than men on items of work not conventionally considered for pay or profit.

2.6 - Measuring Work in NSS/PLFS – Defining Economic Activity

NSS/PLFS employment surveys provide considerable detail of the economic activity of each person in the population. Economic activity is defined according to the following 12 broad categories. Codes associated with each activity are in parentheses. The categories are: self-employed (11), employer (12), unpaid family worker (21 - e.g. working in a family farm or shop); salaried worker (31 - monthly wages); casual worker (daily wages – codes 41, 42 or 51); looking for work (81 - unemployed); enrolled in school (91), attended domestic duties only (92); attended domestic duties *and was also engaged in free collection of **goods** for household use* (93); rentiers etc. (94), not able to work due to disability (95), and other activity (97 – begging, prostitution etc.). *Codes 11 to 51 represent work, 81 is unemployment, and the two together constitute the labor force.*

Besides wage and salary labor, the two categories for work employment are activity 11 – worked (self-employed) in household *enterprise* and 21 – worked as helper in household *enterprise*. The reason for enterprise being italicized is to emphasize that by definition both these categories are "work for pay or profit" and hence employment.

Not work – education (91), domestic duties (92), and domestic duties plus (93).

All labor force surveys have education and domestic duties. But very few countries (if *any* other than India) have activity code 93 - a source of confusion for all, including the statistical authorities. The accepted goal is to identify work for pay or profit. If one collects firewood and sells it in the market, the activity code assigned will be self-employed (11) or unpaid family labor (21). If not sold in the market, it becomes non-work and classified as 93. How does one distinguish between activity code 92 and activity code 93?

Domestic duties mainly refer to work done by women for household consumption. In theory and practice, unpaid family worker (as 21) is work towards production sold in the market; and 93 is production for household consumption and not sold in the *market*. But as pointed out by others (Kapsos - 2014), Desai & Joshi (2019), Costa(2022)) this allocation is judgmental, and arbitrary. There is a market price for most goods (and services). The case of goods is simpler. Many such goods (fruits, vegetables, rice, wheat) are purchased from the market, and, in many farm households, also produced on the farm. If a household only produces vegetables for own consumption, then work towards it comes under classification 93 i.e. not working. The allocation between 93 and 21 is done on the basis of a "majority criterion – if a majority of time was spent helping in the production of goods for the market than in the production of goods for domestic use, it was considered work and employment; if less, then not in the labor force.

ICLS 19 is the latest codification of ILO recommendations. Activity status 21 is the only code not directly paid, which reads as follows: "*worked as helper in h.h. enterprise (unpaid family worker)*". In our opinion, this activity of helping a family enterprise is a profit-making activity that qualifies for employment under ICLS19. Therefore, although no wage is recorded for these workers, they can be classified as workers in accordance with ICLS 19. In addition, NSSO and PLFS define activity status 93 as follows: "*attended domestic duties and was also engaged in free collection of goods (vegetables, roots, firewood, cattle feed, etc.), sewing, tailoring, weaving, etc. for household use*". Our interpretation is that such work produces goods and services only for own use or household use, and thus does not qualify as ICLS 19 employment or NSSO-EU or PLFS employment.

2.7: The Precipitous Paradoxical decline

The domestic duties and domestic duties plus distinction (primarily for women) has been there since the very first employment survey in 1983. It was not relevant for studies on labor force before the release of the 2011/12 survey. This survey documented a big surprise – large, precipitous decline in female LFPR between 2004/5 and 2011/12[4] reported a "precipitous" drop in female

[4] NSS, and now PLFS, data on employment refer to the *agricultural* year July-June ; i.e. 2011/12 means that the survey was conducted between July 2011 and June 2012. Agricultural years are referred to in the text with a "/" separating the two years.

LFPR for ages >=15 years[5], from 42.7 % in 2004/5 to 31.2 % in 2011/12. For the CWS definition, the drop was from 37.0 % to 27.1 %. For men, the decline was 4.2 ppt (84 to 79.8 %, usual status) and 4 ppt, CWS (from 82.5 to 78.5 %). The large female LFPR decline is re highly unusual for any economy, let alone one recording its fastest GDP growth ever, as India did between 2004/5 and 2011/12.

What caused this decline? Considerable research followed the publication of the 2011/12 data. Bhalla & Kaur (2011) suggest increased female enrolments in education as a contributing factor. Choudhary (2011) and Kapsos (2014) offers explanations as to why the decline is real and hence needs explaining. Besides increased educational enrolment, lack of employment opportunities for women was considered important, as well as withdrawal of women from low-income families because of higher family income (due to rising real wages). On lack of employment opportunities for women, Kapsos emphasizes the role of occupational segregation (social norms). Several other papers (Chatterjee, Murgai and Rama (2015), Fletcher et. al. (2017), Neff et. al. (2012), concur with these explanations.

Chatterjee et. al. "attribute decline to higher rural incomes in a patriarchal society" and argue for lack of demand and emergence of employment opportunities suitable for women;
Kapsos: "because employment generation has not kept up with the rise in the working-age population, due to increased competition with men for scarce jobs and an increasing reluctance of women to take up informal (and poorly-remunerated) work". Fletcher et al 2017:"Sustained high economic growth since the early 1990s has brought significant change to the lives of Indian women" (income effect); "willing female non-workers have difficulty matching to jobs." Neff et. al conclude "decline in rural women's LFP could potentially be due to an income effect and partly due to an education effect. We find no evidence of changes in employment opportunities or of social and cultural interaction effects that could explain the decline in rural female LFP".

Only one paper (Desai & Joshi (2019)) suggests, on the basis of NCAER household surveys, that there was no decline in FLFPR[6]. We reach the result that "change in non-communicated

[5] See Andres et.al. (2017); note that this World Bank research paper used the usual status definition of work, rather than the weekly status definition – thereby supporting the conclusion that scholars prefer usual status for interpreting trends in the Indian labor market,

[6] As we will see later, the Desai-Doshi conclusion is only possible if work on animal husbandry in NSS 2004/5 was "work" and not so in 2011/12. In he NCAER survey it constituted work in both the years.

definitions" was in large part responsible for a large part of the observed decline in female LFPR, and especially so for rural women. The non-communicated means that the statistical authorities decided on a change in definition (allocation of some of domestic duties plus (93) to unpaid family worker 21, but it did not get communicated in the survey documents

2.8: NSS 2004/5 the outlier year, and not NSS 2011/12

Researchers have observed the decline in female LFPR between 2004/5 and 2011/12 and believed that both surveys were "normal" i.e. there were no differences in definitions and hence measurement from previous surveys. We look at the survey before 2004/5 (in 1999/00), survey in 2004/5, and survey in 2011/12 and conduct some consistency checks. The null hypothesis (or belief) is that since all three surveys were done by the same organization (NSS), and since there was no announced change in either methodology or definitions, that all three surveys are equally representative of the underlying reality and therefore the result that there was a precipitous drop in female LFPR should be accepted as the statistical truth. Hence, the believed result by all (including early believers Bhalla & Kaur (2011), Choudhary (2011)) that the most historically unusual drop (worldwide) in FLFPR was worthy of discussion and explanation.

It is very unclear as why women in unpaid family enterprise work, and women in domestic duties and home production behave so differently between 2004-05 and 2011-12? As we mentioned earlier, empirically they behave very similarly for all other years, not just in terms of trends, but also in terms of levels. It must be noted that this shift from unpaid family work to domestic duties and home production is primarily responsible for the significant decline in FLFPR.

Two possible reasons can explain these patterns. First, unpaid family work, and attending domestic duties and home production may be similar definitionally, especially for women. According to NSSO/PLFS (and ICLS19 in our opinion), these activities are close, particularly since they are determined by major time or priority criteria. It is often possible to perform these two duties simultaneously. A woman can assist in the family enterprise during the day, while taking care of her kids, and do sewing work for her family in the evening. Moreover, one can move between these activities seamlessly, and in many cases, women not care about which of these two jobs they do as both are unpaid and both are for family income.

Second, in many instances the field personnel conducting the interview might have difficulty distinguishing between helping household enterprises without pay and producing something for family consumption of households or for sale. If women themselves are indifferent to distinguishing between these activities, it will be difficult for field staff to do so. Consequently, it would be difficult to measure these categories accurately as per their definitions.

Two pieces of supporting evidence. First, Sonalde Desai uses IHDS data to find no change in female FLFPR between IHDS surveys for 2004/5 and 2011/12. But if LFPR excludes animal husbandry work (as it should according to NSS 2011/12 (but not according to NSS 2004/5) then there is a large decline in female FLFPR. This is clincher evidence for our thesis that it is the miscoding of code 93 (erroneously included in 2004/5 and excluded in earlier (1983, 1993 and 1999/00) and subsequent years (2011/12) onwards that led to a large portion of female LFPR for rural women.

The second strong evidence is presented in Table 2.1. India's labor market is often compared to Bangladesh's and the latter is viewed as a success story in progress and levels of female labor force participation. But how much of the FLFPR in Bangladesh is due to work related to code 93 counted as work related to code 21? Apparently about 11 percentage points. Bangladesh's female LFPR is reported as 33.9 % in 2016/17. Applying NSS definition of allocating "home production for own consumption" to not work) equivalent to domestic duties 93, lowers the female FLFPR to 22.8 percent.

All things considered, we conclude that the shift of women from unpaid household enterprising to domestic duties and home production during 2004-05 and 2011-12 was by and large a result of data anomalies, not a systematic shift in socio-economic factors.

Kapsos et. al. (2014) also offer the explanation of uncommunicated definitional change: *Additionally, we find evidence that changes in measurement methodology across survey rounds is likely to have contributed to the estimated decline in female participation, due to the difficulty of differentiating between domestic duties and contributing family work.*

As does Costa 2021 on definitional change:

"The decline in female workforce participation between 2005 and 2011-12 may be attributed to data anomalies rather than actual changes in employment. In 2005, the data clearly distinguished between employment in household enterprises and unpaid care work. However, in the 2011-12 data, certain paid activities in household enterprises appear to have been grouped with unpaid care activities. This measurement discrepancy may have occurred when respondents' answers were not double-checked using follow-up questions consistently across surveys. Consequently, a significant portion of female employment may have been misclassified as unpaid work or unemployment, thereby reducing the apparent rate of female labor force participation." (Costa, private communication, March 2021)

2.9 PLFS labor force data for 2017-18 and 2018-19 deemed unusable

The first NSS employment-unemployment (EU) survey, post 2011-12, was conducted in 2017-18. The sample selection was on a eight quarter panel basis; hence the sampling module for 2017-18 and 2018-19 was the same. Broad labor market results for these two survey years along with all NSS employment surveys held since the first survey in 1983, and two EU surveys conducted by the Labor Bureau are also reported[7] in Table 2.??. The table documents the time-trend for the three most important indicators of the labor market – labor force, employment-population ratio and the unemployment rate. The labor market described for 2017/18 and 2018/19 is at a minimum not in sync with any other data for the last 40 years.

Throughout we present data for all years for completeness, and the reader can judge for herself whether there was a problem with these data.

Note that the two years data for 2017-18 and 2018-19 is the worst labor market data for any two years in Indian history. Highest unemployment rate and the lowest labor and employment rates.

[7] The EU surveys for 2014 (conducted between January and July) and 2015 (survey during April to December 2015) did not collect any data on a weekly recall basis. The information contained in the 2014 survey for usual is for the labor market experience between January 2013 (12 month recall) and July 2014 and hence represents the "average" value as of October 2013; analogously the 2015 survey represents the "average" value for January 2015.

Note also how similar the data are for the year immediately preceding 2017/18 and the year immediately following 2018-19.

Box 2.1 – ILO describes PLFS 2017/18 and 2018/19 data as unusable.

It is perhaps because of results contained in the Table that led the ILO to make the following observations in November of 2023: "In the model of labor force participation, the PLFS observations for 2018 (2017-18) and 2019 (2018-19) have been excluded as they appear to present limited comparability with both the previous NSS results and the newer PLFS results." https://ilostat.ilo.org/resources/concepts-and-definitions/ilo-modelled-estimates/

As in previous years, the ILO modelled estimates have been updated to take into account new information. It is important to note that new information can impact and revise older historical data *if newer data is a more trusted type of data source or it creates methodological breaks.* This may lead to the removal of previously included data. Thus, the historical trends of ILO modelled estimates from November 2023 may be different from those of November 2022 because of new data inputs.

An important difference between the ILO modelled estimates of November 2022 and those of November 2023 concerns the inclusion of observations from India's Periodic Labour Force Survey (PLFS). In the November 2022 edition, 2018 and 2019 were the most up to date PLFS data available for India. In the November 2023 edition, PLFS data of 2020, 2021, 2022, and the first half of 2023 became available and have been included in the model. In the model of labor force participation, *the PLFS observations for 2018 and 2019 have been excluded as they appear to present limited comparability with both the previous NSS results and the newer PLFS results*. Given the country's size, this has a sizeable impact the global aggregates."

Section III: Data and Trends in Indian female LFPR

One of the most discussed aspects of Indian labor market is that the female labor force participation rate is low, and especially lower than other countries at similar stages of development. This has consequences for the pattern of development, and whether India can take advantage of the demographic dividend, as argued (correctly) by the World Bank report, SADU (2024).

That is the central question being explored in this section – how much lower is female FLPR than what it "should" be. Tables 3.1(a) and 3.1(b) document the labor force participation rates for women, men, and total for two different classifications, age greater than equal to 15 years (hereafter GE15) and age greater than or equal to 25 years (hereafter GE25). In addition, in conformity with our extended discussion of data and definitions in Section 2, we will report data for all the years, 1983 to 2022/23.

The 2017/18 and 2018/19 data on labor force participation, a key variable in discussions about GDP growth and labor productivity, set of alarm bells in India, and the world. From a level of 38.9 % in 1999/00, after eighteen years of strong per capita GDP growth (likely second only to China), the LFPR for women dropped to a historic low of 23.3 % in 2017/18. Normally, in contentious and polemic India, all data is questioned, but very few questioned the possibly outlier nature of the 2017/18 and 2018/19 historic result. Note that in 2019/20, the data was revealing near identical FLFPR figures for 2011/12 and 2019/20 i.e the seven year drop got reversed in just one year.

3.1 – Problematic LFPR data and its impact on analysis

As is natural, a considerable amount of the expert discussion and commentary on the labor market has concentrated on the latest data, post 2011/12. It is obvious that Indian data have a huge impact in discussions and policy pertaining to the emerging markets. What happens in India colors perceptions and interpretations. International organizations like the World Bank and the IMF have the expertise for discussions about trends in these economies.

In 2020, McKinsey(2020) issued a report (during COVID) about what it would take for India to get back to a growth path of 8 % plus GDP growth after the end of distortions due to COVID (2023 onwards). What the Report says can be taken as an accurate, and authoritative, version of what was understood by policy makers, international organizations, and academic experts alike for the post 2011/12 period. While the Report ends with the 2017/18 PLFS data, the findings are near identical for 2018/19.

The results are very different for years post 2018/19. Given that the ILO has determined that the PLFS 2017/18 and PLFS 2018/19 data are out of sync with all other labor force data, in India and globally, we can take the data India post 2018/19 data as more consistent with reality.[8]

The McKinsey Report emphasized the contribution of the rise of female LFPR to this objective; this is what it said on female LFPR (CWS , GE15 years):

> "The country's current labour force participation rate is just 49 percent…The female labour force participation rate is among the lowest for large economies and is falling; compared to other economies like China at 61 percent, Thailand at 59 percent, Bangladesh at 36 percent, and Sri Lanka at 35 percent, India's female labour force participation was at 21 percent in 2019, and has fallen from about 32 percent in 2005. But it could rebound to 30 percent by 2030, with 55 million more women potentially entering the labour market. The driving force of this increase could be women in the prime age group of 25 to 54 years. Their labour force participation could rise from 28 percent to 46 percent. Such a lift would be a legitimate aspiration for India, in line with the level of female employment seen in other low- and middle- income South Asian emerging economies such as Bangladesh and Sri Lanka. (p.43, emphasis added)."

Table 3.1 (c) documents the female LFPR rates for Indian women, ages 25-54. The McKinsey forecast based on robust GDP growth over the next seven years 2023 to 2030 was for FLFPR to rise to 46 percent from 28 percent (unit level data shows 28.6 percent in 2017/18). Several observations on this important quote from the detailed McKinsey study.

First, that by 2022/23, female LFPR was already at 41 % - and if the more representative usual status data are used, then in 2022/23 India already had exceeded the comparable international target of 46 percent.

[8] It is difficult to estimate the loss in international thinking, output, and (correct) policy that the PLFS "errors" for 2017/18 and 2018/19 have caused. This research report has taken a years duration! because all our thinking and interpretation and analysis had to change post March 2024 when the ILO documentation of the incompatibility of PLFS data for recent years 2017/18 and 2018/19 (in ILO definition 2018 and 2019) was made public. Several expert reports still continue to use 2017/18 and 2018/19 PLFS data in their analysis, including the very recent (ILO-IHD 2024) study on youth unemployment in India.

Second, the increase “suggested” by McKinsey was 18 percentage points over 11 years (from 2019 to 2030) or 1.6 ppt per year. Since the release of the “correct” data for 2019/20, the increase has averaged more than 2 ppt a year.

Third, not shown in the table, is the data from the most recent quarterly PLFS survey for January-March 2024. The quarterly data are only available for urban areas, though it is planned that the quarterly data will cover all-India, and that the data will be released on a monthly basis. These data show that urban female LFPR (weekly status, GE15 years) increased from 22.7 % in Jan-March 2023 to 25.6 % in Jan-Mar 2024. That is an increase of 2.9 ppt in just one year, the highest on record (since 2017/18). If a parallel increase is observed for all India, then the “surprise” FLFPR in 2023/24 could be a figure close to the McKinsey implied estimate for 2028, five years hence!

Collectively, what we can conclude from the above results, is that it would be a mistake to not recognize the structural change that the female labor market is undergoing in India. And that the interpretation that India is in the midst of a problematic low female LFPR (or problematic job growth as discussed in Section 5) maybe vastly exaggerated. Past data problems (especially for 2017/18 and 2018/19, and possibly also 2004/5) should be kept in mind before drawing any conclusions based on these three years.

3.2 Filling the Education Gap

One of the more important aspects of economic development, perhaps the most important, is the filling of the education gap i.e. the parity in education levels of men and women. And education gaps affect other gaps, like wage and productivity gaps. In our documentation of LFPR, we had reported trends for ages GE15 and ages GE25. Most developed countries have completed the education transformation, as well as several emerging markets. India joined the education equality late, and only after another 40 years or so, Indian GE15 LFPR rates will be comparable to the advanced countries.

Education levels for the GE25 group are not distorted and can serve as a useful guide for understanding the trends in labor markets and other economic outcomes. Table 3.2 presents the historical data on male and female levels of educational attainment, and the education gap conventionally defined as (male – female)/male.

Today, there is education parity in India. The gap was 25 % two decades ago, 9 % in 2011/12, and 2 % since 2020/21. Apart from documenting the progress in education, Table 3.3 is helpful in emphasizing that the age GE15 comparisons for India are flawed, and that analysts should look at the representative GE25 age group. Since a fair number of reports only report the GE15 comparison, we document the data; but our emphasis is in GE25 groups or even the more "meaningful" 25-64 age group.

3.3 Cross-Country Perspective on female LFPR

In Section 2, we explored various labor market definition and measurement issues and concluded that years 2004/5, 2017/18 and 2018/19 were problematical. Hence, any discussion about Indian labor market, especially over the last two decades, is best conducted for the three survey years approximately a decade apart – 1999/00, 2011/12 and 2022/23.

In Sections 3.1 and 3.2, we established that there is now education parity in India (for entrants into the labor force over the last decade) and that female LFPR was on a firm trend upward. Nevertheless, the accepted wisdom is that the female LFPR in India is much lower than what it "should" be. In 2022/23, for the >=25 age group, FLFPR is observed to be 41.9 %. In 1999-00, twenty odd years earlier, the rate was a near identical 42.1 %. The question remains, at 42 %, is female LFPR too low? If so, how do we know that it is too low, either in comparison with our own history or history of countries comparable to India?

Unfortunately, comparison on such a structural question is not straightforward. First, we need to ascertain as to which countries are structurally comparable to India. We know that population structure matters for female labor force participation and population structure is shaped by fertility choices which in turn are shaped by educational attainment. Everything is truly endogenous! But we can make a beginning and we do so by looking at Asian (East and South Asia) and Latin American economies (61 countries). Advanced and formerly Eastern Europe economies have a considerably higher average education and income level than India, and are therefore ruled out from comparison. Countries in Middle East and North Africa are not (broadly) comparable given that social norms there for female work force are considerably different than Asia and Latin America. Sub-Saharan African economies are relatively much poorer than Asia and Latin America.

From the list of 61 Asia and Latin America economies, we eliminate economies whose population was less than 5 million in 2022 (small economies). Further, we eliminate the following countries from our sample: China - because of its very large population which can affect weighted population means; Afghanistan, Cuba, Myanmar, North Korea and Venezuela. This leaves us with 29 countries as the comparator group hereafter referred to as AsiaLA-29 or AsiaLA-29 (rest of the world comparable to India).

For analysis, we select two age-groups: ages >=15, ages >=25, and three years approximately a decade apart 1999/00, 2011/12 and 2022/23. How valid is our sample selection of AsiaLA-29? The structure of the population reflects past trends in fertility and therefore can broadly represent AsiaLA-29 group means as valid comparators. Share of population >=15 years or >=25 years was 65 and 66.2 percent for India and AsiaLA-29, respectively, in 1999/00, the beginning year of our analysis. In 2022, the respective figures were 74.7 % India and 74.1 % AsiaLA-29[9]. This gives us confidence in the selection of our 29-country sample of AsiaLA-29 countries (9 from East Asia, 4 from South Asia and 16 from Latin America.)

Table 3.3 contains a summary of the results for age-group >=25 years for the three years 1999/00, 2011/12 and 2022/23. The AsiaLA-29 data does not contain labor market data for usual status; we believe usual status is more representative (as is the >=25 age group because it is uncontaminated by educational enrolment). While the discussion will be on usual status for India compared to AsiaLA-29 current weekly status, the tables report the data for CWS (ILO-modelled data) for AsiaLA-29, and both CWS and US data for India.

One major result is that there is not much difference in the aggregate men and women LFPR rates between India and AsiaLA-29 for the last twenty odd years! This result has to be qualified; the comparison is between usual status for India and CWS for Asia and Latin America. As we have repeatedly stressed, and documented, the CWS is very likely representative of labor market developments in most of the countries of Asia and Latin America, while usual status is more

[9] The Indian sample years are agricultural years 1999/00, 2011/12 and 2022/23. ILO in its data base refers to the second of these years e.g. 1999/00 is referred to as the year 2000. We have made these adjustments to the data so that like is compared to like e.g. 2011/12 Indian data corresponds to 2012 ILO data for ROW countries.

representative for India. If CWS is compared with CWS, then in 2022/23, a 4.6 percentage point gap remains. (But note the discussion of time-use data in the next section). The reason we present both CWS and US for India I so that the reader can make her own choices.

In 1999 (again 1999/00 for India and 2000 for AsiaLA-29) the aggregate LFPR was 67.0 % India, and 67.3 % AsiaLA-29. In 2022, 65.1 % India and 66.1 % AsiaLA-29. Men LFPR is higher for Indian men (88.6 % vs. 83.5 % AsiaLA-29); women LFPR is lower for Indian women (41.9 % vs. 49.5 %, AsiaLA-29).

3.4 Time-Use Data on human capital investments.

The lower FLFPR, and higher male LFPR for India suggests that social norms maybe at work. But norms not in the traditional patriarchy sense of women shouldn't work outsides the home. Rather, the pattern is suggestive of a social contract between men and women in India, a contract involves what Kaur (2023) and others have called concerted cultivation.

Time-use data was collected for India in 2019. The data contains estimates of principal status for all individuals (did you work at least half a year) as well as time-use details for one day. The FLFPR for age-group 25-64 years is observed to be 22.4 %; the FLFPR for the same age-group in PLFS 2019/20 is observed to be 31.5 %. There is a separate category of time devoted to child-care, and within it, the time devoted to human capital investments in children (code 413 – Instructing, teaching, training and helping children and code 414 – Talking with and reading to children). If the time-devoted to these two items exceeds 1 hour (to conform to the CWS definition of work of at least 60 minutes a day) then the labor force participation rate increases by 4.0 percentage points (note that these activities are not included in the ILO definition of work for pay or profit).

Section IV: Employment Growth - India in a Comparative Perspective

Two reasonably similar labor market indicators (LFPR and employment ratio) are used by analysts to describe broadly the same phenomenon. The two will differ slightly in magnitude and trends; and differences in the two indicators are explained by trends in unemployment rates. In the previous section we looked at LFPR's, in this section we look at employment ratios as per the recent World Bank report *South Asia Development Update – Jobs for Resilience, hereafter* (SADU 2024).

The SADU report is about jobs in South Asia. The report concludes (in South Asia and in its largest economy India) that the job performance in the region, and India, is considerably behind the curve. The Report analyses data for the last two decades (1999/00 to 2022/23) for the age-group >=15 years and reaches the worrisome (and correct) conclusion that since 1999/00, job growth between 1999/00 and 2022/23 was *less* than the growth in the Working Age Population (WAP). However, as documented in the next section, the pattern of employment growth in India between 1999/00 and 2022/23 is very varied. For example, employment growth between 1999/00 and 2004/5 was very strong in India, as growth between 2019/20 and 2022/23. In contrast, the seven year period 2004/5 to 2011/12 showed negligible employment growth (and the highest per capita GDP growth ever). And the period 2011/12 to 2018/19 were lost to "unusable" employment data.

Hence, the SADU Report conclusion for India may not correctly reveal the whole picture: "merely positive employment growth alone will be insufficient for South Asia to realize the demographic dividend promised by a still-growing population, this chapter examines the correlates of employment ratios—driven by the rate at which employment growth outpaces working-age population growth—rather than simply employment growth".

World Bank authors offer the evidence of Korea's development as evidence that South Asia (and India), has lagged behind in both employment and productivity growth.

"As an example, consider the Republic of Korea, which in the 1960s had per capita incomes that resembled those in 2022 of Bangladesh, India, Nepal, and Pakistan. The convergence of the Republic of Korea's per capita income toward those in advanced economies, completed by 1987, was marked by a combination of labor productivity growth and increases in its employment ratio. Thus, between 1960 and 1980, labor productivity growth averaged 5 percent a year and the employment ratio increased on average by 0.4 percentage points a year".

The authors are right to look at the difference in employment growth and WAP growth as an indicator of the success of employment policy in developing economies, and we repeat their "test" (does employment growth outpace WAP growth) for several countries. The experience of Korea is also instructive given that among developing countries Korea alone achieved "developed" country status when the OECD defined it as such in 1996.

Korean development pattern is a high standard for all countries, and it is very useful to compare India's development indicators with that of Korea. Our first "informative" test about India is to compare productivity growth in Korea from 1960 to 1980 and India from 1999/00 to 2022/23. Regarding Korea, Penn World Tables records its total factor productivity (TFP) growth for 21 years (1960-1980) at an average of 1.39 % per annum; for India, for the 21 years 1999-2019 (last data available in PWT), India's TFP growth was near identical 1.36 % per annum. The results for labor productivity growth are also broadly comparable. Korea 6.1 % per annum, India 5.3 % per annum. (Employment in PWT for India is defined in terms of the usual status definition, and output as Real GDP at constant 2017 national prices, mil. 2017US$).

Further, Korea's female LFPR , age>=25 years, in 1984 (the approximate year when it had the same per capita GDP level as India in 2022/23, PPP$ 7200, 2011 prices) was 41.7 %, and the aggregate LFPR was 63 %. India's usual status definition: female 41.9 % and aggregate LFPR of 65.1 % in 2022/23.

The results are pleasantly "shocking" since the accepted wisdom is that Korea, *at the same stage of development as India in 2022/23*, was considerably ahead of India. It was not. We will now examine employment pattern in India compared to the select 29 countries in Asia and Latin America (the same set of countries used for our labor force participation analysis in Section 3.)

For assessment of Indian performance, we employ the same procedure as developed for analyzing India's labor force participation[10] i.e. look at developments in India vs. developments in the rest of the world, AsiaLA-29 (29 countries in East Asia, South Asia and Latin America). Data for the age-group >=25 years presented below.

Table 4 presents results on the employment ratio (employment as a percent of working age population) for the two definitions (usual and weekly status), for three years (1999/00, 2011/12 and 2022/23), for males, females, and persons, and for two different age-groups [>=15 and >=25 years].

All the data are presented, but the discussion will be around the usual status definition and age-group >=25 years. [11] India's employment ratio falls from 66.3 in 1999/00 to 62.5 % in 2011/12; AsiaLA-29 shows only a marginal change from 65 to 65.8 %. For the next 11 years, India with stronger job growth increases the employment ratio from 62.5 to 64.1 %. In contrast, AsiaLA-29 shows a marginal decline from 65.8 to 64.8 %. Net result: the employment to population ratio in India and AsiaLA-29 is near identical in 2022/23 – 64.1 % India, 64.8 % AsiaLA-29. An increase in the employment ratio between 2011/12 and 2022/23, for both definitions, shows that it is the flat employment picture during 2004/5 to 2011/12 which led to the "conclusion" that employment growth in India had lagged WAP growth for the 23 year period 1999/00 to 2022/23. Post 2011/12 and especially post 2019/20 job increase has been robust.

[10] Note that the only difference between LFPR and work participation rate (WPR) is in trends in unemployment.

[11] Incidentally, for the popular and probably more relevant age-group 25-64 years (for this classification early aging is less of a conflating factor, the female LFPR in 2022/23 usual status is 70.1 %, and 66.4 % CWS.

Section V. Working Age Population (WAP) and Employment

5.0 Nature of the job problem in India

A major focus of policy everywhere (in both democratic and non-democratic societies) is jobs, and its mirror image, unemployment. The extended discussion in Sections 3 and 4 was to provide a *background* for an in-depth analysis of the magnitude and pattern of job gains in India over the last 40 years, a subject examined in this section.

Possibly the most important input into the study of labor markets is the structural change that takes place due to decline in fertility. As of now only the state of Bihar has a higher fertility rate than the replacement rate of 2.2 per woman; the national average has likely dipped below 2. Fertility declines have been happening in India for the last 30 odd years, and population growth for ages GE15 in India is now down to 1.5% growth year, far below the 3 % plus annual growth rate in the 60s and 70s. For the age-group GE15 years population growth is expected to decline to 1.3 % per annum over the next decade 2022-32, from 1.7 % pa in the previous decade; for the more meaningful age-group 25-64 years[12], population growth is expected to decline to 1.5 % per annum from a 2% rate a decade earlier.

The broad population changes are very meaningful. In terms of levels, according to the latest World Population Council data, 2022 revision, population under the age of 15 in India peaked in 2011/12 at 384 million and declined to 356 million in 2023. This is the source of labor supply going forward (in addition to individuals choosing to work beyond the statutory retirement age of 59 or 65).

WAP growth is exogenous – job growth is endogenous. The former is a function of individual fertility decisions made at least two decades ago, and we need to account for near compulsory schooling for most of the developing world today. Job growth is a function of macro policy in the short-run. Given this reality and dichotomy, it is surprising how little of the *present* jobs debate is couched in terms of the available and likely supply of labor.

[12] For the 15-24 age-group, population is expected to decline by 12 million over the next decade; hence, the 25 to 64 age-group gives an upper bound to the need for job creation.

5.1 Jobs Needed – UN population data settles the debate

There is a method by which some estimates can be constructed for assessing magnitude of jobs required to keep the unemployment rate low and stable. *This method does not require* ***any survey estimates of employment or definitions of employment****.* The population and demographic experts at the UN present estimates of population by age and sex groups for most countries in the world and from 1951 to 2100. Census data are used when available. https://population.un.org/wpp/. These data, along with an estimate of the target unemployment rate, can provide one with a reasonable medium-term estimate of jobs required.

Figure 5.1 is useful for assessing job "requirements" and job supply.

The age-structure is changing (aging!) and we consider the age-group GE15 years as representative of working age (this will give an upper bound to job requirements). The vertical axis represents the change in the *population* for this age-group; this is represented by the dark line. The lower lighter coloured line represents the change in the working age population that is expected to work and is drawn at a 65 % labor force participation rate i.e. if 65 % of the Indian workforce is expected to be working, then this line approximately represents the *new* jobs needed per year.

These long-term population changes need to be understood by those making assessments of job needs, and macro performance of jobs demand. This chart is a ready reckoner for the potential number of jobs needed each year. The horizontal dashed lines represent 5 million and 10 million respectively. The dark line peaks at about 18.3 million increase per year in the working age group GE15 years. This includes *everybody* in that age group – students, housewives, non-workers. *At no time in India's history has there been an increase in the working-age population of 20 million a year. And at no time in India's history has job requirement, ceteris paribus, been more than 11.5 million a year for the working age group GE15 years!* Population changes take place slowly, but the broad magnitudes of jobs required are correct for the medium term, e.g., five to ten years.

What Figure 5.1 convincingly illustrates is that that India's job requirement, for 2024 to 2030, is likely to be no more than 9.2 million a year. At a 70 % LFPR, jobs needed would increase to an average of 9.9 million.

5.2 Nature of the Job problem in India – Not enough quality jobs?

There has been an intensive discussion about jobs needed and growth in WAP in India since the release of the 2011/12 Employment and Unemployment Survey in 2013. It is very likely that the term *jobless growth* originated from the results of this 2011/12 survey. While media and scholarly attention was focused on the internationally unusual decline in female LFPR between 2004/5 and 2011/12, left relatively unattended was the shocking finding that despite the highest per capita GDP growth between 2004/5 and 2011/12, 6.4 percent per annum, job growth (both formal and informal) had been the slowest ever recorded in India: just 0.23 % a year or a paltry 1.1 million a year over 7 years. During those years, population growth for >=15 years was a robust 2.1 % a year. This period *is* the legacy of jobless growth.

This was in sharp contrast to the 2.9 % per annum job growth in India between 1999/00 and 2004/5, a period during which per capita GDP growth expanded by a much lower 3.9 % per annum. The paradoxical nature of high GDP growth and low employment growth between 2004/5 and 2011/12 is perhaps a subject for another discussion. The fact remains that even after adjusting for the higher base in 2004/5 (due to family workers working for home consumption counted as workers working towards market production), job growth numbers do not change by much.

The need for job creation is especially low for the next decade. In terms of annual needs, population 15 to 64 years will expand by only 10 million a year over the next decade. The size of the WAP is expected to increase from 972 million in 2023 to 1059 million in 2032; labor force for a 65 % participation rate in 2023 is 632 million; in 2032 689 million – an increase of just 6.3 million a year. The unemployment rate in 2022/23 was 3.3 % (usual status) and 4.4 % (weekly status). For the age-group 25-64 years, the unemployment rate was usual status 1.6 %, and CWS 2.5 %.

In 2024, total working population *increase* is expected to be 11.6 million; a 65% LFPR indicates that 7.5 million jobs will be needed to preserve the status quo on unemployment. An increase in jobs above 7.5 million will lower the unemployment rate, *ceteris paribus*; lower than 7.5 million jobs will increase the unemployment rate.

Hence, the oft talked about backlog of unemployment is not there. Between 2019 and 2022, 76 million jobs were created or more than 25 million jobs a year. Between 2011 and 2022, 115 million jobs were created or more than 10 million jobs a year. Job needs during this period, to keep the unemployment rate stable at the less than 3 % rate observed in 2011/12, was 9 million. The legitimate question that arises – what is the job problem in India?

The problem is that of aspirations and availability. Unfortunately, that is not a problem easily solved or a question easily answered. Stated differently, not enough "quality" jobs are available. But how does one define quality? One possibility is via movement out of agriculture.

Table 5.1 documents the nature (quality?) of jobs in India, from 1999/00 to the 2022/23. Agricultural jobs are reported for subsistence crop agriculture and for cash crops. Subsistence agriculture now accounts for 33 % of all jobs, a decline from the 45 % level registered in 2011/12. Cash crop jobs have increased from a low fraction of 3.5 % in 2011/12 to almost 12 % in 2022-23.

5.3 Jobs – Paid and Unpaid

There is a fair amount of confusion and uncertainty regarding the evolution of job growth in India. The "confusion" pertains to the contribution of unpaid family labor to job growth over the last decade. Some (e.g. Mehrotra (2024) have asserted that NSS/PLFS is unique in their inclusion of unpaid family labor being part of the labor force. Others (e.g. Mundle (2024)) suggest that unpaid family workers are exclusive to subsistence agriculture, a category that ICLS 19 considers as not in the labor force. Both interpretations/conclusions are incorrect. The ILO has a strict definition of jobs worldwide – the job has to be either for pay or profit. If the work leads to monetary income for the family (e.g. wife sitting and 'manning' the shop) then it is a job. And in emerging economies, unpaid family work can be, and is, important. Hence, the argument that family work is not a job per se is not a valid description of reality in any developing economy. Further, unpaid family worker is a common occurrence in most developing economies, with economies like Bangladesh and Indonesia having approximately the same share of unpaid family workers as India in their labor force (around 15 to 20 %).

Table 5.2 reports the total jobs created according to both current weekly and usual status. Also reported is the unpaid (family worker) jobs component. When the recent 2022/23 data were released, showing greater than 40 million job creation in the first normal post COVID year, there was scepticism about the accuracy of the data, in particular that "most of the increase was due to increase in the unpaid labour category'. Between 2019-20 and 2022-23, 76 million jobs were created, of which only a third were additions to unpaid labor. Further, the share of unpaid family labor in total employment reached a peak of 23.7 % in 2004/5[13] and dropped to 17.7 % in 2011/12. In yet another indication that 2017/18 and 2018/19 data were incorrectly coded, the share of unpaid family labor in these years drops to the lowest ever around 13.3 %. The norm since 2011/12 has averaged around 17 %, a drop from the average of 20.7 % between1983 and 2011/12.

Both categories of job growth between 2011/12 and 2022/23 (paid and unpaid) are the highest observed in NSS/PLFS surveys over the last 40 years. Even after the exclusion of unpaid family jobs, strong job growth was registered over the last decade+. Excluding the unpaid jobs i.e. paid jobs, growth averaged 8.4 million a year between 2011 and 2022.

[13] Recall that 2004/5 was adjudged to mistakenly add workers who should have been in the non labor force category 93 (domestic duties including firewood collection and animal husbandry).

Section VI: Labor Market at Home

6.1 The choice between labor market and home

Macro-level job statistics largely result from the work decisions made at the individual or household level. Economic and socio-demographic changes substantially influence these decisions. The incentives they create and the costs they impose ultimately determine whether individuals participate in the labor market. This section explores these microeconomic aspects of job growth, focusing specifically on Indian women using PLFS 2022-23 data. It examines how the interplay between economic and socio-demographic changes influence a woman's rewards in the labor market (LM hereafter) and at home (HH hereafter), thereby determining their decision to participate in the labor market. Since the majority of labor force participation is accounted for by workforce participation among women, understanding women's workforce participation provides a clear view of labor force participation of women in India.

The analysis suggests that both economic and socio-demographic factors significantly influence female workforce participation decisions (FWFP). Factors such as education, work experience, area of residence (rural/urban), number of children in the household, family earnings contributed by male members, and the proportion of females in the household affect women's rewards from the labor market (LM) and at home (HH), thus shaping the overall female workforce participation rate (FWFPR hereafter). Moreover, the analysis indicates that education impacts rewards from work in a non-linear manner, both in LM and HH. These impacts also differ substantially between the LM and HH sectors. This non-linearity and differential impact in the LM and HH sectors generate the U-shaped relationship between education and FWFPR, consistent with Goldin's (1995) U-shaped curve.

The analytical model is based on sectoral choice. It is well established that the decision to work in the LM or at HH is an economic one (see Heckman and Killingsworth, 1986). Workers benefit economically in both cases, making it a matter of trade-offs. Workers who choose the LM sector typically do so because they can earn more there. Similarly, those who choose the HH sector do so for the same reason. Thus, the comparison of sectoral earnings is a primary basis for these choices (Robins, 1930).

Choices like this are crucial for all workers, especially women. Traditionally, most Indian women engaged in HH activities. Over time, this pattern has somewhat changed. Due to significant improvements in education and socio-demographic shifts, many women now seek employment outside the home. This structural change is ongoing; hence, even today, the proportion of women in the HH sector remains large in India (about two-third in 2022-23) and in countries with similar socio-cultural backgrounds (e.g., Bangladesh, about two-third in 2023 as well).[14] One reason for this constancy may be that many women still find it rewarding to engage in household activities, such as raising and caring for children, which is an important investment (Heckman, 2006; Attanasio et al., 2020). It is thus imperative to understand how changes in HH affect implicit HH rewards or earnings and, hence, the FWFPR hereafter.

Despite the importance of the HH sector, most studies on the female workforce participation rate (FWFPR) of Indian women focus on labor market-related factors (Andres et al., 2017; Behrman et al., 1999; Chatterjee et al., 2018; Das and Desai, 2003). A few studies discuss aspects of the HH sector but do not formally examine their influence on HH earnings (Afridi et al., 2018). The primary reason for this gap is likely the unobservability of HH earnings.

We address this important gap in the literature by presenting and estimating a structural model that examines LM and HH earnings and their influence on sectoral choices. Our goal is to identify structural patterns in women's economic opportunities and determine their implications for the female workforce participation rate (FWFPR).[15] To achieve this, we utilize Roy's selection framework (Roy, 1951), which outlines explicit earnings-based criteria for sectoral choices. Roy's original model is a model of self-selection, where an individual chooses between two occupations. However, due to its broad applicability, this framework has been adopted in various contexts, such as immigration (Borjas, 1987), labor unions (Lee, 1978), and many other areas. Our analysis of FWFPR fits well within this framework and is suitable for understanding choices between LM and HH sectors.

[14] ILO modeled estimates obtained from the World Bank Gender Data Portal.
[15] Later we show that our model predicts FWFPR fairly closely.

6.2: A Roy model of female work force participation in India: interaction of labor market and home

The sectors: LM and HH

A brief description of the model is provided below.[16] Consider two sectors: labor market (LM) and household (HH). Each sector requires its workers to possess specific skills. Let LM require skill S_W and HH require skill S_H. These skills may be related or independent. Each sectors rewards its skill differently. Let the LM pays π_W for each S_W unit and the HH pays π_H for each S_H unit. Workers are skill-price takers; therefore, π_W and π_H are given to them. Furthermore, workers can switch between LM and HH sectors any time without incurring any costs.

Worker's earnings

Given the skill prices, if she works in LM, her potential earnings would be:

Consider a woman, i, deciding whether to work in the labor market (LM) or at home (HH). She possesses S_{Wi} units LM skill and S_{Hi} units HH skills. Given the skill prices, if she works in LM, her potential earnings would be:

$$Y_{Wi} = \pi_W S_{Wi}$$

Alternatively, if she works at home (HH), her potential earnings would be:

$$Y_{Hi} = \pi_H S_{Hi}$$

Note that Y_{Hi} is shadow earnings. It is observed to the worker, but unobserved to the analyst. As such, these earnings can be construed as the amount of money a woman would pay to an outsider to complete the same household task.

[16] The full model and parameter identification is provided in Heckman and Honore (1990); French and Taber (2011).

Determinants of worker's skills

Various factors influence worker skills. Some of them are observed to the analyst, some are not. A subset of observed determinants such as education, work experience, etc., generally affect both S_{Wi} and S_{Hi}. The other subset of factors are typically more exclusive and only influence skills in one sector or another. For instance, holding a college degree equips one to signal high productivity in the LM sector. However, the same college degree sends no such signals to the HH as such signalling is not needed there.

The unobserved factors (to the analyst) also determine skills. Let ϵ_{Wi} and ϵ_{Hi} be the unobserved components that affect skills in LM and HH sectors respectively. Combining all determinants together, the skill now equations can be expressed as:

$$\ln\,(S_{Wi}) = X'_{0i}\,\beta_{0W} + X'_{Wi}\,\beta_W + \epsilon_{Wi} \qquad (6.1a)$$

$$\ln(S_{Hi}) = X'_{0i}\,\beta_{0H} + X'_{Hi}\,\beta_H + \epsilon_{Hi} \qquad (6.1b)$$

where X_0 represents vector of factors that influences skill in both sectors, whereas X'_W and X'_H are the vectors of factors that influence skills in either LM or HH sectors respectively. The β's are the coefficients that determine the impact of these factors on respective skills.

The earnings function

Given the expression of skills above, the worker's potential earnings (in logs) can now be expressed as

$$\ln(Y_{Wi}) = \ln\,(\pi_W) + x'_{0i}\beta_{0W} + x'_{Wi}\beta_W + \epsilon_{Wi} \qquad (6.2a)$$

$$\ln(Y_{Hi}) = \ln(\pi_H) + x'_{0i}\beta_{0H} + x'_{Hi}\beta_H + \epsilon_{Hi} \qquad (6.2b)$$

As shown below, we estimate the *structural* parameters using these two earnings functions. Note that $\ln(Y_{Hi})$ is unobserved. Hence, it is impossible to directly estimate (6.2b). However, we adopt the identification strategy outlined in Heckman and Honore (1990) and French and Taber (2011) that enables us to estimate all model parameters, including those from HH sectors.

The sectoral choices: LM versus HH

After comparing her potential earnings, the woman decides whether to work. In line with Roy (1951), we assume that a woman makes this sectoral choices to maximize her earnings. Hence her choice rule is:

$$\begin{cases} Work\ in\ LM = 1 \text{ if } \ln(Y_{Wi}) \geq \ln(Y_{Hi}) \\ Work\ in\ LM = 0 \text{ if } \ln(Y_{Wi}) < \ln(Y_{Hi}) \end{cases}$$

where $Work\ in\ LM = 1$ means work in LM; $Work\ in\ LM = 0$ means work in HH.

Given this choice rule, the woman's probability of participating in LM is

$$\mathrm{P}[Work\ in\ LM = 1] = \mathrm{P}[Y_W \geq Y_H]$$

Note that the aggregation of this participation probability constitutes the overall FWFPR.

6.3 Estimation and Data

Estimation

We derive the estimable earnings function for LM and HH sectors above. Putting together

$$\ln(Y_{Wi}) = \ln\,(\pi_W) + x'_{0i}\beta_{0W} + x'_{Wi}\beta_W + \epsilon_{Wi} \qquad (6.3a)$$

$$\ln(Y_{Hi}) = \ln(\pi_H) + x'_{0i}\beta_{0H} + x'_{Hi}\beta_H + \epsilon_{Hi} \qquad (6.3b)$$

The variables and parameters are defined above. For estimation, we further assume ϵ_{Wi} and ϵ_{Hi} follow a bivariate normal distribution with zero mean and Σ variance-covariance matrix.

$$\binom{\epsilon_W}{\epsilon_H} \sim N\left(\binom{0}{0}, \Sigma\right)$$

$$\text{where } \Sigma = \begin{pmatrix} \sigma_W^2 & \sigma_{WH} \\ \sigma_{WH} & \sigma_H^2 \end{pmatrix}$$

where σ_W^2 and σ_H^2 represent the variances of ϵ_{Wi} and ϵ_{Hi}, respectively, and σ_{WH} represents their covariance. When σ_{WH}=0, LM and HH skills are uncorrelated. If σ_{WH} is not zero, then skills are related, and the strength of this relationship depends both on the sign and the magnitude of σ_{WH}. Later, we will show that the variances and the covariance play important roles in sectoral choice.

Identification

The earnings of the HH sector are not available. Hence, it is not possible to directly estimate the earnings function parameters for the HH sector. However, within Roy's framework, Heckman and Honore (1990) and French and Taber (2011) derived the condition under which all model parameters are identified. As such, the requirement is that a variable such as X_W' be available, which affects earnings in LM but not in HH.[17] We argue that college degree holding status can serve as such a variable. Once years of education and other academic credentials are taken into consideration (major indicators of human capital), the degree holding status or diploma becomes merely a signalling device. It only indicates that the holder is capable of completing the program as opposed to someone who has the same human capital but was unable to complete it. As such, a diploma does not enhance work productivity per se, but it equips workers with the skills to communicate about their productivity to potential employers, which they would not otherwise observe (asymmetric information on the job market, see Spence, 1973). This leads to higher wage offer. *In case of HH sector, however, this signal is irrelevant, since household members are usually well informed of one another's capabilities and productivities and thus do not suffer from such information gaps*. We use this variable to generate exclusion restrictions and estimate the full model (including the variance-covariance matrix) with Heckman two-step or Tobit-2 (Heckman, 1979) procedure.

[17] See Heckman and Honore (1990) and French and Taber (2011) for details.

Functional forms: education and age (work experience)

Usually, Mincer type earnings function (Mincer, 1974) include years of schooling in a linear fashion. The efficacy of education can, however, change as technology advances and the economy improves. Mincer (1997) shows that in the United States, log(earnings) are a concave function of educational attainment until 1980. However, as computers and advanced technology evolved during the 1980s and 1990s, the sign of the quadratic term reversed (turned convex). Gary Becker describes this as a shift from inequality of opportunity society (unskilled biased technological change) to inequality of cognitive ability society (skill biased technological change). To capture these potential changes over time, our specifications include years of schooling as explanatory variable in both a linear and quadratic form.

It is also well known that age-earnings profile is concave (Ben-Porath, 1967; Mincer, 1964). Incentive to invest in human capital declines as one ages, which adds concavity in the age-earnings profile. To incorporate this theoretical restriction, we also include age and age-squared as explanatory variables in the earnings functions.

Data

This study utilizes data from the latest round of the Periodic Labor Force Survey (PLFS), 2022-23. Section 2 provides details of the PLFS and NSS data on the labor market. This subsection focuses on a specific subsample and a defined set of variables. We include only women aged 25-64 who are not attending school. This yields final working samples ranging from 83,632 observations.

User-ready variables include age (in years), region of residence (urban or rural), and whether the individual has a college degree (yes=1, no=0). Constructed variables are based on survey information. For instance, a respondent's years of education (in years) are calculated based on general completed education levels and technical education levels.

Real earnings are calculated based on weekly nominal earnings recorded in the dataset and state-specific price indices (CPI-AL for rural areas and CPI-IW for urban areas). The PLFS reports the earnings of self-employed individuals (usual activity status 11) and employers (usual activity status 12), but not those of family enterprise helpers (usual activity status 21). Since family helpers contribute to household self-employment economic activity, their contributions are reflected in the earnings of the employer or self-employed family member.

To account for each member's contributions, we revise and impute their earnings. This is done as follows. First, we calculate the total earnings of household members who are either self-employed or employers (E11-12). Next, we determine the total number of household members who are self-employed, employers, or family enterprise helpers (N11-12-21). Finally, we divide ‘E11-12’ by ‘N11-12-21’ to compute the per person household earnings from self-employment, employership, and family enterprise help. These per person earnings are then imputed to each household member engaged in either of these three activities.

Other variables, such as household size, the number of children under age 10, and average male earnings, are determined by the composition of household members and their earnings. Work status is calculated based on respondents' *usual activity status* (employed or not) and whether they received any earnings during the period. It takes the value of 1 if the person is working and 0 if not.

6.4 Results

Our structural estimation yields several key insights. First, nearly all included independent variables—such as years of education, work experience proxied by age, place of residence, the proportion of women in the household, and average male earnings—influence earnings regardless of whether the worker is in LM or HH. Since earnings form the basis for sectoral choice, these factors can potentially alter LM participation.

Second, unobserved skills in LM and HH sectors are highly correlated. This strong association indicates that more productive HH workers tend to be more productive LM workers as well. This finding contradicts the belief that women do not work in LM because their HH sector expertise is not valuable in the LM sector.

Third, the variance of unobserved skills is greater in HH than in LM. Along with the strong positive association between LM and HH skills, this suggests that more capable women may choose to remain in the HH sector. There is positive sorting in the HH sector and negative sorting in the LM sector: the best HH workers stay in the HH sector while the relatively less capable LM workers join the LM sector.

Last, whether in the LM or HH sector, the effect of education on earnings is non-linear. This finding is particularly important as it results in a U-shaped FWFPR when plotted against years of schooling. The statistics in Table 6.1 serve as the basis for all subsequent computations. Based on this table, we present each of these results in more detail below.

Distribution of the unobserved determinants of skills in LM (ϵ_W) and HH (ϵ_H)

Before discussing the results, it is instructive to justify the distributional assumptions which underly the analysis. Earlier, we assumed that errors (ϵ_W and ϵ_H) follow a bivariate normal distribution. Though this may be a possibility, one cannot directly test it. However, distribution of log(earnings) suggests (Figure 6.1) that the assumption of log-normality is reasonable.

Earnings function estimates

Years of schooling

Years of schooling affect earnings. However, if the magnitude of these effects in LM differs from the HH sector, changes in years of schooling may alter FLFPR. We find empirical evidence supporting this assertion. The returns to schooling are 0.38 in the LM sector and -0.39 in the HH sector (see Table 6.2). If a woman with an average level of education (6 years in 2022-23) gains an additional year of education, her LM earnings will increase by 0.38 percent. Conversely, if a woman with the same level of education gains an additional year of education, her HH earnings would decrease by 0.39 percent. This decline likely occurs because investing more in formal education reduces investment in the skills needed for household operations. Additionally, since education is a full-time pursuit, investing in it results in withdrawal from HH activities, leading to a depreciation of the skills necessary for those activities. Given this difference, FWFPR is expected to vary with changes in years of schooling. However, note that these estimates are for the average person in the population. The return to education may vary by sub-groups or at the individual level.

Table 6.2 disaggregates returns to education by education quantiles. Clearly, the returns to education vary distinctly and substantially by education levels and from sector to sector. Among the least educated women (bottom 20 percent of the education distribution), an extra year of schooling would lower LM earnings by 0.34 percent and raise HH earnings by 5.1 percent. In comparison, for the most educated women (top 20 percent), an additional year of schooling increases LM earnings by 1.6 percent and lowers HH earnings by 9.4 percent. In fact, as education levels increase, returns to schooling gradually rise in the LM sector and decline in the HH sector (see Table 6.2). Hence in India, where female education is rising rapidly, we will likely see an increase in FWFPR in the near future as a result of this sector-specific non-linearity in returns to education. (as mentioned in Section 4, the 2023-24 data for urban India, shows a significant jump in female LFPR).

Implication of concavity and convexity

The non-monotonic pattern in schooling returns arises because earnings are a quadratic function of schooling. The theory section justifies using the quadratic form. Interestingly, the coefficients of the squared term of education in Table 6.1 show that the impact of years of schooling on LM earnings is convex, while the effect on HH earnings is concave. *This concave/convex combination reveals a crucial aspect of labor markets*. The positive coefficient of the quadratic schooling term in the LM sector suggests that schooling impacts LM earnings at an increasing rate, eventually leading to positive returns. In contrast, the negative sign of the quadratic term in the HH regression indicates that earnings rise with education at a declining rate in HH sectors. Thus, once education reaches a certain level, any further increase in education results in lower earnings in the HH sector, meaning returns become negative. These differential returns to schooling have significant implications for women's participation in the formal labor market. When education levels are low, an increase in education may lead to a withdrawal from LM, causing FWFPR to decline. Conversely, when education levels are high, further increases in education boost LM participation, leading to a rise in FWFPR. This pattern is consistent with Goldin's (1995) U-shaped relationship between FLFPR and stages of development.

College degree holding

The average LM earnings of women with a college degree are 15.5 percent higher than those without one, *ceteris paribus*. Note that this return differs from conventional returns to education. It does not result from aspects of human capital but from reducing employers' asymmetric information about workers' capabilities (Spence, 1973). This coefficient indicates the value of a college degree or the "sheepskin effect" (Hungerford and Solon, 1987). Note that the coefficient for college diplomas is missing in the HH sector because such signals are not relevant to HH sector jobs. Therefore, one would expect that a college diploma would only raise FWFPR when years of education are held constant.

Work experience

Whether in the LM or HH sector, work experience enhances skills. Typically, work experience is calculated using the formula "(age – schooling – 5)". Generally, this method may be inaccurate and associated with regression error terms. To avoid this problem, we use age as a proxy variable for work experience. The estimates reveal a convex relationship between earnings and experience in both the LM and HH sectors, consistent with the intermittent labor force participation behavior observed among women (Polachek, 1981). Compared to older women, younger women, particularly those of childbearing age, are more likely to withdraw from the labor market.

Age cohorts

Age also exerts an opposing influence on FWFPR. Younger cohorts of women are expected to participate more actively in the labor market, attributed to the concept of education vintage. This concept posits that the same level of education in newer generations holds more informational content than in older generations with equivalent schooling (Rosen, 1987). Such enriched education better equips these younger cohorts for the labor market, potentially leading to higher returns and, consequently, greater workforce participation. These results are consistent with the education vintage hypothesis.

Place of residence: rural-urban

A person's place of residence, whether rural or urban, affects their productivity and earnings. As Table 6.1 shows, on average, urban women earn 14.1 percent more than rural women in the LM sector. With better technology readily available for production in urban areas, it is not surprising that women in urban LM earn more than their rural counterparts. However, women who manage households in urban areas earn (in terms of shadow earnings) 65.0 percent more than those who manage households in rural areas. A possible reason for this large rural-urban gap in HH earnings is that modern urban households have a wide array of productivity-enhancing devices, such as washing machines and dishwashers, which many rural households may lack. This disparity in household resources likely enhances the productivity of urban HH women workers, thereby increasing their shadow earnings. Moreover, due to this large gap, the FWLFR in urban areas is expected to be substantially lower than in rural areas. In 2022-23, urban female workers had a more than 10 ppt lower LFPR than their rural counterparts.

Household size

Home time negatively impacts productivity in the LM earnings. Spending more time at home reduces labor market experience, resulting in lower earnings. When other household members are present, the need to stay at home for long periods decreases, which increases productivity at work and earnings. Table 6.1 confirms this intuition and inference. Each additional household member increases labor market earnings by 6.5 percent.

Household size can significantly impact the HH sector in a different way. A large household can provide more training and assistance at home, increasing productivity and implicit or shadow earnings. Accordingly, Table 6.1 shows that for every additional household member, HH earnings increase by 15.8 percent. Given that the impact is substantially larger in HH, an increase in household size is expected to lower the FWFPR.

Contribution of male members' earnings and education

A woman's performance at work and at home is influenced by her husband's earnings. Higher male earnings lead to a wealthier household, which, in turn, boosts the LM productivity of women, resulting in higher labor market earnings. Table 6.1 shows that women's LM earnings increase by 0.74 percent for every one percent increase in household per capita male earnings. Additionally, higher male earnings enable households to purchase more household gadgets, enhancing the HH productivity of women. According to Table 6.1, for every one percent increase in men's household earnings, women's implicit household earnings increase by 1.6 percent, which is more than double the effect in LM. This disproportionate impact may lead to a decline in FWFPR.

Male education, on the other hand, may enhance the productivity of women through peer effects. This peer effect should, however, be smaller in the labor market than in the household sector. Table 6.1 shows that women's earnings increase by 0.3 percent for every additional year of male education. A one-year increase in male education leads to a 1.0 percent increase in women's implicit HH earnings (i.e., shadow earnings). Here as well, one would expect a decline in FWFPR due to this gap between LM and HH.

Work force participation estimates

As seen above, nearly all variables in the earnings function estimates are statistically significant at the 5 percent level. Moreover, the impact of these variables varies substantially between the LM and HH sectors. This implies that any change in these variables can potentially alter FWFPR. Table 6.1, column (4), confirms this inference. Factors such as years of schooling, age, residential area (rural/urban), number of children under the age of 10, household size, average male earnings per person, male educational levels, proportion of women in the household, and various age cohorts all significantly affect FWFPR.

Work participation first declines with education and then rises, as implied by the earnings function estimates for LMs and HHs. However, as women age, work participation increases at a declining rate, as shown by the negative coefficient of the second term. These findings align with studies that have examined the impact of education and work experience (Mincer, 1997).

Women in families with more children under ten years of age, higher per capita male earnings, and higher male educational levels are less likely to work. In contrast, women who live in families with a higher proportion of female members are more likely to work. Younger cohorts of women are more likely to be employed than older cohorts (aged 57-64).

The Variance-Covariance matrix of the unobserved skills (ϵ_W, ϵ_H)

Thus far, our discussion has centered on the observed determinants of skills that impact earnings in the LM and HH sectors, thereby affecting FWFPR. However, numerous other factors, such as innate sector-specific skill endowments and health shocks, also shape these skills but often remain unrecorded in labor surveys. Given their potential influence on earnings, these factors are likely to affect FWFPR as well. This subsection turns to these unobserved determinants of skills. As previously mentioned, it is impossible to identify or estimate unobserved components at the individual level. However, under the normality assumption and the structure of the Roy model, we can identify and estimate the variance-covariance matrix of these errors. It is presented below:

$$\begin{bmatrix} \epsilon_W \\ \epsilon_H \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \hat{\sigma}_W^2 = 0.36 & \hat{\sigma}_{WH} = 0.97 \\ \hat{\sigma}_{WH} = 0.97 & \hat{\sigma}_H^2 = 3.13 \end{bmatrix}\right)$$

First, variance-covariance matrix estimates reveal two distinct features regarding the distribution of unobserved skills. First, the variance of ϵ_H is higher than that of ϵ_W (3.13 versus 0.36). This difference is somewhat expected. Performing household tasks often requires a wide variety of skills, such as obtaining resources, scheduling tasks, cooking, and cleaning. Unlike task-specific skills in the LM, the skills needed in the HH are generally more diverse. They are akin to entrepreneurial skills, which combine a number of specific abilities. Women engaged in the HH often have to be entrepreneurial and play the role of "jack-of-all-trades" (see Lazear (2004) for the phrase in the context of entrepreneurship).[18] Most working (LM) Indian women (over 95 percent) are not entrepreneurs, so their entrepreneurial skills are rarely utilized. In contrast, women in the HH sector almost always use this general set of skills, leading to a higher variance. Figure 6.2 plots the simulated distribution of the unobserved skills.

Second, the estimate of $\hat{\sigma}_{WH} = Cov[\epsilon_W, \epsilon_H]$ indicates a high correlation (0.90) between these skills. This suggests commonalities between unobserved skills in the LM and HH sectors. Many

[18] Specialized chefs can successfully perform their jobs in the field of cooking. However, a restaurant owner needs many other skills to succeed.

household tasks today have LM equivalents (paid cooking assistants, cleaners, tutors, sewing service providers, etc.), so an individual's skills in specific HH tasks would also be useful in the LM. Later, we will show the implications of these variances and covariance on the effectiveness of potential policy interventions.

The high correlation also suggests that the best HH workers are likely to be the best LM workers. Since $(\hat{\sigma}_H^2 - \hat{\sigma}_{WH}) > 0$, best HH workers stay in household sectors. Conversely, $(\hat{\sigma}_W^2 - \hat{\sigma}_{WH}) < 0$ suggests that not so skilled LM workers join the LM sector. This sectoral sorting is noteworthy because moving women from HH to LM could increase average women's earnings and reduce the gender wage gap.

Considering the variance and covariance structure, many female workers from the right tail of the ϵ_H distribution remain in the HH sector. In contrast, many workers from the left tail of the ϵ_H (or ϵ_W) distribution join the LM market. Anecdotally, the large proportion of women in low-wage employment (e.g., construction work) supports this estimated pattern. The high correlation and variance in the household sector result in many female workers at the right tail of the ϵ_H distribution remaining in the HH sector and implicitly enjoying earnings.

Model prediction: FWFPR

By utilizing the coefficient estimates, the mean values of the corresponding independent variables, and simulated unobserved skills, we can now simulate and predict the FWFPR, which is our main topic of analysis. Figure 6.3 presents the simulated data, plotting predicted-simulated HH earnings on the vertical axis and predicted-simulated LM earnings on the horizontal axis. The straight line is a 45-degree line. Anyone above this line would earn more in the HH sector than in the LM sector and thus choose the HH sector. Conversely, anyone below this line would earn more in the LM sector and therefore choose the LM sector. The proportion of women below the 45-degree line indicates the FWFPR. ***According to our structure-based simulation, we predict a 42.0 percent FWFPR in 2022-23, which is reasonably close to the actual 41.5 percent FWFPR in the same year.***

FWFPR and education: the U-shaped relationship

Our model predicts a U-shaped relationship between FWFPR and years of schooling. The estimates in Table 6.1 indicate that education and earnings are non-linearly related. For LM, the relationship is convex, while for HH, it is concave. Due to these non-linearities, FWFPR may initially decline and then rise as education increases. In line with this assertion and Goldin's (1995) findings, our simulations produce a U-shaped relationship between education and FWFPR (Figure 6.4). At low levels of education, schooling is more beneficial in the HH sector than in the LM sector. However, as education levels rise, the returns to schooling in the LM sector eventually exceed those in the HH sector, leading to higher LM earnings compared to HH or reservation earnings. To the best of our knowledge, no previous studies have explored this mechanism in detail. Up to about six years of education, an increase in education results in a decrease in FWFPR. Beyond six years, the FWFPR gradually increases with higher levels of education. By 18 years of education (a master's degree), the model predicts that 70 percent of women aged 25-64 will be employed in the LM sector, comparable to the male labor force participation rate.

Section VII: Gender Wage Differences

This section explores gender wage differences in Indian labor markets since 1983. Measurement of wage differential between genders was initiated by Becker (1957) in his seminal paper on economics of discrimination. Since then, greater availability of microdata has allowed labor economists to estimate and explain the likely causes of gender wage differential.

Gender wage gap is measured as the difference between average earnings of men and average earnings of women expressed as a percentage of average earnings of men. A negative value for the Gender Wage Gap implies that women on an average have a higher earning than that of men. ILO (2018) finds that for 73 countries comprising of 80 per cent of the world's population, the weighted gender pay gap is 16 per cent.

In table 7.1 we report the gender wage gap in India for workers with intermediate education. Intermediate education is defined as having some high school and advanced education is defined as having some college (or above). We separate the gender wage gap by different age groups as there has been a large expansion in women education in recent years. This expansion in education attainment by women would imply a relatively higher wage for younger women when compared to their older counterparts. Table 7.1 shows that even for workers with intermediate education, gender-wage gap for younger women is negative. That is, women aged 20-29 on an average have a higher wage than their male counterparts. Much of the observed aggregate gender wage gap in India is driven by older women.

Workers with advanced education are expected to have a relatively higher wage due to higher human capital levels. The gender wage gap for them shows a similar trend as the gender wage gap for younger women is negative indicating that women ages 20-29 on average earn more than men in the same age group.

Tables 7.1 indicates a decline in the overall gender wage gap in Indian labor market. The decline, particularly for younger workers implies further reduction in the aggregate gender wage gap in India over the next few years. Table 7.2 further compares the percentage gap in years of education between women and men for those with intermediate and advanced education status. The gap in years of education has declined substantially over the last four decades and the decline is substantial for younger women.

An equally important aspect is to compare gender wage gap in India with other countries, particularly emerging market economies. In Table 7.3 we compare the mean gender pay gap by education attainment for select emerging market economies and average gender pay gap by World Bank's income classification. Across 75 countries, the average gender pay gap is 17.4 per cent for those with advanced education attainment. India's gender pay gap is therefore not very different than its peers.

Another useful measure is to compare the mean gender pay gap over different occupations. In particular, we report the total gender pay gap, gender pay gap for managers and for professionals (Table 7.4). The results indicate two sources of variations that are important. The first is the variation across countries and this is largely driven by different labor markets in each of these individual countries. The second is the variation in gender pay gap by occupation within a given country. Even across occupations, there is not much difference between India and other countries on the gender wage gap. In particular, India is the among very few countries with a negative gender wage gap for managers.

To explore whether emerging markets have on an average a higher mean gender wage gap, we explore the relationship between gender wage gap and per-capita income (a proxy for level of development). A higher per-capita income would be synonymous with higher average education better functioning institutions, robust laws against discrimination and efficient enforcement of contracts. Therefore, the relationship between gender wage gap and per-capita income should be a negative one. Figure 7.1 shows the relationship between gender pay gap and per-capita income levels (PPP $) for 74 countries thereby indicating that the gender pay gap is higher in countries with a higher PPP$ per capita income.

To explore whether this positive relation is driven by a particular set of countries, we repeat the analysis by restricting our focus to individual World Bank income classifications of high-income, upper-middle income, lower-middle income and low-income countries in Figure 7.2. Across the four panels, we find a systemic positive relationship between the mean gender pay gap (for advanced education) and per-capita income levels.

The relationship is not as straightforward when we look at the relationship between mean gender pay gap (for those with intermediate education) and per-capita income (2017 PPP$) for lower-middle income countries that show a negative relationship in contrast with the other three categories.

Two important conclusions follow. The first, gender wage gap in India has been on a decline, and that for younger women, the gender wage gap is negative. *These results hold true both for workers either with intermediate education or advanced degrees.* The second, the gender wage gap in India is not very different than other countries, particularly emerging markets. Given the decline in the gender wage gap for younger women, the underlying trend of reduction in the gender wage gap will continue.

Section VIII: Time Use Surveys

The labor force participation decision of women is determined by their education status, family income, household size, marital status, and the number of children's. Put simply, a woman's decision to participate (or not) in the workforce is contingent on the implicit opportunity cost of not working. Therefore, their reservation wage is determined given this implicit cost, and it is conditional on the decision to participate in the workforce. `

Standard labor supply models, particularly choice-models invoke preferences over two choices to model individual decisions. Such models often jointly determine the decision to work and the number of hours of work for a given wage. That is, the labor force participation decision and the number of hours to supply are determined jointly. Such a structure is particularly appealing given the availability of time-use data which allows us to study household preferences over time-allocation, and gender differences.

We explore the time allocated to individual activities by households in the age group of 15 – 64. There are several broad categories of activities in these surveys, these include paid work, unpaid work, leisure activities, personal care. These categories allow comparability of time allocated to different activities across a cross-section of advanced and emerging economies. Naturally, a higher share of time allocated to non-paid work categories would imply a lower availability of time for paid work. However, the Time-Use survey does not allow one to explore whether greater allocation of time to unpaid work is due to self-selection by individuals or due to the lack of paid-employment opportunities.

We pay particular attention to the gender difference in time spent on family-care (child-care). Indian women spend the most amount of time on childcare among a set of advanced and emerging market economies, and by an order of magnitude (Table 8.1).[19] The average time spent on childcare by men is 15 minutes, while women on the average spend 38 minutes on childcare. Indian men spend about 15 minutes on childcare which is consistent with the global average, however, Indian women spend 70 minutes on childcare, which is substantially higher than the global average.[20]

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[19] Sri Lanka does not have a recent Time-Use survey and a translated version of the latest Bangladesh Time-Use Survey was not available at the time of the study.

[20] We show in Section IV that if a woman spends 60 minutes or more on *education* childcare and is not formally classified as being in the labor force, then she can be considered as being in the labor force. This adds about 4 percentage points (2019 time-use survey) to female LFPR.

Polish women come a close second in terms of the minutes spent on childcare (55 minutes) while German women spend the least (25 minutes).

The average time spent on childcare by women has an interesting statistical relationship with the labor force participation rate (Figure 8.1).[21] Higher amount of average time spent on childcare results in a lower observed labor force participation rate for women. It is difficult to ascertain whether Indian women chose not to work due to more time spent on childcare, or if they spend more time on child-care since they are unable to find suitable formal employment. The lack of flexibility in terms of number of hours could also be a feature behind the relatively lower participation rate of women in the labor force.

It is evident that there is a higher burden of child-care on Indian women relative to other countries, and this is likely to have implications for labor market participation rates of married women with kids. Therefore, is a need to recognize this new Goldin Gap (Goldin, 1994) in FLPR due to disproportionate time spent by women on childcare.

Any analysis focused on evaluating India's FLPR would have to consider this increased burden and its implication for women's choice to participate in labor markets. There could be several reasons behind the higher time spent on childcare by Indian women. It could be due to preferences or social structures or also due to lack of adequate childcare alternatives outside of the household. The latter can be addressed through policies such as economic incentives that create childcare alternatives in an effort to encourage greater participation of women in workforce.

[21] Taş and Ahmed (2021) used the Time-Use survey for Bangladesh (2018). They find women with children aged 0-5 years have lower likelihood of labor market participation. Further, they find mothers of young children spend more time on childcare and less time on paid work. For those women with children who undertake paid work, childcare is their secondary activity.

Conclusion

This report reexamines a critical policy issue concerning the Indian economy: the labor market, with a particular focus on female labor force participation. India's relatively low female labor force participation rate has generated significant interest in recent years. Consequently, a large body of literature has emerged that attempts to explain the observed low FLPR in India. This report reassesses this existing literature from a different perspective and attempts to compare Indian labor market dynamics within the context of structural changes in Indian economy over the last three decades.

India is characterized by two distinct trends: the ongoing improvement in educational achievements and a decline in fertility rates. These developments are poised to significantly reshape labor market dynamics and overall economic progress. Therefore, any analysis or estimation of Indian labor market statistics must consider these concurrent shifts during empirical investigations. These trends have important implications for labor market statistics in India given that increased educational enrollment by definition implies lower LFPR, and declining fertility rate has implications for future working age populations.

We re-examine the issue of the observed decline in FLPR in India between 2004-05 and 2011-12. Our analysis reveals that the data from 2004-05 are of inconsistent quality and should not be used for analyzing shifts in the female labor force participation rate. Unfortunately, much of the existing research on this subject relies on this NSSO 2004-05 employment-unemployment data to explore a supposed decline in female labor force participation from 2004-05 to 2011-12. The shifts of family helpers into and out of the labor force, the shifts that is central to the decline in female labor force participation from 2004-05 to 2011-12, are primarily the result of data irregularities, not systematic shifts in socio-economic factors. Additionally, in alignment with the findings of the International Labor Organization, this report finds that the Periodic Labor Force Surveys (PLFS) from 2017-18 and 2018-19 fail to meet the quality standards necessary for reliable labor market statistics.

In addition, we discuss the importance of definitions for measurement of employment status. The National Sample Survey Office (NSSO) employment-unemployment surveys and the Periodic Labor Force Surveys (PLFS) employ various definitions of employment, including usual status, current weekly status, and current daily status. While most international labor market statistics rely on current weekly status for computations and comparisons, this report contends that this measure may not be fitting for the Indian context.

Given India's stage of economic development, the labor market is expected to experience considerable fluctuations, with frequent changes in occupations, jobs, and locations. Amid this churn, measuring employment and labor force statistics on a weekly status basis is less practical (especially where the demarcation of domestic work and labor market engagements is thin such as family enterprise helper) compared to international standards, where labor markets are more stable.

We revisit numerous existing studies that discuss the Indian labor market and female labor force participation (e.g., McKinsey, 2020; SADU, 2024). A significant deviation introduced in this report to accommodate structural changes, which other studies overlook, is the redefinition of the working-age population as those over 25 years of age. This adjustment, diverging from the internationally recognized threshold of 15 years, provides a more stable measure amidst socio-economic shifts due to increased educational attendance between ages 15 and 24.

After implementing these essential adjustments, the report concludes that there is limited evidence that Indian women's labor force participation rates differ significantly from those in comparable countries (AsiaLA-29). Additionally, by employing time use surveys to explore the dynamics at a more disaggregated levels, the report reaches similar conclusions. Even comparisons with a developing country like Korea during a similar stage of development (1960-80) as India (1999 – 2022) show that labor force participation rates for females (41.7 percent in Korea vs. 41.9 percent in India) and overall (63.0 percent in Korea vs. 65.1 percent in India), for individuals aged 25 and above, are closely aligned between the two nations.

Furthermore, due to the declining fertility levels, most current forecasts or estimations of future job growth are positively biased. In projecting the required job growth, these studies often assume that the future will mirror the past—an assumption that may not hold in an economy experiencing structural changes. Once the decline in fertility is considered, the annual job requirement would be approximately 6-8 million, significantly lower than the figures suggested in existing studies.

Using NSS data, we find a significant decline in the gender wage gap for younger workers. This decline is consistent with the decline in years of education between men and women. India's gender wage gap is not significantly different from other emerging market economies and incidentally, India is among the few countries where women managers have a higher average wage than their male counterparts.

In addition, a structural estimation exercise that thoroughly examines the interplay between labor market participation, earnings, and home production helps evaluate the individual decision to participate in the labor market. Two distinct sectors, household sector and labor market are proposed to evaluate the role of variables such as education in the decision to participate in labor market. This analysis offers a clear perspective on the opportunity costs and reservation wages associated with labor market entry. Our results reveal a U-shaped relationship between education and female labor force participation. Furthermore, the significantly higher variance in unobserved skills within the home sector and their strong correlation with those in the labor market indicate that policies aimed at creating labor market incentives could have multiple unintended effects.

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Section II: Tables & Figures

Table 2.1 Female labor force statistics, 2016-17 (age>=15)

	Level (in thousands)	Rates (%)
Working Age Population	54974	
Pay-or-profit	12522	62.7
Own consumption	6124	30.7
Labor Force		**LFPR**
Bangladesh	19976	36.3
NSSO, definition	13852	25.2
Employment		**WPR**
Bangladesh	18646	33.9
NSSO, definition	12522	22.8
Unemployment		**URATE**
Bangladesh	1330	6.7
NSSO, definition	1330	9.6

Note: Home production for own consumption is equivalent to NSSO activity status 93, and not part of labor force or employed as per NSSO definition.

Section III: Tables & Figures

Table 3.1 (a): LFPR India Usual Status

Year	Women		Men		All	
	>=15	>=25	>=15	>=25	>=15	>=25
1983	44.4	46.1	87.4	92.3	66.2	69.5
1993	42.7	45.4	85.6	92.8	64.6	69.5
1999	38.9	42.1	83.6	91.4	61.6	67.0
2004	42.7	46.3	84.0	91.6	63.7	69.0
2011	31.2	35.0	79.8	91.1	55.9	63.0
2017	23.3	27.1	75.8	87.4	49.8	57.1
2018	24.5	28.5	75.5	86.8	50.2	57.5
2019	30.0	34.4	76.8	87.8	53.5	60.8
2020	32.3	37.4	76.3	87.4	54.5	62.1
2021	32.8	37.9	77.2	87.7	55.2	62.7
2022	37.0	41.9	78.5	88.6	57.9	65.1

Source: Authors computations using NSS EU-S and PLFS (various years)
Note – Usual status – worked at least 30 days in the last year.

Table 3.1 (b): LFPR India CWS

Year	Women		Men		All	
	>=15	>=25	>=15	>=25	>=15	>=25
1983	31.3	33.0	83.6	89.0	57.8	61.3
1993	35.5	38.1	83.6	91.1	60.1	65.0
1999	33.8	36.9	82.0	89.8	58.3	63.5
2004	37.0	40.5	82.5	90.2	60.0	65.4
2011	27.1	30.5	78.5	89.8	53.2	60.1
2017	20.7	24.1	74.0	85.9	47.6	54.9
2018	21.3	24.9	73.9	85.3	47.8	55.0
2019	26.1	30.1	74.7	85.8	50.5	57.6
2020	27.2	31.7	74.5	85.8	51.0	58.4
2021	26.9	31.5	75.2	86.2	51.2	58.7
2022	31.3	36.0	76.8	87.5	54.1	61.5

Source: Authors computations using NSS EU-S and PLFS (various years)
Note – CWS – Current Weekly Status – worked at least 1 hour last week

Table 3.1 (c): Female Labor Force Participation Rate

Year	Females ages 25-54	
	LFPR CWS	LFPR US
1983	37.2	51.5
1993	42.4	50.4
1999	41.1	47.0
2004	44.9	51.4
2011	33.8	38.8
2017	27.9	31.2
2018	28.6	32.5
2019	34.3	38.9
2020	36.1	42.6
2021	36.0	43.2
2022	40.7	47.2

Source: Authors computations using NSS EU-S and PLFS (various years)
Notes – 1) Usual status – worked at least 30 days in the last year.
2) CWS – Current Weekly Status – worked at least 1-hour last week

Table 3.2: Table: LFPR (in %) - A cross Country Perspective

	Ages >=15 years			Ages >=25		
	India		**AsiaLA-29**	**India**		**AsiaLA-29**
	Usual	CWS	CWS	Usual	CWS	CWS
All						
1999	61.6	58.3	62.3	67.0	63.5	67.3
2011	55.9	53.2	62.4	63.0	60.1	67.8
2022	57.9	54.1	61.0	65.1	61.5	66.1
Females						
1999	38.9	33.8	44.2	42.1	36.9	47.1
2011	31.2	27.1	46.4	35.0	30.5	49.9
2022	37.0	31.3	46.2	41.9	36.0	49.5
Males						
1999	83.6	82.0	80.3	91.4	89.8	87.7
2011	79.8	78.5	78.6	91.1	89.8	86.2
2022	78.5	76.8	76.2	88.6	87.5	83.5

Source: NSS, PLFS, and ILO data on current weekly status
Notes – 1) Usual status – worked at least 30 days in the last year.
2) CWS – Current Weekly Status – worked at least 1-hour last week
3) AsiaLA - 29: Twenty nine countries in Asia and Latin America - All countries in Asia and LA excluding economies with population less than 5 million in 2022, and the following six economies: Afghanistan, China, Cuba, Myanmar, North Korea and Venezuela. China excluded because its population size would dominate the weighted population averages

Section IV: Tables & Figures

Table 4: Share of Employment (in %) - A cross Country Perspective

	Ages >=15 years			Ages >=25		
	India		**AsiaLA-29**	**India**		**AsiaLA-29**
	Usual	CWS	CWS	Usual	CWS	CWS
All						
1999	60.2	56.2	58.8	66.3	62.2	65.0
2011	54.7	51.5	59.6	62.5	59.0	65.8
2022	56.0	51.8	58.9	64.1	60.0	64.8
Females						
1999	38.2	32.7	41.1	41.8	36.2	45.1
2011	30.5	26.1	43.9	34.6	29.7	48.1
2022	35.9	30.0	44.4	41.3	35.1	48.5
Males						
1999	81.5	78.8	76.4	90.4	87.7	85.1
2011	78.1	76.1	75.4	90.3	88.3	84.0
2022	76.0	73.5	73.7	87.3	85.3	82.0

Source: NSS, PLFS, and ILOSTAT data on current weekly status

Section V: Tables & Figures

Table 5.1: Structure of jobs in India 1999 to 2022/23; usual status; ages >=15

Year	(1) Crop Agriculture	(2) Cash Crop Agriculture	(3) Manufacturing	(4) Services	(5) Finance	(6) Total	(7) (6)-(2)-(1)	(8) (6)-(1)
1983						265.9		
1993						329.1		
1999	217.1	5.6	38.8	74.0	36.5	372.0	149.3	154.9
2004	234.6	4.0	47.5	95.7	39.9	421.7	183.1	187.1
2011	193.3	15.5	54.7	123.8	37.9	425.2	216.4	231.9
2017	172.8	22.1	54.2	136.5	46.2	431.8	236.9	259.0
2018	167.2	23.2	55.2	145.4	49.0	440.0	249.6	272.8
2019	193.8	26.8	55.9	157.2	48.8	482.5	261.9	288.7
2020	197.5	31.3	56.0	159.3	47.7	491.8	263.0	294.3
2021	181.1	42.0	60.4	165.2	48.4	497.1	274.0	316.0
2022	172.2	60.1	63.1	178.4	49.6	523.4	291.1	351.2
Change in jobs per year								
1999/2004	3.5	-0.3	1.7	4.3	0.7	9.9	6.8	6.4
2004/11	-41.3	11.5	7.2	28.1	-2.0	3.5	4.8	6.4
1999/11	-2.0	0.8	1.3	4.2	0.1	4.4	5.6	6.4
2022/11	-21.1	44.6	8.4	54.6	11.7	8.9	6.8	10.8
2019/22	-7.2	11.1	2.4	7.1	0.3	13.6	9.7	20.8
Per year %								
1999/2004	1.6	-6.7	4.0	5.1	1.8	2.5	4.1	3.8
2004/11	-2.8	19.4	2.0	3.7	-0.7	0.1	2.4	3.1
1999/11	-1.0	8.5	2.9	4.3	0.3	1.1	3.1	3.4
2022/11	-1.1	12.3	1.3	3.3	2.4	1.9	2.7	3.8
2019/22	-3.9	26.9	4.0	4.2	0.5	2.7	3.5	6.5

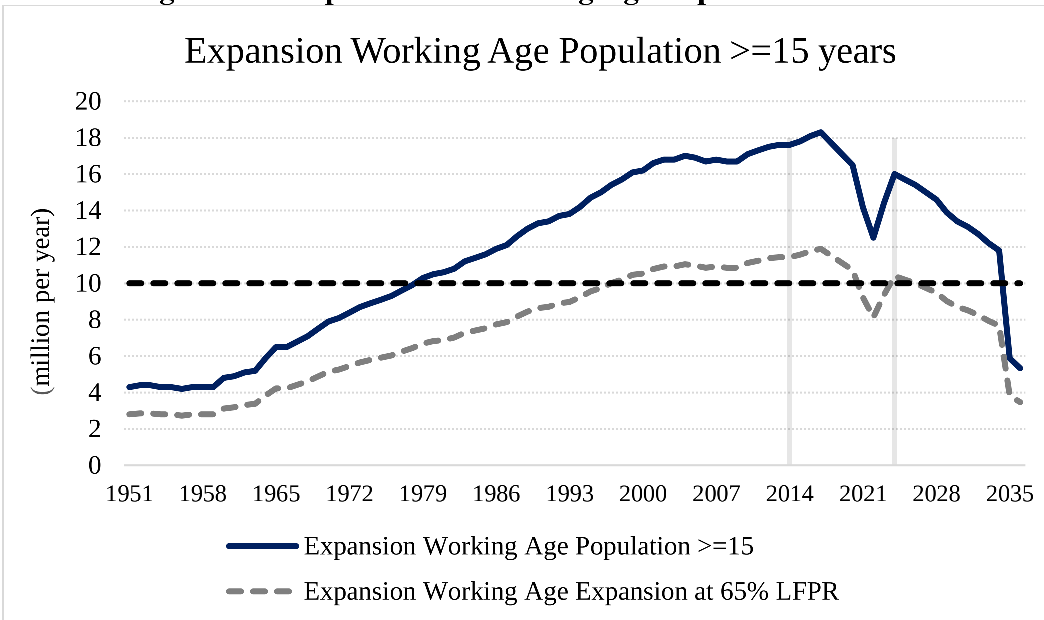
Source: Authors computations using NSS EU-S and PLFS (various years)

Table 5.2: Employment for Age Group 15 years and above

Year	Usual status		Weekly status		Share of unpaid/total	
	Total	Unpaid	Total	Unpaid	US	CWS
1983	295	57	253	43	19.2	16.8
1993	368	82	339	70	22.2	20.7
1999	404	84	377	75	20.8	19.9
2004	470	111	436	97	23.7	22.2
2011	478	85	450	74	17.7	16.4
2017	459	62	433	52	13.5	12.0
2018	472	62	442	50	13.2	11.4
2019	517	82	474	66	15.9	13.9
2020	538	92	491	73	17.2	14.9
2021	554	96	505	74	17.4	14.7
2022	593	108	549	85	18.2	15.5

Source: Authors computations using NSS EU-S and PLFS (various years)

Figure 5.1: Expansion of Working Age Population in India



Section VI: Tables & Figures

Table 6.1: the structural estimates (LM, HH and work decision), 2022-23

Explanatory variables	Earnings function Dep Var: ln(wage/day) LM (2)	 HH (3)	Selection equation Dep Var: whether work or not (work =0/1) Coefficient (4)	 Marginal effect (5)
Years of schooling (in years)	-0.003	0.051	-0.044***	
Years of schooling (squared)	0.001	-0.005	0.004***	
Marginal effect (schooling)	*0.004***			*0.003*
Whether has a college degree (D=1/0: Yes/No)	0.156***		0.125	0.049
Age (in years)	-0.018	-0.317	0.239***	
Age-squared	0.000	0.003	-0.003***	
Marginal effect (age)	*-0.006**			*0.011****
Area of residence (Urban=1, Rural=0)	0.141***	0.650	-0.407***	-0.162***
No. of children below age 10, in HH			-0.062*	-0.024**
Household size	0.065***	0.158	-0.074***	-0.029***
(log) Per capita male earnings	0.742***	1.559	-0.655***	-0.260***
Average male education years, in HH	0.003	0.010	-0.006	-0.002
Proportion of female in HH		-0.542	0.434***	0.172***
Whether in Age group 25-31	-0.085	-0.419	0.268*	0.106**
Whether in Age group 32-44	-0.009	-0.066	0.045	0.018
Whether in Age group 45-56	-0.162***	-0.310	0.119	0.047*
Intercept	2.651***	5.717	-2.454**	

Source: PLFS, 2022-23, authors own computations.

Notes:

1) (log) Per capita male earnings are calculated as follows. We divide a household's total male hourly wage by its total number of male workers. We then take a log of it.

2) The reference/omitted age group is 57-64.

3) The coefficients presented for LM (col 2) and HH (col 3) sectors earnings function also represent marginal effects as the earnings functions are linear.

4) The selection equation indicated whether the individual worked or not. If work=1 then the individual participated in the LM sector; if work=0 then the individual participated in the HH sector.

5) The selection equation coefficient estimates do not reflect the impact of independent variables on the probability of LM sector participation. Because of that, we compute the marginal effects and report them in col (5). Standard errors are calculated using the delta method.

6) Household sector estimates are calculated from the LM sector earnings function and selection equation estimates, so they do not have standard errors.

7) Since log(earnings) is a quadratic function of schooling and age, we compute their marginal effects using the following formula: ME of schooling = -.00339 + 2*.00063*6.1, where 6.1 is the average female (25-64 age) years of schooling in 2022-23; ME of age = -.0181812 + 2*0.00016*40.1, where 40.1, is the average female (25-64 age) age in 2022-23; We find the schooling and age effect on probability of participation in the LM sector by taking the partial derivative of the predicted probability.

8)*: 10 percent level; **: 5 percent level; ***: 1 percent level of significance.

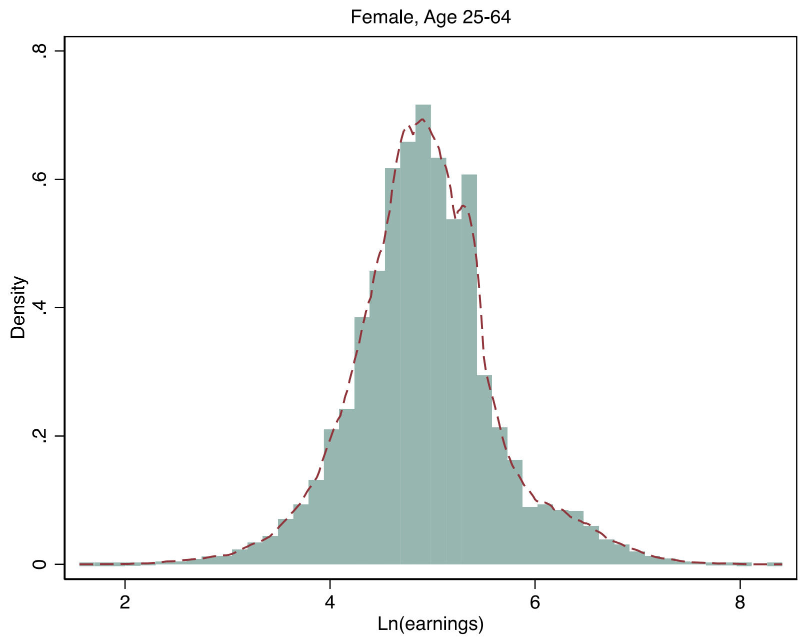
9) The unit of (100*marginal effects) in earnings equation is in %, expect of (log) male earnings (for this one is elasticity); for the selection equation, 100*marginal effects) are in percentage points units.

Table 6.2: Returns to schooling by education group (in %)

Schooling percentiles	LM sector	HH sector
0-20	-0.34	5.12
20-40	0.17	1.25
40-60	0.61	-2.13
60-80	0.96	-4.86
80-100	1.55	-9.40
All	0.38	-0.39

Source: PLFS, 2022-23; authors own computations.

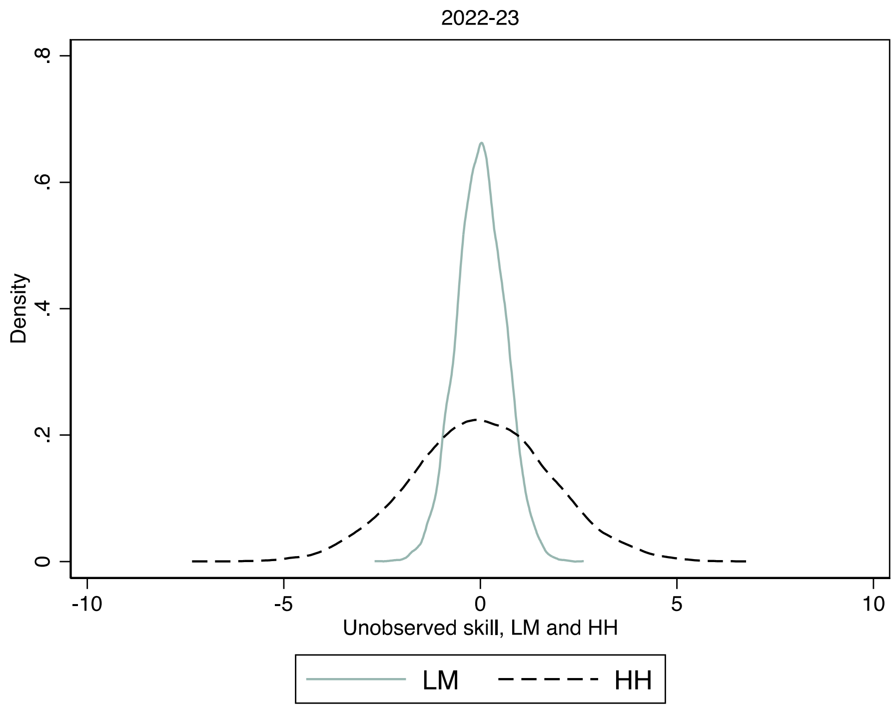
Figure 6.1: Distribution of earnings (Rs./hour)



Source: PLFS, 2022-23.

Note that earnings are only available for LM sector.

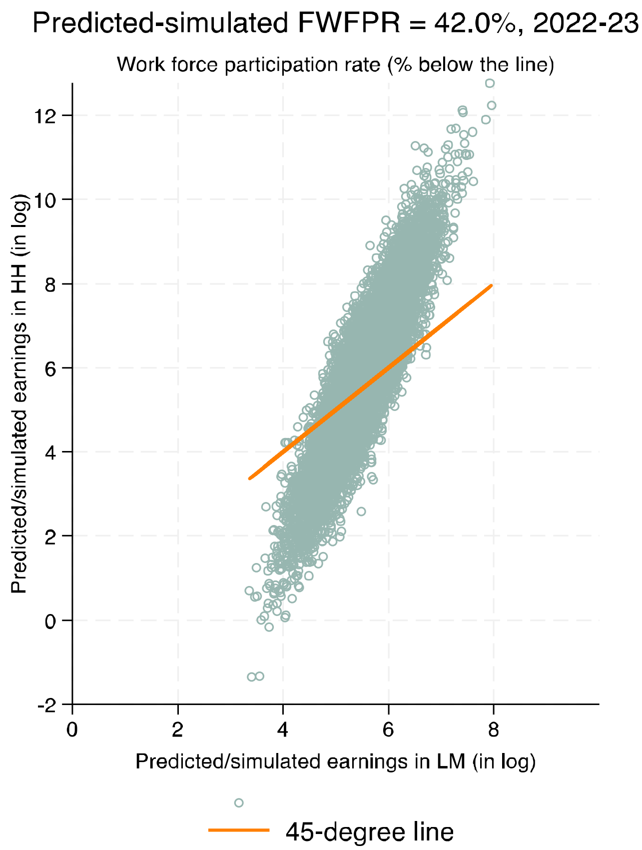
Figure 6.2: Simulated distributions of ϵ_W, ϵ_H



Source: PLFS, 2022-23.

Note that earnings are only available for LM sector.

Figure 6.3: Predicted female work force participation rate (FWFPR)

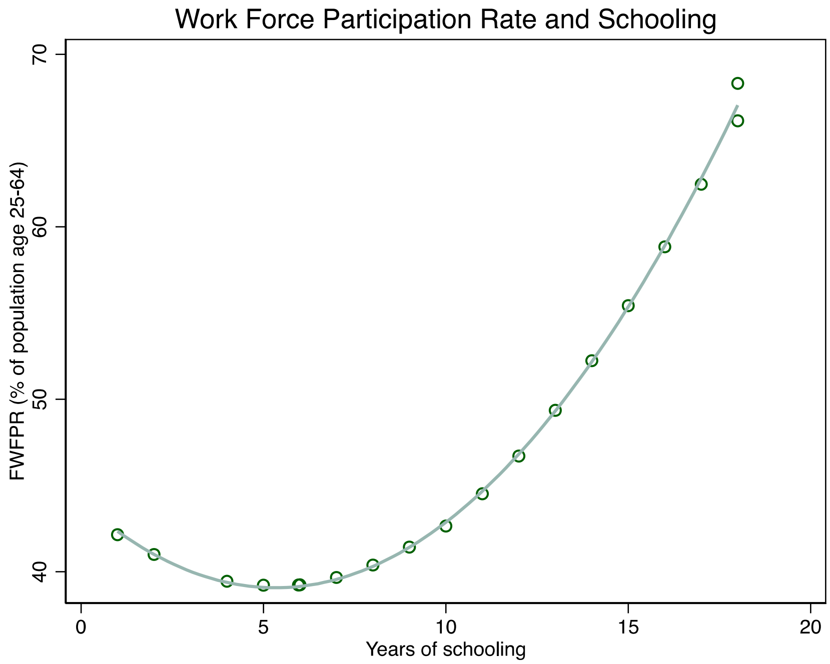


Source: PLFS, 2022-23.

Note that earnings are only available for LM sector.

Figure 6.4: Simulated female work force participation rate, 2022-23

Age group: 25-64



Source: PLFS, 2022-23.

Note that earnings are only available for LM sector.

Section VII: Tables & Figures

Table 7.1: Average Gender Wage Gap in India

year	Intermediate Education			Advanced Education		
	20-29	30-39	40 and above	20-29	30-39	40 and above
1983	7.4	34.1	47.6	-15.0	8.8	12.6
1993	9.6	24.9	33.7	1.1	6.6	8.3
1999	11.0	13.1	25.0	6.9	-5.3	-2.7
2004	7.2	30.1	38.2	6.4	15.0	11.5
2011	0.6	29.9	33.4	1.3	17.3	7.7
2017	-4.8	21.6	28.3	-2.3	12.6	5.6
2018	-3.8	16.6	30.0	-1.8	6.8	13.4
2019	-9.2	14.0	29.5	-7.5	2.5	7.4
2020	-7.9	22.0	32.2	-6.0	13.8	16.5
2021	-17.8	22.2	32.5	-14.7	17.4	14.9
2022	-8.7	16.1	31.5	-5.9	9.5	16.4

Source: Authors computations using NSS EU-S and PLFS (various years)
Note – PLFS 2017-18 and 2018-19 data are reported for completeness. ILO raised several data quality issues regarding these two rounds.

Table 7.2: Average Education Gap in India

year	Intermediate Education			Advanced Education		
	20-29	30-39	40 and above	20-29	30-39	40 and above
1983	50.0	59.5	70.8	-0.9	0.0	0.0
1993	43.1	48.0	63.9	-2.3	2.9	2.2
1999	35.4	43.6	59.5	-3.0	0.7	2.9
2004	26.8	41.3	56.3	-1.6	1.6	2.4
2011	18.2	31.6	49.1	-0.8	1.6	3.2
2017	12.1	25.3	44.3	-0.8	0.8	1.6
2018	10.8	24.4	43.8	0.0	0.8	1.6
2019	8.7	21.8	42.2	-0.8	0.0	0.8
2020	6.7	21.3	41.5	-1.5	0.8	1.6
2021	7.6	20.0	42.4	-0.8	0.8	0.8
2022	6.9	18.6	40.9	0.8	1.5	1.6

Source: Authors computations using NSS EU-S and PLFS (various years)
Note – PLFS 2017-18 and 2018-19 data are reported for completeness. ILO raised several data quality issues regarding these two rounds.

Table 7.3: Mean Gender Pay Gap by Educational Attainment

Country	Intermediate Educational Attainment	Advanced Educational Attainment
Bangladesh	-2.5	8.6
Brazil	28.0	32.1
India	17.6	10.1
Indonesia	61.6	33.3
Mexico	18.2	15.8
Pakistan	41.1	35.2
Sri Lanka	20.1	34.4
Thailand	20.9	15.5
Country Classification		
High Income	25.3	19.3
Upper Middle Income	21.8	17.6
Lower Middle Income	18.3	16.0
Low Income	4.5	18.6

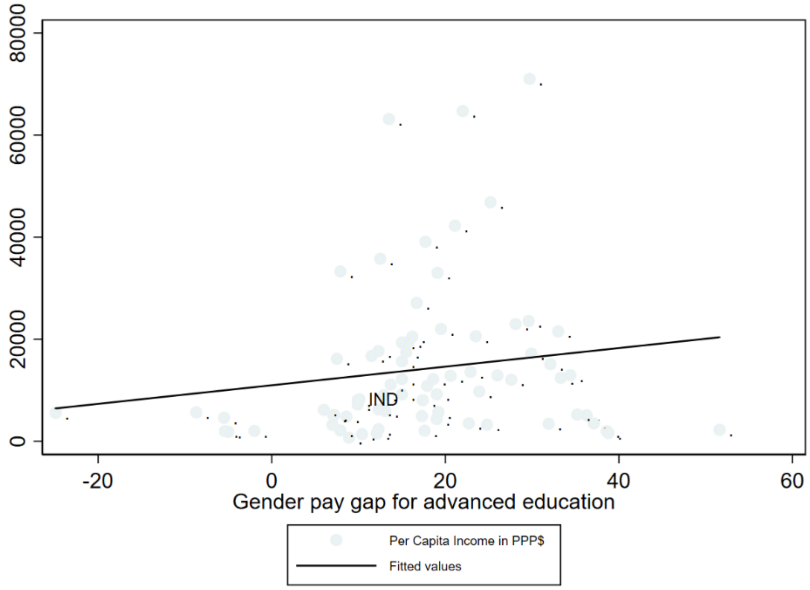
Source: ILO (2018)

Table 7.4: Mean Gender Wage Gap by Occupation Choice

	Brazil	Chile	India	Mexico	US	Viet Nam
Gender wage gap by occupation (%)						
Occupation (ISCO-08): Total	8.91	16.56	21.57	-1.77	11.19	8.70
Occupation (ISCO-08): 1. Managers	12.77	14.18	-12.05	8.35	7.55	11.82
Occupation (ISCO-08): 2. Professionals	26.62	26.69	31.39	10.47	14.34	13.99

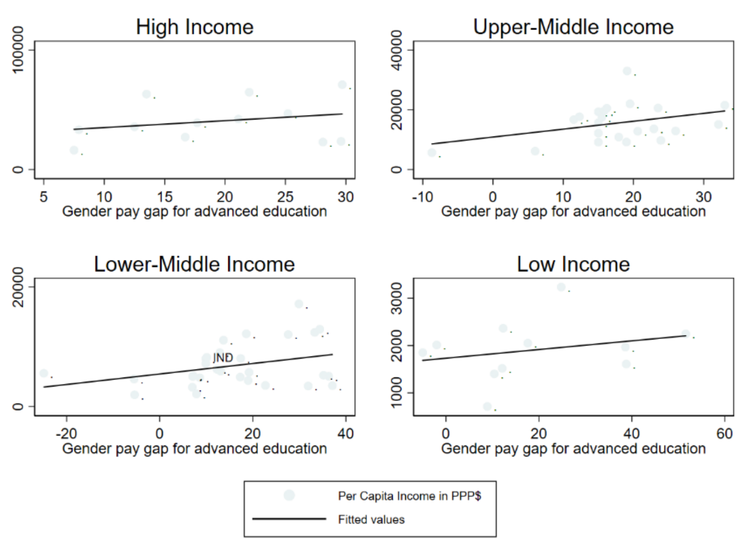
Source: ILO (2018)

Figure 7.1: Mean Gender Pay Gap & Per Capita Income



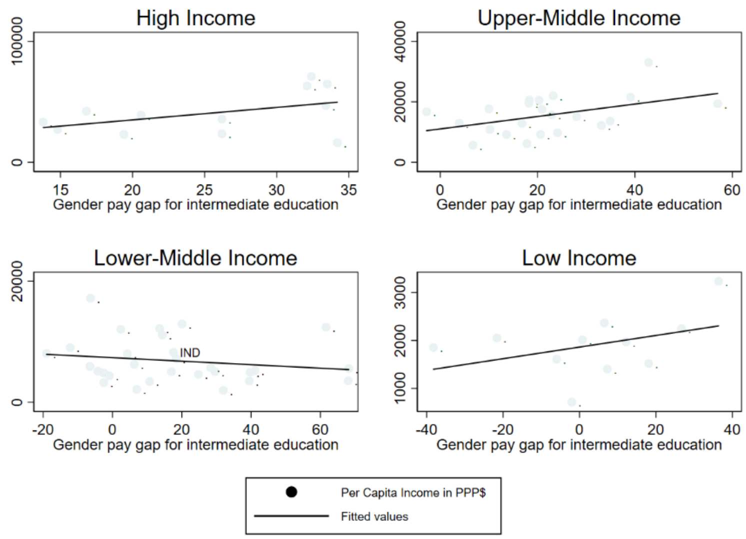
Source: ILO (2018)

Figure 7.2: Mean Gender Pay Gap & Per Capita Income



Source: ILO (2018)

Figure 7.3: Mean Gender Pay Gap & Per Capita Income



Source: ILO (2018)

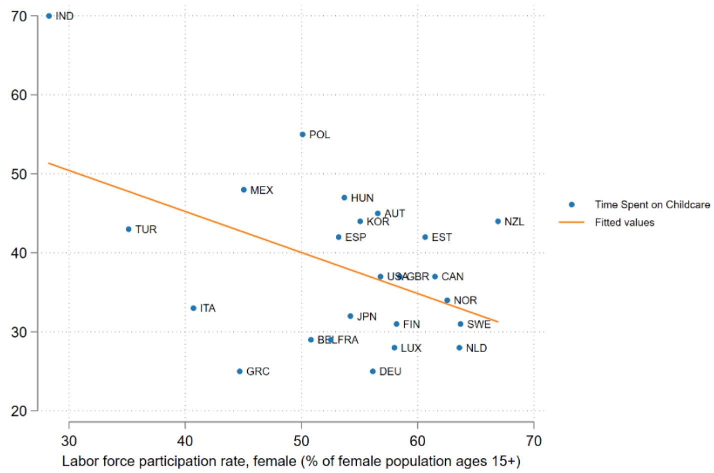
Section VIII: Tables & Figures

Table 8.1: Time Spent on Childcare

Country	Time spent on Childcare (minutes)	
	Men	Women
Austria	20	45
Belgium	14	29
Canada	18	37
Estonia	18	42
Finland	13	31
France	13	29
Germany	11	25
Greece	13	25
Hungary	18	47
Italy	16	33
Japan	7	32
Korea	11	44
Luxembourg	12	28
Mexico	14	48
Netherlands	14	28
New Zealand	16	44
Norway	14	34
Poland	22	55
Spain	23	42
Sweden	19	31
Turkey	10	43
UK	15	37
USA	17	37
India	15	70

Source: OECD Data and Authors computation using Indian Time Use Survey

Figure 8.1: Time Spent on Childcare & FLPR



Source: Time Use Surveys & World Bank