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Gender Gap and Decline in Female Labour Force Participation in India: A Joint Search Perspective

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Abstract

India, on top of having a large gender gap in labour force participation, also experienced a significant decline in participation rate of women in the recent years. In order to understand, and to decompose the gender gap and the decline in female labour force participation into demand and supply side factors, we present an equilibrium joint search model of couples with gender-specific wage offers and home productivities. In this heterogeneous agents setup, our counterfactual exercises show that, gender disparities in labour demand can account for only 6.4% of the level difference, while the differential trends in labour demand can explain around 35% of the decline in female participation over time. We find that the increase in average household income driven by a large increase in male wages compared to female wages, reduced the need for women to supplement the family income, in turn causing them to drop out of the labour force.

JEL codes: E24, J22, J64.
Keywords: Labour force participation, Gender gap, Household search, Home production

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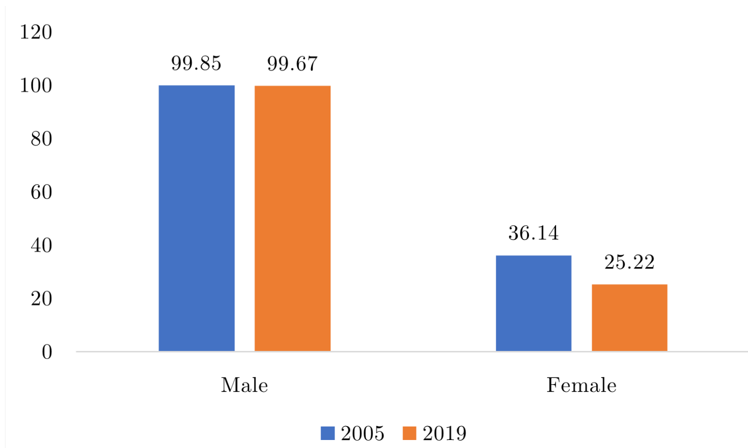
1. Introduction

Globally, and particularly in advanced economies, there has been an increase in labour market participation of women along with the narrowing of gender gap in various labour market outcomes (Goldin (2006), Olivetti and Petrongolo (2016), Ortiz-Ospina and Tzvetkova (2017)). In contrast, India, even though being one of the fastest growing economies in the world, witnessed a steady decline in female labour force participation over the past couple of decades. Between 2005 and 2019, the participation of married women in the Indian labour market has declined from 36% to 25% (Lahoti and Swaminathan (2016), Afridi et al. (2018), Klasen (2019)). Figure 1 shows the gender gap in labour force participation and the decline in participation rate of married women between 2005 and 2019. This declining trend is even more troubling as India has one of the lowest female employment rates along with Middle East and North Africa (Jayachandran (2021)).[1] According to the World Bank estimates, India has one of the largest gender gap in participation even among the lower-middle income countries, and removing India from this group decreases the average gender gap for the remaining lower-middle income countries by 10 percentage points.[2] The present paper investigates this large and widening gender gap in labour force participation using a macroeconomic setup.



Source: Authors' calculations using Employment and Unemployment Survey (2004-05) and Periodic Labour Force Survey (2018-19).

Figure 1: Gender Gap and Decline in Female Labour Force Participation

The empirical literature on female labour force participation rate in developing countries including India has focused only on the correlates of the participation rates. These frame-

[1] ILO modelled estimates for 2019 shows that, in India, only 25% of the married women were a part of the labour force, compared to the global average of around 48%.

[2] https://genderdata.worldbank.org/data-stories/flfp-data-story/

works do not permit the quantification of relative importance of demand and supply side factors in determining the participation in the labour market. The contribution of our paper is, we present an equilibrium joint search model of couples facing participation decisions, which enables us to quantify the role of demand and supply side factors in driving both the gender gap and the decline in female labour force participation in India. We contribute to the benchmark household joint search models by introducing home production to capture the unequal supply-side constraints faced by women, in particular in an emerging economy like India. One of the most widespread and persistent gender norms is that, women should take care of almost all of the household activities compared to men (Bittman et al. (2003), Sayer (2005), Jayachandran (2021)). Since women spend disproportionately more time on home production, it limits their time available to participate in labour market, thus potentially constraining their supply of labour.[3] On the other hand, male and female workers also face differential labour demand that can affect their participation in the labour market. Our model incorporates the gender differences in both demand and supply sides in a single unified framework. This enables us to decompose and quantify the relative magnitude of demand and supply side channels in explaining the level difference and the decline in female labour force participation.

Using our model, we find that the gender gap in labour force participation is predominantly driven by supply-side factors, with gender disparities in labour demand, reflected by differential wage offers, accounting for only about 6.4% of the total gap in participation. On the other hand, gender differences in the evolution of labour demand over time can explain around 35% of the decline in female labour force participation between 2005 and 2019 as seen in the data. During this time, the average real wage of male workers increased a lot more compared to that of female workers. Since the average income of the households, primarily driven by male earnings increased over time, it reduced the need for the females to continue to work and contribute to the family income, in turn causing them to drop out of the labour force. Our model results show that, the increase in gender wage gap over time has contributed significantly to the decline in female labour force participation in India.

Even though striving for gender equality is a desirable goal in itself, encouraging women's

[3]Home production has long been accepted as an important ingredient of household analysis (see for example Becker (1981)) and has also been considered for explaining female labor force participation in many studies including Greenwood et al. (2005), House et al. (2008), Albanesi and Olivetti (2009), Afridi et al. (2018), among others. In many analyses, home production is also crucial in the context of general labor supply (as in Ríos-Rull (1993), Rupert et al. (2000), Gomme et al. (2004), Baxter and Jermann (1999) Aguiar and Hurst (2007b), Ngai and Pissarides (2008) among others), and other macroeconomic aspects including consumption, investment, business cycle, and monetary policy (see for example, Baxter and Jermann (1999), Aguiar and Hurst (2007a), Aguiar and Hurst (2007b), Gomme et al. (2001), Fisher (2007), Benhabib et al. (1991), Greenwood and Hercowicz (1991), Aruoba et al. (2016), among others).

participation in the labour market could also lead to substantial gains in aggregate productivity and income (Cuberes and Teignier (2012), Ostry et al. (2018)).[4] Additionally, in a rapidly aging economy, which India is expected to become in a couple of decades, higher participation of women in the labour force can to a certain extent mitigate the impact of the shrinking workforce (Elborgh-Woytek et al. (2013)). Hence, understanding the reasons behind the huge gender gap and the decline in participation of women in the labour force is critical for sustaining India's growth momentum.

We start by empirically documenting the labour force participation rates of married men and women for 2005 using Employment and Unemployment Survey (EUS 2004-05) and for 2019 using Periodic Labour Force Survey (PLFS 2018-19). We find that there is a substantial gender gap in labour force participation rates in both the years, and this gap has widened over time due to declining participation among women. Female labour force participation has reduced from 36% in 2005 to 25% in 2019, while the male participation has remained steady at around 100%. Using these data sources, we also document a sizable gender gap in wages, and this gap has also increased over time, with male wages having grown a lot more compared to female wages between 2005 and 2019. In order to capture the disparities in the supply side constraints faced by men and women, we make use of the Time Use Survey (TUS 2019) to analyse the gender gap in time disposition patterns. In particular, we find that there is a large gender difference in the time spent on home production, with an average woman spending around 54% of her time, while an average man spending just 6% of his time on these activities.[5]

In order to disentangle the gender gap and decline in female participation into demand and supply effects, we write down a household search model along the lines of Guler et al. (2012) and Flabbi and Mabli (2018) where the decisions of an individual depend on the labour market state of their partner or spouse. Capturing these interactions within a given household is especially important for explaining the labour market dynamics of women, as the participation decisions of majority of women are influenced by the employment status and the wages of their husbands.[6] In the benchmark joint search model, we introduce supply-side constraints through home production to reflect the fact that Indian females spend disproportion-

[4]Cuberes and Teignier (2012) using a calibrated model shows that, Middle East and North Africa suffers an income loss of around 20% due to the gender gap in labour force participation, while the corresponding loss is 17% in South Asia, and around 10% in the rest of the world.

[5]This pattern holds true across the world. According to Ferrant and Thim (2019), women on average spend thrice as much time on unpaid care work compared to men, ranging from 1.5 times in North American countries to 6.7 times in South Asian countries.

[6]As pointed out by Doepke and Tertilt (2016), families and therefore decision making within families are typically ignored in macroeconomic models. According to them, family dynamics should be an integral part of macroeconomics and accounting for the family leads to new answers to classic macroeconomic questions. For our purpose, it's extremely important to capture the influence of family interactions on labour market decisions.

ately higher amount of time in household activities compared to men. Each model household is made up of two individuals – a male and a female, and the agents are heterogeneous with respect to their productivity in the home production process. Each individual can either be employed part-time or full-time, unemployed, or out of the labour force. Employed individuals spend time on market work, while unemployed individuals spend time on job search. All the individuals, including those out of the labour force, allocate their remaining time between home production and leisure. The decision of each household member to either be a part of the labour force or exit the market depends on the gender-specific wage offers they face (labour demand) and on their respective productivity in the home production process (labour supply), in addition to the labour market state and wages of their partner or spouse. Thus, our model integrates both the demand and supply side factors in a unified framework, in turn enabling us to quantify the relative importance of demand and supply side factors in driving the gender gap and decline in female labour force participation in India. This is in contrast to most other empirical studies on labour force participation, as they concentrate on identifying a single mechanism rather than perform a macroeconomic evaluation to quantify the relative magnitude of demand and supply side factors in determining the female labour force participation in India.

In order to quantitatively evaluate the ability of our model to generate the gender differences in labour force participation and time disposition, we calibrate the model for the year 2019 using data from PLFS 2018-19 and TUS 2019. Specifically, we recover the underlying wage offer distributions by targeting the corresponding distributions of accepted wages, and calibrate the individual productivities in the home production process to match the time spent on home production activities from the data. Simulating our model, we find that the model is able to capture the stark gender differences found in the data across various dimensions. First, the model is able to generate an almost complete labour force participation among men along with a very low (around 25%) participation among women as seen in the data. Even though not explicitly targeted, the model successfully captures the heterogeneity in the household distribution, with around 74% of the households having an employed male and out of labour force female, while around 24% of the households having both male and female members employed. Second, the model is able to generate the gender gap in wages among both part-time and full-time workers. Third, the model also captures the large disparity in the time spent on home production, with women, on average, spending a lot more time compared to men.

We then use our calibrated model to decompose the gender gap and the decline in female labour force participation into demand and supply side effects. The gender-specific wage offers reflect the labour demand faced by the workers, while the individual home productivity broadly captures the supply side constraints. In order to isolate the role of labour demand in driving the gender gap in participation, we remove the gender disparity in labour demand by providing females with male wage offer distributions. Equalizing the labour demand does increase the labour force participation among women, but quantitatively this channel can explain only around 6.4% of the total gender gap in participation. Thus, the huge gender difference in labour force participation is predominantly driven by supply-side factors, with differential labour demand accounting for a small fraction of the gap.

To investigate the decline in labour force participation between 2005 and 2019, we re-calibrate the wage offer distributions to capture the differential growth in male and female wages over time, while keeping the supply-side factors fixed at the 2019 levels. Upon simulation, the model successfully generates the decline in labour force participation among women as seen in the data, and the increasing gender wage gap can account for around 35% of the overall decline in female participation between 2005 and 2019. In order to understand the mechanism behind this decline, we simulate a household where the male is earning exactly the average wage in both 2005 and 2019, while the female is faced with the decision of whether she wants to participate in the labour market or not. Our model shows that, the reservation wage for the female in this household to accept a job offer and be in the labour force has increased from 13% above the average female wage in 2005 to over 62% above the average wage in 2019. Since the rapid growth in the average male wage has led to an increase in the total income of this household, the need for female wages to supplement the household income has decreased, resulting in women dropping out of the labour force. Our analysis shows that, this channel is quantitatively important to explain the decline in female labour force participation in India.

In order to empirically validate our mechanism of increased gender wage gap playing a vital role in explaining the decline of female labour force participation, we look into the evolution of participation rates and wages separately for rural and urban regions. We find that the entire decrease in aggregate female participation rate between 2005 and 2019 is driven by the decline in participation of rural women, while the participation of urban women has been roughly constant over this time period. The labour force participation rate of rural women declined sharply from 41.7% in 2005 to 27.3% in 2019, while the participation of urban women increased slightly from 19.5% to 20.2% during the same period. Consistent with our model mechanism, we also find that, the increase in the overall gender wage gap is predominantly concentrated among the rural workers, while the gender wage gap among urban full-time workers experienced a slight decline over the same time. This analysis provides support to our model findings that the increased gender wage gap has led to a decline in labour force participation of women. In addition, our model calibrated separately for rural and urban regions can successfully generate the contrasting trends in female participation rates over time. Specifically, the model calibrated to match the increased gender wage gap in rural India can explain around 34% of the decline in labour force participation of rural women, while the model calibration capturing the urban wage dynamics generates a constant participation of urban women over time, consistent with the empirical data.

Our paper contributes to the models of household search such as Guler et al. (2012), Flabbi and Mabli (2018), and Pilossoph and Wee (2021) by explicitly incorporating gender differences in supply-side constraints through home production. Accounting for supply side factors is critical for understanding the dynamics of female labour force participation, particularly in an emerging economy context like that of India. We also add to the vast and active empirical literature on female labour force participation such as Klasen and Pieters (2015), Afridi et al. (2018), and Klasen et al. (2021). A common feature in a number of these studies is to identify certain factors that are correlated with the female participation in the labour market. In contrast, we develop a comprehensive search-theoretic model of labour force participation, where both demand and supply side factors, along with the spousal labour market status, jointly determine the participation decisions in the equilibrium.

The rest of the paper is organized as follows. Section 2 provides the empirical evidence for the gender gap and decline in female labour force participation. Section 3 develops a household joint labour search model with gender-specific wage offers and home productivities. Section 4 details the calibration strategy and discusses the model fit, while section 5 describes the results of our decomposition analysis. Section 6 examines the rural and urban regions separately, while section 7 concludes.

2. Empirical Evidence

Using nationally representative data on the labour market for the years 2005 and 2019, and time use data for the year 2019, we document the empirical patterns and gender differences among married couples across three dimensions – labour force participation, wage distribution, and time disposition.

2.1 Household Distribution and Labour Force Participation

We start by estimating the household distribution with respect to the labour market status of husbands and wives. An individual can either be Employed (E), Unemployed (U), or out of the labour force (N). If an individual is working either full-time or part-time, we classify them as employed. Those who aren't working at present but are actively searching for a job are classified as unemployed. Finally, the people who are out of labour force are those who do not have a job and are not searching for one. This gives rise to nine different kinds of households based on the labour market status of the couple. Finally, we calculate the labour force participation rate as the total number of people either employed or unemployed as a share of total population.

We measure the household distribution and the labour force participation rates for the year 2019 using Periodic Labour Force Survey 2018-19 (PLFS 2018-19), while the distribution and participation rates for the year 2005 are obtained using Employment and Unemployment Survey 2004-05 (EUS 2004-05). Both these surveys are nationally representative data sources documenting the labour market status and wages of individuals working in both formal (regular salaried/wage labour) and informal (casual wage labour) sectors. In addition to the labour market data, they also contain demographic information including age, gender, educational attainment, and marital status of the individuals. We concentrate our attention on married couples aged between 15 and 65 for our analysis. Individuals are classified into employed, unemployed, or out of labour force based on their principal activity status. This is determined on the basis of the activity on which the individual spends the longest time during the 365 days preceding the date of survey. We further classify employed people working less than 40 hours a week to be working part-time while the others are considered to be working full-time. Appendix A provides more details regarding the data and variable construction.

Table 1 shows the household distribution for the years 2019 and 2005 obtained from PLFS 2018-19 and EUS 2004-05 respectively. Rows represent the labour market status of the male in the household, while the columns represent that of the female. Looking at the estimates for the year 2019, we find that around 73.5% of couples in our data are made up of employed man and out of labour force woman. Thus, around three-fourth of the households are single-worker EN households, with men working and women not involved in the labour market. The other major fraction are the EE households, where both the man and the woman are employed, and this constitutes about 24% of the households. The other kinds of households make up only a tiny fraction of the entire distribution. Thus, there is a huge gender gap in labour force participation, with only 25% of women are in the labour force, while almost 100% of the men are a part of the labour market. Even within employed population, there is a gender gap in terms of part-time and full-time jobs. Among employed individuals, around 26% of women do not work full-time, while this fraction is around 13% for men. Thus, a lot less women participate in the labour market compared to men. And, even among those who work, women on average spend less

Table 1: Household Distribution and Labour Force Participation

	2019			2005		
	E	U	N	E	U	N
Employed (E)	24.34	0.57	73.56	35.09	0.74	63.45
Unemployed (U)	0.20	0.04	0.96	0.14	0.06	0.37
Out of labour force (N)	0.07	0	0.26	0.11	0	0.04
Unemployment rate – Male	1.20			0.57		
Unemployment rate – Female	2.46			2.21		
Share of part-time workers – Male	13.40			15.75		
Share of part-time workers – Female	26.41			29.96		
Labour Force Participation (LFPR) – Male	99.67			99.85		
Labour Force Participation (LFPR) – Female	25.22			36.14		

Note: Distribution of households based on the labour market status of husbands and wives. Rows represent the status of the male in the family while the columns represent the female. Estimates for 2019 constructed from Periodic Labour Force Survey (PLFS 2018-19) while the estimates for 2005 obtained from Employment and Unemployment Survey (EUS 2004-05).

time on their jobs compared to men.

Empirical fact 1: There is a large gender gap in labour force participation in 2019, with only 25% of women participating in the labour market compared to almost 100% of men.

Looking into the household distribution for the year 2005, we find similar empirical patterns. Around 63% of the households have an employed male with female out of labour force, while 35% of the households have both husband and wife employed. Similar to 2019 data, we do find a large gender gap in participation with around 36% of women participating in the labour market compared to almost 100% of men. Again, within employed individuals, around 30% of women work part-time compared to around 16% of men. Even though the pattern of the household distribution is similar for both the years, we find that the labour force participation of women has actually declined from 2005 to 2019. Female participation, which was around 36% in 2005 has reduced to 25% in 2019. Looking through the lens of household distribution, the fraction of EN households has increased from 63.5% in 2005 to 73.6% in 2019, while the share of EE households has declined from 35.1% to 24.3%.

Empirical fact 2: Between 2005 and 2019, female labour force participation rate has declined from 36% to 25%. This decline is reflected in the increased share of EN households and reduced proportion of EE households.

Thus, the gender gap in labour force participation, which was already high to begin with, has widened over time. The aim of this paper is to decompose this large gender gap in labour force participation, and also the decline in female participation over time using an integrated framework.

2.2 Wage Distribution

We now document the distribution of hourly wages earned by male and female workers in both 2019 and 2005. We continue to use PLFS 2018-19 to obtain the wage data for 2019 and EUS 2004-05 for 2005. Further, we work with real wages by converting the 2005 wages to 2019 currency units using Consumer Price Index (CPI). In order to compare the distributions of wages across gender and over time, it is important to take into account the differences in demographic factors that could affect the gender gap in wages, and also its evolution over time. Following papers like Heathcote et al. (2010) and Autor et al. (2008), we control for the demographics by calculating the residual wage distributions. In particular, we regress log wages on the key

Table 2: Residual Wage Distribution

	2019				2005			
	Part-time		Full-time		Part-time		Full-time	
	Male	Female	Male	Female	Male	Female	Male	Female
Mean	4.46	3.61	3.86	2.96	3.95	3.47	3.24	2.63
Stddev	0.42	0.47	0.47	0.51	0.46	0.49	0.54	0.56

Note: Lognormal estimates of residual hourly wage distribution for male and female, working part-time and full-time. Those working less than 40 hours a week are considered part-time and greater than 40 hours to be full-time. Estimates for 2019 constructed from Periodic Labour Force Survey (PLFS 2018-19) while the estimates for 2005 obtained from Employment and Unemployment Survey (EUS 2004-05).

observable factors as follows.

$$\log w_i = \beta' X_i + \epsilon_i, \tag{1}$$

where X_i is a vector of demographic variables, which include dummies for age (15–25, 26–30, 31–36, 37–42, 43–48, 49–54, 55–65), education (no education, less than high school, high school completed, some college, college and more), state, region (rural or urban), and sector (formal or informal). The term ϵ_i refers to the residual wage after taking into account the demographic characteristics of the workers. We run this regression separately for male and female (both part-time and full-time) wages, to generate four different residual wage series for the years 2005 and 2019. We characterize these residual wages into lognormal distributions, and the estimated lognormal means and standard deviations are given in table 2.

From the estimates in table 2, we can see that there is a sizable gender gap in wages even after controlling for age, education, and other demographic variables. For instance, in 2019, the average wage of a full-time male worker was around 53 INR (Indian Rupee), while a female working full-time earned only around 22 INR on average. Similarly, we find that there is gender gap in wages in 2005 as well, and controlling for demographic factors doesn't close the gap.

Empirical fact 3: Residual wage distribution points to significant gender gaps in wages, with women earning less than men even after controlling for demographic characteristics.

Analysing the evolution of wages over time, we find that the average wage of male workers has grown faster compared to that of female wages. Between 2005 and 2019, part-time wages of male workers has grown by around 62.5%, while the full-time has increased by 79.3%. In contrast, part-time female wages has grown by a meagre 13.9%, while the full-time wages has grown by 35.6%. Thus, the female wages has grown much less compared to male wages, exacerbating the gender gap in both part-time and full-time wages.

Empirical fact 4: Between 2005 and 2019, male wages, both part-time and full-time, have grown a lot more compared to female wages, resulting in the widening of gender wage gap over time.

2.3 Time Disposition

We document the gender differences in time disposition patterns among Indian couples using the first nationally representative time use survey (TUS 2019) conducted in 2019. Participants of the time use survey provide information regarding the different activities they undertook in slots of 30 minutes each, starting from 4:00 AM the day before the interview to 4:00 AM on the day of the interview. Thus the survey provides a snapshot of how men and women spend their time over an entire day.

Using the data from TUS 2019, we are interested in capturing the gender disparities in time allocation across various activities, namely, market work, home production, leisure, and job search. We group the various activities under these categories based on the definitions used in Aguiar et al. (2013). Any time spent on employment related activities are classified as market work, while the time spent on searching for a new job constitutes job search. Time spent on home production is measured by combining the time spent on unpaid domestic and caregiving services for household members, and also any time spent on being a volunteer, trainee, or other unpaid work. Finally, leisure is measured as the time spent on learning, socializing, media, sports, and any other leisure activity except self-care and maintenance. More details about the TUS 2019 data and the classification of various activities are provided in appendix A.

The time disposition patterns across various activities obtained from the time use survey are given in table 3. The share of time spent measures the percentage of time spent on a given activity as a share of total time, net of self-care and maintenance. Employed men and women spend similar amounts of time in market work. Part-time workers, both male and female, spend around 20% of their time working, while full-time workers spend around 40% on average. Similarly, men and women spend almost equal time on leisure, which is around 33% of the total time. We find unemployed women spend less time in searching for a job compared to unemployed men. Unemployed men spend around 18% of their time searching for a job, while women spend around 13%. Thus women, on top of having a lower labour force participation, also search less intensively in the labour market compared to men. Thus, there is a gender gap

Table 3: Time Disposition

Activity	Definition	Share of Time Spent	
		Male	Female
Market work	Employment and related activities		
	– part-time	20.90	19.67
	– full-time	42.28	38.98
Job search	Time spent by unemployed searching for a new job	18.24	13.12
Home Production	Unpaid domestic services for household members, Unpaid caregiving services for household members, Unpaid volunteer, trainee, and other unpaid work	6.39	54.09
Leisure	Learning, Socializing and communication, community participation and religious practice, Culture, leisure, mass-media and sports practices	34.43	32.96

Note: Time spent by an average male and female member on various activities estimated from Time Use Survey 2019. Share of time spent measures the percentage of time spent on a given activity as a share of total time available, net of self-care and maintenance.

in search behaviour both on the extensive and on the intensive margin.

Unsurprisingly, the activity that has the biggest gender gap in time disposition is home production. Women, on average, spend around 54% of their time on home production while men allocate just 6% of their time on these activities. Thus, it is safe to say, women take care of most of the activities at home with men contributing minimally on average. This is consistent with the existence of social norms as outlined in Jayachandran (2021), that women have to take care of the bulk of household chores compared to men. Since a large portion of women's day is spent on taking care of their households, it limits their time available to participate in the labour market, in turn restricting their supply of labour. Although we have documented the time disposition of an average woman, women who are in the labour force also spend a lot more time on home production compared to men. An out of labour force woman spends around 59% of her time on home production, while a woman who is in the labour force spends around 37% of her time. Both these numbers are orders of magnitude bigger than the 6% of the time an average male spends on home production.

Empirical fact 5: There is a huge gender gap in time spent on home production, with women on average spending 54% of their time, while men spending just 6% of their time on these activities.

Our empirical analysis shows that there is a substantial gender gap in labour force participation among married couples, and this gap has widened over time with declining participation of women. The gender gap and decline in female labour force participation could be driven by a combination of demand and supply side factors. As we documented before, women earn less than men, and this gender wage gap has increased over time, with male wages increasing a lot more compared to female wages. This could reflect a low and falling demand for women in the Indian labour market. Similarly, women spend significantly more time on home production compared to men, which could potentially constrain the supply of female labour. In order to disentangle the behaviour of female labour force participation into demand and supply factors, we need an equilibrium model of couples with differential wage outcomes and home production patterns, which is what we turn to next.

3. Model

In this section, we present a joint search model of couples, where the labour market decisions of an individual depends on the status of their partners in the household. We introduce supply-side restrictions in the benchmark joint search models like Guler et al. (2012) and Flabbi and Mabli (2018) by explicitly incorporating home production.

3.1 Setup

The model has a unit measure of infinitely lived households, each consisting of a husband (male) and a wife (female). Each member optimally make their decisions regarding their labour market outcomes and time disposition, and their choice depends on the state of their partner or spouse. Different from the benchmark models of Guler et al. (2012) and Flabbi and Mabli (2018), the individuals in our model also spend time on home production, and their consumption depends on both market good and home good. Both members of the household pool their income together to maximize their joint household utility. Each individual in the household can be in one of the three labour market states, namely, employed (E), unemployed (U), or out of labour force (N). Thus, there are nine different kinds of households in the model, depending on the labour market status of the couple. Before setting up the joint household model, let's look at the labour market flows and the time allocation decisions an individual faces.

Employed individuals, both male and female, works either in a part-time or in a full-time job, and earn wages associated with the job. At the end of every period, both male and female face an exogenous risk of losing their job. Apart from market work, an employed individual allocates their remaining time optimally between home production and leisure. Unemployed individuals spend time on searching for jobs, and the time spent on job search, i.e., search intensity, affects the probability of receiving a job offer. The job offer received by an individual is a package consisting of hourly wages and the hours requirement, namely, part-time or full-time. Once they receive an offer, the unemployed individual can choose to either accept the offer and become employed or reject the offer and continue to remain unemployed. Unemployed persons, on top of spending their time on job search, also choose to spend time on home production and leisure. Individuals are considered to be out of the labour force when they do not have a job and also do not spend any time on job search, i.e., their search intensity is zero. When the search intensity is zero, the individuals do not receive any wage offers anymore, and hence do not transition out of this state. Thus, being out of labour force is an absorbing state in our model. Since these individuals do not spend any time on job search or market work, they optimally split their entire time between home production and leisure. Having seen the decisions at the individual level, we now look at how these decisions depend and interact with those of their partners using the joint search model.

3.2 Value Functions

We now elaborate on the joint search problem of the household. Since there are three possible labour market states for each individual, a household consisting of a husband and a wife can be in one of nine possible states. Let EE be the value function of the household where both the male and the female are employed. And, let EU and EN denote the value functions of the household where the male works, while the female is unemployed and out of labour force, respectively. Similarly, let UE, UU, and UN denote the households where the man is unemployed, while the women are employed, unemployed, and out of labour force, respectively. Finally, NE, NU, and NN denote those households where the man is out of labour force, with woman occupying the different labour market states.

The flow utility of the households is given by $u\Big(\mathcal{I}, \mathcal{H}(hp_m, hp_f, \mathcal{I}), l_m, l_f\Big)$, where $\mathcal{I}$ represents the income earned by the couple from the labour market, $\mathcal{H}(.)$ denotes the amount of home production, while l_m and l_f signify the leisure of the male and female member, respectively. The output of home production for a given household, $\mathcal{H}(hp_m, hp_f, \mathcal{I})$, depends on the time spent on these activities by both the husband (hp_m) and the wife (hp_f), along with the market income $\mathcal{I}$ earned by the household. Thus, the utility of a household depends on the joint consumption and leisure of both the individuals, where the consumption is a combination of both market income and home production. We now start by defining the problem faced by an EE household.

$$
\begin{aligned}
rEE(w_m, h_m, w_f, h_f) = \max_{l_m, l_f} \Bigg\{ u\Big(\mathcal{I}, \mathcal{H}(hp_m, hp_f, \mathcal{I}), l_m, l_f\Big) + \\
\delta_f \Big(\max \Big\{ EU(w_m, h_m), EN(w_m, h_m), UU, UN, NU, NN \Big\} - EE(w_m, h_m, w_f, h_f) \Big) + \\
\delta_m \Big(\max \Big\{ UE(w_f, h_f), NE(w_f, h_f), UU, UN, NU, NN \Big\} - EE(w_m, h_m, w_f, h_f) \Big) \Bigg\}.
\end{aligned} \tag{2}
$$

In an EE household, both the members are employed. The male member earns a wage of w_m per hour, with h_m representing the work hours, which is either part-time or full-time. Similarly, the female member is employed with the hourly wage of w_f and hours h_f. The total income earned by this household is given by

$$\mathcal{I} = w_m h_m + w_f h_f,$$

while the time spent on home production is the net of time spent on market work and leisure, and is given by

$$
\begin{aligned}
hp_m &= 1 - h_m - l_m, \\
hp_f &= 1 - h_f - l_f.
\end{aligned}
$$

The employed male faces a risk of losing his job with probability δ_m. In the event of getting separated from the job, he chooses to either remain unemployed (UE) or completely exit the labour force (NE). Importantly, the shock faced by the husband also influences the wife and affects her decisions. In response to her husband getting separated from his job, the wife would optimally choose to either continue working (UE, NE) or voluntarily quit her job to be in one of the four possible states – UU, UN, NU, NN. Analogously, the female could lose her job with probability δ_f, and would choose to remain unemployed (EU) or exit the labour force (EN). Just like in the previous case, the shock hitting the female will have ramifications for the decisions of the male in the household, with him choosing to either continue with his job (EU, EN) or quit voluntarily (UU, UN, NU, NN). Thus, the labour market transitions of one household member affects the decisions of the other member, and this helps us capture the labour market dependencies within a given household. Both male and female members choose their respective leisure time, which in turn determines the time they spend on home production, to maximize the lifetime utility of the household.

A household where the male is employed while the female is unemployed is given by

$$rEU(w_m,h_m) = \max_{l_m,l_f}\Big\{u\Big(\mathcal{I},\mathcal{H}(hp_m,hp_f,\mathcal{I}),l_m,l_f\Big) + \delta_m\Big(\max\Big\{UU,UN,NU,NN\Big\} - EU(w_m,h_m)\Big) + \alpha_f s_f\Big(\int_w \max\Big\{EU(w_m,h_m),EE(w_m,h_m,w,h),UE(w,h),NE(w,h)\Big\} - EU(w_m,h_m)\Big)dF_f(w,h)\Big\}. \tag{3}$$

In this household, only the male is employed, working h_m hours and earning an hourly wage of w_m. The female member is unemployed and spends s_f hours in searching for a new job. Thus, the total income of the household is

$$\mathcal{I} = w_m h_m,$$

while the time spent on home production is given by

$$\begin{aligned} hp_m &= 1 - h_m - l_m, \\ hp_f &= 1 - s_f - l_f. \end{aligned}$$

Thus, the home production time provided by the unemployed female is the net of time spent on job search and leisure, while the time allocated by the employed male is the net of market work and leisure. The problem of employed male is similar to that of an EE household, where he can lose his job with probability δ_m, and this in turn may have an effect on the labour market decisions of the unemployed female. On the other hand, the unemployed female spends s_f hours on job search, and receives a job offer from the distribution $F_f(w,h)$ with probability $\alpha_f s_f$. The job offer received by the female is a pair (w,h) consisting of both hourly wage w and the work hours h. The unemployed female has to spend s_f hours on job search in order to receive the job offers. Thus, the cost of being unemployed is to spend time on job search, which could have otherwise been spent on either home production or leisure to increase the flow utility of the household. Similar to the previous case, labour market decisions of the unemployed female can also affect the state of the employed male. If the unemployed female receives a wage offer, she can choose to either reject the offer, thus continuing in the same state EU, or she can accept the job offer. Once she accepts the offer, the male member can choose to continue working (EE), or can voluntarily quit the job and become unemployed (UE) or exit the labour force (NE). Thus, once the female starts working, the male might quit his current job to start looking for better opportunities, or with female receiving a sufficiently high offer, he might even choose to completely exit the labour force.

We next define the problem faced by the households with working males and out of labour force females. As we saw in our empirical evidence from both PLFS 2018-19 and EUS 2004-05, these households constitute the vast majority in India, with around 73.6% in 2019 and around 63.5% in 2005. The problem faced by an EN household is given by

$$rEN(w_m, h_m) = \max_{l_m, l_f} \left\{ u\Big(\mathcal{I}, \mathcal{H}(hp_m, hp_f, \mathcal{I}), l_m, l_f\Big) + \delta_m \Big(\max \Big\{ UN, NN \Big\} - EN(w_m, h_m) \Big) \right\} \tag{4}$$

Here again, only male is the earning member of the family, working for h_m hours receiving an hourly wage w_m. Hence, the total income of the household is same as an EU household,

$$\mathcal{I} = w_m h_m.$$

The female member is out of labour force and hence doesn't spend any time on job search. She divides her time between home production and leisure, and the time spent on home production is given by

$$\begin{aligned} hp_m &= 1 - h_m - l_m, \\ hp_f &= 1 - l_f. \end{aligned}$$

Out of labour force females do not receive any labour market shocks, and continue to stay out of the labour force. The problem of the employed male is very similar to the previous cases we have discussed so far.

Finally, we look at the value function of the household where both the members are unemployed and actively searching for a job.

$$\begin{aligned} rUU = \max_{l_m, l_f} \Bigg\{ & u\Big(\mathcal{I}, \mathcal{H}(hp_m, hp_f, \mathcal{I}), l_m, l_f\Big) + \\ \alpha_m s_m \Big(\int_w \max \Big\{ UU, EU(w,h), EN(w,h), \Big\} - UU \Big) & dF_m(w,h) + \\ \alpha_f s_f \Big(\int_w \max \Big\{ UU, UE(w,h), NE(w,h), \Big\} - UU \Big) & dF_f(w,h) \Bigg\}, \end{aligned} \tag{5}$$

where the male member spends s_m hours on job search, while the female member spends s_f hours. Hence, the home production time allocated by the members of this household is given by

$$\begin{aligned} hp_m &= 1 - s_m - l_m, \\ hp_f &= 1 - s_f - l_f. \end{aligned}$$

We can define the value functions of other households, namely, UE, UN, NE, NU, and NN in similar vein, and the detailed description of the model is provided in appendix B. In this framework, we model the gender disparity in labour demand by making the offer distributions to be gender specific, with males receiving their offers from $F_m(w, h)$ with probability $\alpha_m s_m$, while females getting their offers from $F_f(w, h)$ with probability $\alpha_f s_f$. Similarly, gender differences in time spent on home production captures the disparity in the supply-side constraints faced by the two genders.

4. Calibration

We now discuss the calibration of the model. We start by deciding on the functional forms, and then choose the parameter values for the year 2019 to match a set of data moments obtained from the PLFS 2018-19 and TUS 2019. Finally, we talk about the fit of the model across various dimensions of the data.

4.1 Functional Forms

Utility and Home Production

Following the majority of literature including Albanesi and Olivetti (2009), we model the home production, $\mathcal{H}(hp_m, hp_f, \mathcal{I})$, to depend on the hours put in by the male (hp_m) and the female member (hp_f), along with the household income $\mathcal{I}$. In particular, the home production function takes a CES form as given below,

$$\mathcal{H}(hp_m, hp_f, \mathcal{I}) = \left[(A_m hp_m)^{\phi} + (A_f hp_f)^{\phi}\right]^{\frac{1}{\phi}} \psi\mathcal{I}, \tag{6}$$

where $1/\phi$ represents the elasticity of substitution between male and female hours in home production. A_m and A_f represent the relative home productivities of the husband and wife respectively, while ψ denotes the fraction of market income that is being used as input into the home production process.[7] Our formulation of the home good production function is comprehensive in capturing both the time and the expenditure on market goods needed for the home production. We follow the standard procedure of using a CES formulation to combine the male and female labour adjusted by their relative home productivities, similar to Afridi et al. (2022) and Ngai and Petrongolo (2017). This functional form can also be viewed as a special case of a Cobb-Douglas home production function with respect to combined labour and market good as in Aruoba et al. (2016), Afridi et al. (2022) among others, where the elasticities are assumed to be equal. In fact, the multiplicative form of the home good production can be seen as a version of Ngai and Petrongolo (2017), where the market input represented by the fraction of total income replaces the overall labor productivity.

Additionally, we assume that both males and females are ex-ante heterogeneous in terms of their home productivity. We capture the underlying heterogeneity in the gender-specific home productivity using a two-point distribution, i.e., $A_i \in \{A_i^1, A_i^2\}$, with $A_i^1 > A_i^2$, and the corresponding probability of drawing these productivities is given by $(p_i^{hp}, 1-p_i^{hp})$, where $i \in \{m, f\}$. Thus, both the values of home productivity and the underlying probabilities are different for males and females, and these are calibrated to reflect the gender differences in time spent on home production as detailed in the next section. In the case of India where the government does not provide any unemployment benefits, the market income for the households such as UU, UN, NU, and NN is absent, and hence the home production depends solely on the time input of the husband and the wife.

A household consumes a CES combination of both market good and the home good produced by the couple at home, and is given by

$$c = \left[\left((1-\psi)\mathcal{I} \right)^{\omega} + \mathcal{H}(hp_m, hp_f, \mathcal{I})^{\omega} \right]^{\frac{1}{\omega}}, \tag{7}$$

where $1/\omega$ is the elasticity of substitution between market and home goods. Since ψ fraction of market income is used as an input for home production, the rest $1-\psi$ fraction of income is used for direct consumption.[8] And, consumption of the households with no earning member purely comes from home production as they don't receive any market income.

The utility of the household depends on the consumption and the leisure of the individual

[7] We interpret home productivity more broadly in our context. In addition to representing the idea of productivity in the production of home good, home productivity is also a reduced form way of capturing various supply side factors including social norms, safety, preferences, etc., that might influence the labour supply decisions of the husbands and the wives.

[8] Combining market and home good to derive aggregate consumption is well accepted in the literature (see for example Gronau (1977)).

members. Following Flabbi and Mabli (2018), we assume the flow utility of the household is given by

$$u(c, l_m, l_f) = (1 - \eta_m - \eta_f)\frac{c^{1-\sigma_c}}{1-\sigma_c} + \eta_m \frac{l_m^{1-\sigma_m}}{1-\sigma_m} + \eta_f \frac{l_f^{1-\sigma_f}}{1-\sigma_f}, \tag{8}$$

where σ_c, σ_m, and σ_f are the curvature parameters over consumption and leisure, while η_m and η_f capture the relative importance the husband and the wife place on leisure, respectively.

Wage Distribution

Following Flabbi and Mabli (2018), we assume that the job offers originate from a lognormal distribution, and the distribution is specific to the gender and the hours requirement, i.e., part-time and full-time. Thus, we have four different job offer distributions of the form

$$f_i(w, h) = \frac{1}{\sigma_i^h w}\varphi\left(\frac{\ln w - \mu_i^h}{\sigma_i^h}\right), \tag{9}$$

with $i \in \{m, f\}$ and $h \in \{pt, ft\}$. φ represents the density of the standard normal distribution. $f_i(w, h)$ represents the distribution from where the wage offers originate, while the empirical data consists of only the accepted wages and does not contain all the wage offers that led to it. Hence, we need to be able to recover the underlying offer distribution from the truncated wage distribution obtained from the data. Lognormal distribution enables us to back out the original offer distribution from the empirical wage distribution, and hence the majority of literature including Flabbi and Mabli (2018) and Pilossoph and Wee (2021) use lognormal assumption to model wage distribution.

4.2 Parameter Values

We now detail our calibration strategy to choose the values for all the model parameters. Some of the parameter values are set externally based on literature, while the majority of parameters are calibrated internally to match a set of empirical moments derived from PLFS 2018-19 and TUS 2019 for the year 2019.

Chosen Externally

Each model period represents a week. We choose r to be 0.001, which corresponds to a yearly real interest rate of 5.3%. We have three curvature parameters governing the utility function. Following Flabbi and Mabli (2018), we set the curvature on consumption, σ_c, to be 0.9744, while the curvatures on individual leisure, σ_m and σ_f to be 0.9448 and 0.9657, respectively. The values of search intensity i.e., the time spent on job search by unemployed male (s_m) and female (s_f) workers are taken directly from TUS 2019. As documented previously, unemployed men spend 18.24% of their time, while unemployed women spend 13.12% of their time on job search. Hence, s_m takes the value of 0.1824 while s_f is set to 0.1312. The home production elasticity parameter, ϕ, is chosen to be 0.5963 as done by Afridi et al. (2022). We pick the elasticity of substitution between market and home goods to be 1.8 in line with Aruoba et al. (2016), and this implies the value of ω to be 0.44. Finally, ψ represents the fraction of income used in the process of home production. In order to calibrate ψ, we use the Consumer Price Index (CPI) weights associated with food and beverages, except non-alcoholic beverages and prepared meals, sweets, snacks, etc.[9] The CPI weights represent the expenditure share of various categories of goods, and we concentrate on the expenditure of goods that are used as inputs for home cooking.[10] This gives us the total share of market income in home production, ψ, to be 0.39.

Chosen Internally

In addition to the parameters whose values were chosen externally, we have 22 more parameters which are calibrated internally by repeatedly solving our model to match a set of empirical moments. The model is calibrated using the 2019 data from Periodic Labour Force Survey (PLFS 2018-19) and Time Use Survey (TUS 2019). Gender specific job separation rates, δ_m and δ_f, are chosen to match the male and female unemployment rates, while the base job finding rates α_m and α_f are set to match the respective unemployment durations from the data. The utility weights on leisure, η_m and η_f are set to target the proportion of time an average male and female spend on leisure. The data on unemployment rate and duration are obtained from PLFS 2018-19, while the time spent on leisure is calculated from TUS 2019.

An employed worker can be working either part-time or full-time. We classify those working less than 40 hours a week as part-time employed, and those working more than 40 hours to be full-time employed. Using PLFS 2018-19 data, we find that, on average, a part-time employed individual works for 29.5 hours a week, while an average full-time worker spends around 60.2 hours a week on their job. The labour supply associated with part-time (h^{pt}) and full-time (h^{ft}) employment are calibrated by normalizing the respective average hours over a total time en-

[9] The CPI weights for the entire basket of goods is accessed from the website of the Ministry of Statistics and Programme Implementation, and is available at https://www.mospi.gov.in/sites/default/files/press_release/CPI_PR_13mar23.pdf.

[10] The exact categories of goods considered are cereals and products, meat and fish, egg, milk and products, oils and fats, fruits, vegetables, pulses and products, sugar and confectionery, and spices.

Table 4: Parameter Values

Parameter	Definition	Source/Target	Value Male	Value Female
Chosen Externally				
r	Interest rate	Period = week	0.001	
σ_c	Utility curvature on consumption	Flabbi and Mabli (2018)	0.9744	
σ_i	Utility curvature on leisure	Flabbi and Mabli (2018)	0.9448	0.9657
s_i	Search intensity	Time Use Survey (2019)	0.1824	0.1312
ϕ	ES between male and female hours	Afridi et al. (2022)	0.5963	
ω	ES between market and home goods	Aruoba et al. (2016)	0.44	
ψ	Share of income in home production	CPI weights	0.39	
Chosen Internally				
δ_i	Job separation rates	Unemployment rate	$3e-4$	$6e-7$
α_i	Job finding rates	Unemployment duration	0.316	0.049
η_i	Utility weights on leisure	Time spent on leisure	0.196	0.257
$[\mu_i^{pt}, \sigma_i^{pt}]$	Offer distribution (part-time)	Accepted wage distribution	[3.30, 1.03]	[2.04, 1.01]
$[\mu_i^{ft}, \sigma_i^{ft}]$	Offer distribution (full-time)	Accepted wage distribution	[2.05, 0.99]	[1.59, 1.04]
p_i	Probability of part-time offer	Share of part-time workers	0.044	0.273
$[A_i^1, A_i^2]$	Home productivity	Mean and std. dev. of home prod. hours	[2.38, 43.07]	[2.25, 42.72]
p_i^{hp}	Probability of low home productivity	Labour force participation	0.998	0.219

Note: $i \in \{m, f\}$. ES refers to Elasticity of Substitution. Model is calibrated for the year 2019. Labour market moments and wage distribution are obtained from Periodic Labour Force Survey (PLFS 2018-19), while moments related to leisure and home production are calculated from Time Use Survey (TUS 2019).

dowment of 144 hours.[11] We calibrate the gender-specific probabilities of receiving a part-time offer, p_m and p_f to match the proportion of male and female part-time workers in the data.

We have four different wage offer distributions to calibrate, namely part-time and full-time offers, for both male and female. Since we assume that the wage offers originate from a log-normal distribution, we can recover the parameters of the offer distribution from the truncated wage distribution observed in the data. In particular, we choose the means and standard deviations of all the four wage offer distributions, that is, $\{\mu_i^h, \sigma_i^h\}$ with $i \in \{m, f\}$ and $h \in \{pt, ft\}$, to target the corresponding moments of the accepted wage distribution from the data.

Finally, we need to calibrate the two-point home productivity distribution for males and females, $\{A_i^1, A_i^2\}$, with $A_i^1 > A_i^2$ and $i \in \{m, f\}$. We choose these four parameters to match the mean and standard deviation of hours spent by men and women on home production respectively. And the probability of receiving the low home productivity for men (p_m^{hp}) and women (p_f^{hp}) are calibrated to match the corresponding labour force participation rates.

For a given set of parameter values, we solve and simulate our model to calculate our model generated moments. We compare the model moments with the corresponding data moments to update our initial guess of the parameter values. This procedure is repeated until the distance between the empirical moments and the corresponding model generated moments is minimized. Table 4 gives the resulting parameter values along with the values of the parameters that are chosen externally.

4.3 Model Fit

We now discuss how well the model captures the different moments that we targeted during the calibration procedure. We analyse the performance of our model along three different categories of moments, namely, the household distribution, wage distribution, and time disposition.

Household Distribution and Labour Force Participation

We start by looking at the household distribution and the labour market moments. Table 5 compares the moments generated by our model simulation with their corresponding data counterparts. Even though we don't explicitly target the household distribution in our calibration exercise, the model is able to almost capture the empirical distribution from the PLFS 2018-

[11] Normalizing the average hours of part-time and full-time work over the total time available, we obtain h^{pt} to be 0.205 and h^{ft} to be 0.418. Thus, on average, a part-time worker spends around 20% of their time on market work, while the corresponding number for a full-time worker is around 42%.

Table 5: Household Distribution and Labour Force Participation

	Data			Model		
	E	U	N	E	U	N
Employed (E)	24.34	0.57	73.56	23.77	0.42	74.25
Unemployed (U)	0.20	0.04	0.96	1.07	0.01	0.50
Out of labour force (N)	0.07	0	0.26	0	0	0
Unemployment rate – Male		1.20			1.56	
Unemployment rate – Female		2.46			1.68	
Share of part-time workers – Male		13.40			16.33	
Share of part-time workers – Female		26.41			26.40	
Labour Force Participation (LFPR) – Male		99.67			100	
Labour Force Participation (LFPR) – Female		25.22			25.26	

Note: Distribution of households based on the labour market status of husbands and wives. Rows represent the status of the male in the family while the columns represent the female. Data moments are for the year 2019 and are constructed from Periodic Labour Force Survey (PLFS 2018-19). Corresponding model moments are obtained from model simulations at the calibrated parameter values.

19. In the data, we find around 73.5% of the households have an employed male and out of labour force female, while the model generates this proportion to be 74.25%. Similarly, the next big fraction of the households are those where both male and female are employed. In data, around 24.3% of the households fall under this category, while the corresponding model simulated data has around 23.8% of households as EE households. The model is also able to generate comparable numbers of the other kinds of households in the data.

The model again does a good job of capturing the moments that are explicitly targeted during the calibration. The empirical male and female unemployment rates are 1.2% and 2.46%, while the corresponding unemployment rates in the simulated data are 1.56% and 1.68% respectively. When it comes to the share of part-time workers, the model is able to generate around 16.3% for men and 26.4% for women. This is again very close to what we find in the data, which is 13.4% and 26.4% respectively. Finally, with respect to labour force participation rates, the model is again able to capture the data very closely. According to PLFS 2018-19, almost all of married men (99.67%) are in the labour force, while the model generates this number to be 100%. Importantly, the model is able to simulate the low labour force participation of women, which is around 25.2% in both the empirical data and in the model simulation. Thus, the model can replicate the stark gender difference in labour force participation rate found in the data, which we aim to decompose and analyse the importance of demand and supply side factors in driving this gap.

Wage Distribution

Using the wages accepted by the unemployed workers in our model simulations, we estimate the means and standard deviations of the lognormal wage offer distributions. Table 6 compares the accepted wage distributions from the data with the corresponding distributions generated by our model. We are able to match the empirical distribution of accepted wages quite closely for both male and female workers, working part-time and full-time, and the model is able to generate sizable gender gaps in the accepted wages. The empirical gender wage gap for part-time work is around 56% and the full-time work is 59%, while the corresponding wage gaps generated by the model are around 63% and 40%, respectively. One of the attractive features of this model is, we can recover the underlying wage offer distributions that led to these accepted distributions in the data. We find that, the calibrated offer distributions have smaller means and larger standard deviations compared to the accepted wages, as the accepted wage distributions are truncated from the underlying offer distributions. The model shows that there is a large gender gap in wage offers as well, with gender difference in part-time offers of 72%, and

Table 6: Wage Distribution

	Data (Accepted)		Model (Accepted)		Model (Offers)	
	Male	Female	Male	Female	Male	Female
Part-time						
Mean	4.46	3.61	4.57	3.53	3.30	2.04
Std dev	0.42	0.47	0.59	0.67	1.03	1.01
Full-time						
Mean	3.86	2.96	3.83	3.22	2.05	1.59
Std dev	0.47	0.51	0.55	0.70	0.99	1.04

Note: Lognormal estimates of wage distribution for male and female, working part-time and full-time. Those working less than 40 hours a week are considered part-time and greater than 40 hours to be full-time. Data moments are for the year 2019 and are constructed from Periodic Labour Force Survey (PLFS 2018-19). Corresponding model moments are obtained from model simulations at the calibrated parameter values.

the corresponding difference in full-time offers of around 34%. This gender gap in wage offers gives us a measure of the differences in the labour demand faced by men and women in the labour market, and could potentially play a role in explaining the gender difference in labour force participation. We quantify the magnitude of this effect in the next section.

Time Disposition

Finally, we look at the performance of the model in terms of the time allocation across different activities. Regarding market work, we choose the time spent on part-time and full-time employment to match the average work hours of male and female workers from the PLFS 2018-19 data. Normalizing the work hours to the total time available, we find that the part-time workers on average spend around 20.5% of their time on market work, while those in full-time employment work for around 41.8% of their time. With respect to leisure time, the model almost matches the time spent by females on leisure, but it overstates the leisure time enjoyed by males. Importantly, the model is able to successfully generate the huge gender gap in home production time that we documented in our empirical section. An average male in the model spends around 8.6% of his time on home production, which is close to 6% that we find in the data. On the other hand, an average woman in the model spends around 60.5% of her time on home production activities, again comparable to 54% as seen in the data. This large gender

Table 7: Time Disposition

Activity	Data		Model	
	Male	Female	Male	Female
Market work				
– part-time	20.9	19.67	20.49	
– full-time	42.28	38.98	41.83	
Leisure	34.43	32.96	53.36	30.43
Home Production	6.39	54.09	8.61	60.53

Note: Average time spent by male and female on various activities as a share of total time available. Data moments are for the year 2019 and are constructed from Time Use Survey (TUS 2019). Corresponding model moments are obtained from model simulations at the calibrated parameter values.

difference in home production hours could in part reflect the supply-side constraints faced by women, and could in turn play a role in curtailing the participation of women in the labour force. In the next section, we use our calibrated model to quantify the effects of demand and supply-side factors in driving the low labour force participation among women.

5. Decomposition of Gender Gap and Decline: Demand vs. Supply

Compared to men, only a few women participate in the labour market. This might be because, women aren't paid as much as men and hence women do not find it profitable to spend time on market work. Alternatively, the low female participation might be due to barriers such as household work, social norms, etc. that predominantly affect women and hence prevent them from supplying their labour. It is critical to understand which of these two channels – lack of demand or supply-side restrictions, predominantly causes the low female labour force participation in India. We will now use our calibrated model to answer this question.

In the previous section, we saw that the model is able to generate the huge gender gap in labour force participation consistent with the data. In addition, the model captures the gender difference in labour demand through the gender gap in wage offer distributions. Similarly, the model reflects the supply-side restrictions faced by women through gender-specific home productivities, which in turn lead to gender differences in time spent on home production. In order to quantify the role of demand-side (and hence supply-side) factors in driving the low female participation, we perform a counterfactual experiment where we equalize the labour demand by providing females with male offer distributions. This exercise would enable us to quantify the gender gap in labour force participation due to the differences in labour demand.

We next use our model to decompose the decline in labour force participation of women from 2005 to 2019. In our second counterfactual experiment designed to address this question, we recalibrate the wage offer distributions of both male and female workers to capture the evolution of empirical wage distributions over time. Through this analysis, we can identify the decline in female labour force participation driven by the changes in labour demand between 2005 and 2019, while keeping the supply-side factors fixed at 2019 levels.[12]

5.1 Gender Gap in Labour Force Participation

In our first experiment, we look at the behaviour of labour force participation by counterfactually making the labour demand identical for both male and female workers. We achieve this by providing females with the offer distributions and part-time offer probability of males. Since the offer distributions characterize the labour demand in our model, this exercise will enable us to isolate the effect of gender differences in labour demand on labour force participation.

As can be seen from table C1 in appendix C.1, when male and female workers face equal demand in the labour market, it almost closes the gender gap in accepted wages. We also find that the average time spent by females on home production reduces marginally from 60.53% to 58.89%, with no perceptible change among men. More importantly, our interest is in understanding its impact on the household distribution, and in particular the labour force participation, as shown in table 8. We can clearly see that, when women receive higher wage offers, it leads to an increase in their participation. When the gender differences in labour demand is removed, the female labour force participation increases from the benchmark value of 25.26% to 30.04%. This is reflected in the distribution where the share of EN households declines from 74.25% to 69.44%, while the share of EE households increases from 23.77% to 28.16%. Thus, as one might expect, lower demand for female workers as signified by the gender differences in wage offers does play a role in generating low labour force participation among women. However, quantitatively, the labour demand channel explains only around 6.4% of the gender gap in labour force participation, as even with equal wage offers, only 30% of the females are in the labour force compared to 100% of the males. Thus, this decomposition exercise indicates that, even though the differences in labour demand leads to fewer women participating in the labour

[12] It would be ideal to discuss the effect of changes in labour demand on labour force participation after explicitly controlling for any change in supply-side factors over time. But unfortunately, we do not have the data to capture this change over time, as there is no corresponding time use survey data available for the year 2005. In fact, the only nationally representative time use survey available for India is for the year 2019.

Table 8: Household Distribution under Equal Offers

	Benchmark			Counterfactual		
	E	U	N	E	U	N
Employed (E)	23.77	0.42	74.25	28.16	0.67	69.44
Unemployed (U)	1.07	0.01	0.50	1.19	0.01	0.53
Out of labour force (N)	0	0	0	0.02	0	0
Unemployment rate – Male		1.56			1.72	
Unemployment rate – Female		1.68			2.25	
Share of part-time workers – Male		16.33			15.84	
Share of part-time workers – Female		26.40			13.61	
Labour Force Participation (LFPR) – Male		100			99.98	
Labour Force Participation (LFPR) – Female		25.26			30.04	

Note: Benchmark represents the estimates of household distribution calibrated to match the Periodic Labour Force Survey (PLFS 2018-19) and Time Use Survey (TUS 2019). Counterfactual denotes the corresponding distribution when both males and females face the same wage offer distribution.

market, the majority of the gender gap seems to be driven by the supply-side factors. This is consistent with a number of studies such as Jayachandran (2021) and Afridi et al. (2022) who discuss the importance of supply-side restrictions such as social norms, mobility restrictions, etc., in influencing the participation decisions of women. We add to this discussion by performing a novel decomposition analysis using our calibrated model to quantify the magnitude of demand and supply-side effects in driving this huge gender gap in labour force participation.

5.2 Decline in Labour Force Participation

In a similar vein, we can decompose the decline in female labour force participation between 2005 and 2019 to quantify the role of demand-side changes in causing this decline. We recalibrate the wage offer distributions and the probability of part-time offers for both male and female workers to capture the changes in accepted wages over time, while keeping the supply-side conditions implied by home productivities fixed at the benchmark levels. This analysis answers the question, how much of the decline in labour force participation among women can be explained by the evolution of wages from 2005 to 2019, provided the supply-side constraints didn't change during that time.

Table 9: Household Distribution under 2005 Wages

	Benchmark			Counterfactual		
	E	U	N	E	U	N
Employed (E)	23.77	0.42	74.25	27.31	0.74	70.31
Unemployed (U)	1.07	0.01	0.50	1.21	0.01	0.43
Out of labour force (N)	0	0	0	0.005	0	0
Unemployment rate – Male	1.56			1.64		
Unemployment rate – Female	1.68			2.56		
Share of part-time workers – Male	16.33			16.15		
Share of part-time workers – Female	26.40			32.84		
Labour Force Participation (LFPR) – Male	100			99.995		
Labour Force Participation (LFPR) – Female	25.26			29.27		

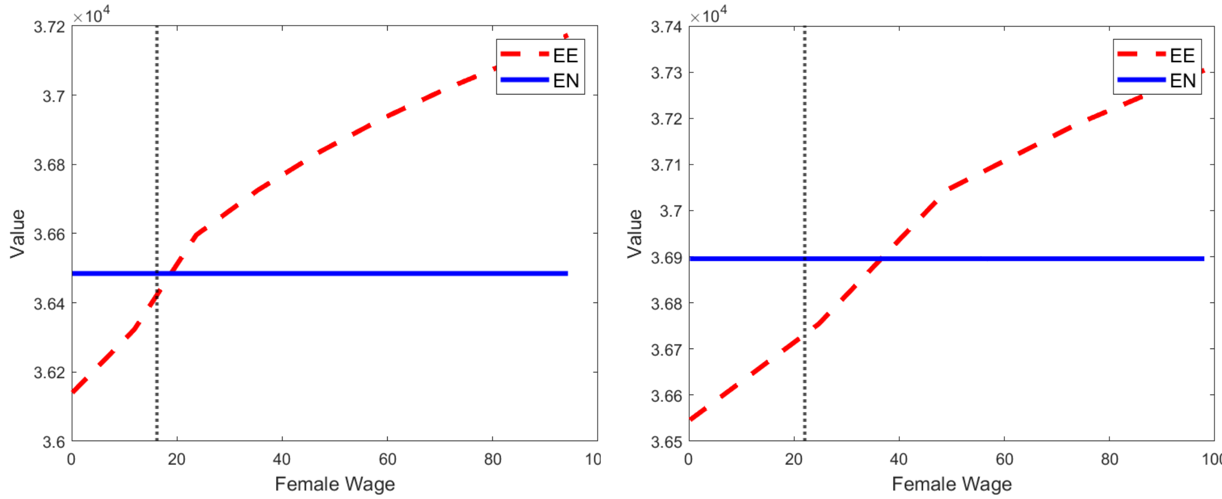
Note: Benchmark represents the estimates of household distribution calibrated to match the Periodic Labour Force Survey (PLFS 2018-19) and Time Use Survey (TUS 2019). Counterfactual denotes the corresponding distribution when the offer distributions are re-calibrated to match the 2005 wages from Employment and Unemployment Survey (EUS 2004-05).

We are able to closely match the wage distributions for the year 2005 by re-calibrating the parameters governing the wage offer distributions. This can be seen from table C2 in appendix C.1, which shows the fit of the model with respect to 2005 wages. The implications of this exercise for household distribution and labour force participation is shown in table 9. As can be seen, when the individuals, both male and female, receive wage offers consistent with the 2005 wages, it leads to an increase in the labour force participation among women. Calibrating our model to 2005 wages, we find that the female labour force participation increases from the benchmark value of 25.26% to 29.27%. This can be seen from the changes in the household distribution, where the share of EN households reduces from 74.25% to 70.31%, while the proportion of EE households goes up from 23.77% to 27.31%. From the EUS 2004-05, we documented that, the labour force participation among women was higher in 2005 compared to 2019. Our model, with 2005 wage offers is able to capture this decline in female labour force participation as seen in the data. Empirically, we find that, between 2005 and 2019 the participation of women has reduced by 10.92 percentage points (from 36.14% in 2005 to 25.22% in 2019). Through this counterfactual exercise, we find that the model is able to generate a decline of 4 percentage points. Thus, the evolution of labour demand captured by the changes in the offer distributions can explain around 35% of the decline in female labour force participation as observed in the data.

Through our counterfactual exercises, we find that the gender gap and the decline in female labour force participation are potentially driven by different underlying factors. While the gender differences in labour demand accounts for only around 6.4% of the gender gap, the changes in labour demand over time can explain around 35% of the decline in labour force participation of women. Thus, even though the gender gap is not majorly driven by differences in labour demand, the gender differences in evolution of labour demand plays a significant role in explaining the decline in female labour force participation over time.

Mechanism

We now explore further to understand the reason behind the decline in female labour force participation through the lens of our model. When we feed in the evolution of male and female wages into our model, the model generates a decline in the labour force participation of women, and this accounts for around 35% of the overall decline found in the data. In order to understand the mechanism behind this decline, we discuss in detail the participation decision faced by a female and how it has changed from 2005 to 2019. In particular, we consider the case of a household where the male is employed full-time and earns exactly the average wage



(a) 2005 (b) 2019

Note: This figure captures the evolution of the labour force participation decision faced by the female in a household where the male is employed full-time and earning exactly the average wage. Vertical dotted line denotes the average wage received by a female working full-time in the given year.

Figure 2: Participation Decision of Females in 2005 and 2019

in both 2005 and 2019. We are interested in the decision of the female, whether she joins the labour force and becomes full-time employed (an EE household) or stays out of the labour force (an EN household), and how the dynamics of this decision has changed between 2005 and 2019, thus having implications for the labour force participation rates.

The average full-time male wage was 29.54 INR in 2005 and it increased to 52.96 INR in 2019. Thus, the average full-time male wage grew by 72.97% between 2005 and 2019. On the other hand, the corresponding full-time female wage grew from 16.26 INR in 2005 to 22.04 INR in 2019. Thus, the female wage has just increased by 35.57% during the same period, and this has an effect on the participation decision of women. Figure 2a shows the optimal participation decision for the woman in this household for the year 2005, while figure 2b shows the corresponding decision for the year 2019. In both the figures, the red dashed line plots the value of the EE household as a function of the female wage, with the male in the household earning the average wage (29.54 INR in 2005 and 52.96 INR in 2019). Similarly, the solid blue line shows the value of the EN household, where the male, as before, is employed at the average wage, while the female is out of the labour force. Finally, the vertical dotted line represents the average wage earned by the female (16.26 INR in 2005 and 22.04 INR in 2019).

Looking into the situation in 2005, the female in the household with an average earning male would choose employment as long as the offered wage was at least 18.43 INR. Equivalently, the reservation wage for the female in this household to accept a full-time job in 2005 was 13.4% above the average female wage. In contrast, in 2019, the reservation wage for the female to choose employment in a similar kind of household has jumped to 35.74 INR. Comparing with the corresponding average wage in 2019, the female chooses to work only when the wage offer is 62.2% above the average wage of the females. Since the male wages has increased a lot more compared to the female wages over time, there seems to be a less need for women in 2019 to supplement the household income by earning in the labour market. Hence, the joint household decision implies that the women have become more selective, and choose to be in the labour market only when the wage offers in 2019 are relatively much higher compared to 2005.[13] This channel has led to a 4 percentage point decline in female labour force participation between 2005 and 2019 as seen through our model simulations, and this translates to around 35% of the total decline as seen in the data.

6. Discussion

The model results in the previous section showed that, one of the important reasons for the decline in female labour force participation rate is the widening of the gender wage gap over time. We found that the male wages has increased a lot more compared to female wages, and this has led to a significant decline in participation rates of females. We now provide additional empirical support for this mechanism by looking at the participation rates and wage dynamics separately for rural and urban India. Table 10 shows the evolution of participation rates in rural and urban regions, and compares it with the wage growth, and the ensuing changes in the gender wage gap over time.

There is a stark contrast between rural and urban experience both in terms of changes in participation rates and wage growth. By analysing the rural and urban sample separately, we find that the entire fall in the aggregate female labour force participation is driven by the declining participation of rural women. The participation rates of rural women has declined drastically from 41.7% in 2005 to 27.3% in 2019, while the participation of urban women has been

[13] This mechanism is consistent with the empirical evidence documented by Klasen et al. (2021). Looking into household level data from a selection of emerging economies, they show that, for India (along with Bolivia and Indonesia), higher household income is strongly negatively correlated with female participation in the labour market. On the other hand, for comparatively richer countries in their sample, particularly, Brazil and South Africa, they do not find any significant relationship between household income and participation of women. Blau and Kahn (2007) and Heim (2007) document a huge decline in the labour supply elasticity of married women with respect to household income in the United States, while Bargain et al. (2014) shows a weak impact of household income on female labour supply in European countries.

Table 10: Labout Force Participation and Gender Wage Gap

	All				Rural				Urban			
	2005		2019		2005		2019		2005		2019	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
LFPR (%)	99.85	36.14	99.67	25.22	99.86	41.7	99.74	27.29	99.83	19.52	99.48	20.19
Wage Growth (%)												
Part-time			62.52	13.89			51.13	2.09			– 18.1	– 25.36
Full-time			79.27	35.57			73.69	34.27			64.43	75.93
Gender Wage Gap												
Part-time	1.6		2.29		1.27		1.87		2.05		2.25	
Full-time	1.82		2.4		2.04		2.64		2.01		1.88	

Note: Estimates for 2019 constructed from Periodic Labour Force Survey (PLFS 2018-19) while the estimates for 2005 obtained from Employment and Unemployment Survey (EUS 2004-05). Those working less than 40 hours a week are considered part-time and greater than 40 hours to be full-time. LFPR is Labour Force Participation Rate. Wage growth measures the growth in average wage from 2005 to 2019. Gender wage gap is the ratio of male to female average wage.

almost constant showing a slight increase from 19.5% to 20.2% during the same time. According to our model, one of the reasons for this contrasting evolution of female labour force participation rates could be due to differential changes in gender wage gap over time. As can be seen from table 10, the male wages grew a lot more rapidly in the rural sector compared to female wages, while the wage growth was more balanced across genders in the urban areas. This led to a huge increase in the gender wage gap among the rural workers, while the gender wage gap among urban full-time workers declined slightly during the same time. Thus, we find an increasing gender wage gap in the rural sector and an almost constant, albeit slightly decreasing, gender wage gap in the urban sector, consistent with the predictions of our model.

We now calibrate our model separately for the rural and the urban regions to analyse the performance of our model in explaining the differential trends in female participation rates over time. Tables in appendix C.2 show the model fit of our benchmark calibration in terms of household distribution, wage distribution, and time disposition for the rural sector, while the corresponding tables for the urban areas are given in appendix C.3. As with the case of the entire sample, the model does a good job of capturing the gender disparities across different dimensions both in the rural and in the urban regions. Importantly, the model calibrations reproduce the low female participation rates in 2019 for both the sectors, i.e., 27.3% in rural and 20.2% in urban.

Having calibrated our model economies at the benchmark 2019 levels for both rural and urban regions, we can now study the model's ability to generate the differential trends in female participation rates over time among rural and urban workers. As with the case of all-India sample, we re-calibrate the wage offer distributions and part-time offer probabilities of rural and urban areas to capture the differential change in wage distribution over time. Tables C6 in appendix C.2 and C10 in appendix C.3 show the model fit when re-calibrated to match the 2005 wages for rural and urban respectively. More importantly, the implications of these differential trends in wage growth for household distribution and labour force participation rates for rural and urban are shown in tables 11 and 12, respectively. As can be seen from table 11, re-calibrating the rural wage offer distributions to match the 2005 wages leads to an increase in female participation rates from the benchmark level of 27.29% to 32.22%. Empirically, as shown in table 10, female labour force participation in rural areas declined by 14.4 percentage points (from 41.7% in 2005 to 27.29% in 2019). Thus, our model shows that, the differential evolution of wages among rural men and women, and the resulting increase in the gender wage gap can explain around 34% of the decline in female participation rates as observed in the data.

On the contrary, as seen in table 12, urban households facing 2005 wages results in almost

Table 11: Rural Household Distribution under 2005 Wages

	Benchmark			Counterfactual		
	E	U	N	E	U	N
Employed (E)	26.0	0.37	72.26	30.08	1.08	67.45
Unemployed (U)	0.91	0.015	0.45	1.05	0.02	0.33
Out of labour force (N)	0	0	0	0	0	0
Unemployment rate – Male		1.38			1.40	
Unemployment rate – Female		1.41			3.40	
Share of part-time workers – Male		15.97			16.57	
Share of part-time workers – Female		24.21			33.77	
Labour Force Participation (LFPR) – Male		100			100	
Labour Force Participation (LFPR) – Female		27.29			32.22	

Note: Benchmark represents the estimates of household distribution calibrated to match the Periodic Labour Force Survey (PLFS 2018-19) and Time Use Survey (TUS 2019). Counterfactual denotes the corresponding distribution when the offer distribution is re-calibrated to match the 2005 wages from Employment and Unemployment Survey (EUS 2004-05).

Table 12: Urban Household Distribution under 2005 Wages

	Benchmark			Counterfactual		
	E	U	N	E	U	N
Employed (E)	19.02	0.3	79.27	18.50	0.29	79.05
Unemployed (U)	0.85	0.025	0.54	1.31	0.03	0.84
Out of labour force (N)	0.005	0	0	0	0	0
Unemployment rate – Male		1.42			2.17	
Unemployment rate – Female		1.61			1.57	
Share of part-time workers – Male		4.58			4.21	
Share of part-time workers – Female		15.57			13.40	
Labour Force Participation (LFPR) – Male		99.995			100	
Labour Force Participation (LFPR) – Female		20.20			20.12	

Note: Benchmark represents the estimates of household distribution calibrated to match the Periodic Labour Force Survey (PLFS 2018-19) and Time Use Survey (TUS 2019). Counterfactual denotes the corresponding distribution when the offer distribution is re-calibrated to match the 2005 wages from Employment and Unemployment Survey (EUS 2004-05).

no change in female participation rate compared to the 2019 levels. The urban re-calibration with 2005 wages shows that around 20.12% of women participate in the labour force, which is very similar to the benchmark value of 20.2%. The model generated results are consistent with the empirical evidence as observed in table 10. The empirical participation rates of urban females didn't change much between 2005 and 2019, showing a slight increase from 19.5% to 20.2% over time. Thus, taking into account the evolution of wages and the gender wage gap over time, our model can successfully explain the differential trends in female participation rates over time, generating both declining rate of participation in the rural areas, and a constant rate in the urban regions.

Studying the rural and the urban context separately reiterates our benchmark model results and the mechanism driving them. The model simulations establish that, gender-biased growth in wages in turn widening the pre-existing gender wage gap in the rural sector leads to a decline in female participation rates, while a gender balanced wage growth which doesn't affect the gender wage gap in the urban areas leaves the female participation rates almost unchanged over time. Thus, our model results from rural and urban areas show that, in addition to just an increase in the average income over time, the structure of economic growth is critical for determining the evolution of female participation rates. Even though both rural and urban areas saw an increase in real wages over time, it led to diverging trends in female participation rates across the two sectors. Rural growth characterized by a disproportionate increase in male wages compared to female wages, thus exacerbating the gender wage gap, led to a decline in female participation. In contrast, the urban areas which experienced an economic growth that is more gender-balanced, didn't see a similar decline in female participation rates. Thus, the composition of economic growth and its effect on gender wage gap is an important determinant of the female participation rates over time.

7. Conclusion

We use a joint search model of couples with gender-specific wage offers and home productivities to study the gender gap and the decline in female labour force participation in India. Using a household search framework is vital for understanding the participation decisions of the females, as their labour market choices critically depend on the employment status and the wages of their husbands. Calibrating our model framework to India, we find that, gender differences in labour demand can account for only 6.4% of the level difference in 2019 while the differential evolution of the labour demand can explain around 35% of the decline in female labour force participation between 2005 and 2019. During this time, the increase in gender wage gap due to the rapid increase in male earnings compared to that of females reduced the need for women to support the family economically, in turn leading them to exit the labour force. Importantly, when we account for the evolution of wages and the gender wage gap, the model can successfully explain the diverging trends in female participation rates across rural and urban regions, by generating a declining participation rate over time in rural and a constant trend in urban regions. Our paper shows that the increase in gender wage gap has played an important role in causing the decline in female labour force participation in India. Investigating the reasons behind the increased gender wage gap is critical to further our understanding of the channels driving the participation decline, which we plan to do in our future research. Even though this paper concentrates on India, the insights from our analysis could hold considerable relevance for other developing economies and influence their policy choices as well.

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Appendix

A. Data

This appendix provides more details on the various data sources we use and also the definitions of variables we employ in our analysis.

A.1 Data Sources

We use Employment and Unemployment Survey 2004-05 (EUS 2004-05) to obtain labour market information for the year 2005, while the corresponding quantities for the year 2019 are constructed from Periodic Labour Force Survey 2018-19 (PLFS 2018-19). Finally, information about time disposition for the year 2019 comes from Time Use Survey 2019 (TUS 2019).

Labour Market Surveys (EUS 2004-05 and PLFS 2018-19)

We use Employment and Unemployment Survey 2004-05 (EUS 2004-05) to obtain labour market information for the year 2005, while the corresponding labour market data for the year 2019 is obtained from Periodic Labour Force Survey 2018-19 (PLFS 2018-19). Even though the name of the survey has changed over time, the data from EUS 2004-05 and PLFS 2018-19 are comparable. EUS 2004-05 was conducted from July 2004–June 2005. It canvassed information from 398,025 and 204,808 individuals residing in 79,306 rural and 45,374 urban households respectively. On the other hand, PLFS 2018-19 was conducted from July 2018–June 2019, and the survey included information from 239,817 and 180,940 individuals residing in 55,812 rural and 45,767 urban households respectively. Both the surveys are representative at the national and state level, and by rural and urban regions. Every household is assigned a sampling weight thereby permitting us to generate estimates for the population as a whole and also for sub-populations like gender and rural/urban regions.

Time Use Survey 2019

In case of developing countries, time use surveys are more an exception rather than a norm. For the first time, India conducted a nationwide TUS from January to December 2019 as part of which a total of 82,897 rural and 55,902 urban households were surveyed. Information on time use was collected from 273,195 and 174,055 individuals aged 6 years and above, and living in rural and urban households respectively. Similar to the labour force surveys, TUS 2019 is also a nationally representative survey, allowing us to construct population wide estimates of time disposition on various activities.

A.2 Variable Definitions

Demographic Characteristics

Both EUS 2004-05 and PLFS 2018-19 contains information on the demographic variables like age, gender, educational attainment, and marital status. More importantly for our purpose, they also capture the relationship of an individual to the household head, using which we can identify the couples living in a household.

Labour Market Status

Labour market status of an individual are identified using their principal activity status in both EUS 2004-05 and PLFS 2018-19. This is determined on the basis of the activity on which the individual spends the longest time during the 365 days preceding the date of survey. The principal activity status is one of the following -– self-employed (own account worker, employer, unpaid family worker), regular salaried/wage employee, casual wage labour, unemployed, attended educational institution, engaged in domestic duties, and others. Based on the principal activity status we can classify an individual as employed, unemployed or out of labor force. In particular, we consider an individual to be employed if their principal activity status is either self-employed, regular salaried/wage employee, or casual wage labour. An individual is classified as unemployed if their activity status is unemployed, and the rest are considered as out of the labour force.

Wages

We use wage per hour as the measure of wages. Both the labour market surveys provide information on the total labour market earnings of individuals engaged in a salaried job or in casual labor. PLFS 2018-19 contains information on the number of hours worked by the individuals, while in the EUS 2004-05, we know whether an individual worked half day or full day. In order to construct the residual wage distribution, we regress the hourly wages of the individuals on the demographic characteristics like age, education, along with state, region (rural or urban), and sector (formal or informal) fixed effects.

Time Disposition by Activity

For all members of the household, time use pattern was coded based on activity undertaken starting from 4:00 AM on the day before the date of interview to 4:00 AM on the day of the interview. Each individual reports their activity for the entire 24 hours split into 48 slots of 30 minutes each. The codes to classify the reported activities are in line with the International Classification of Activities for Time Use Statistics. There are 9 major divisions (1-digit), 56 divisions (2-digit) and 164 groups (3-digit) for classifying different activities. The 9 major divisions are Employment and related activities (Division 1), Production of goods for own final use (Division 2), Unpaid domestic services for household members (Division 3), Unpaid caregiving services for household members (Division 4), Unpaid volunteer, trainee and other unpaid work (Division 5), Learning (Division 6), Socializing and communication, community participation and religious practice (Division 7), Culture, leisure, mass-media and sports practices (Division 8), and Self-care and maintenance (Division 9). Within Division 1, there is an activity status specifically for time spent on seeking employment (Division 160). We consider the time spent on Divisions 1 and 2 to constitute market work, while any time spent by the unemployed on Division 160 is considered as job search. We measure total home production time as the sum of time spent on Divisions 3,4, and 5, while Divisions 6,7, and 8 capture the leisure time.

B. Model Description

EE Household

$$
\begin{aligned}
rEE(w_m, h_m, w_f, h_f) = \max_{l_m, l_f} \Big\{ u\Big(\mathcal{I}, \mathcal{H}(hp_m, hp_f, \mathcal{I}), l_m, l_f\Big) + \\
\delta_f \Big(\max \Big\{ EU(w_m, h_m), EN(w_m, h_m), UU, UN, NU, NN \Big\} - EE(w_m, h_m, w_f, h_f) \Big) + \\
\delta_m \Big(\max \Big\{ UE(w_f, h_f), NE(w_f, h_f), UU, UN, NU, NN \Big\} - EE(w_m, h_m, w_f, h_f) \Big) \Big\},
\end{aligned}
$$

where

$$
\begin{aligned}
\mathcal{I} &= w_m h_m + w_f h_f, \\
hp_m &= 1 - h_m - l_m, \\
hp_f &= 1 - h_f - l_f.
\end{aligned}
$$

EU Household

$$
\begin{aligned}
rEU(w_m, h_m) = \max_{l_m, l_f} \Big\{ u\Big(\mathcal{I}, \mathcal{H}(hp_m, hp_f, \mathcal{I}), l_m, l_f\Big) + \delta_m \Big(\max \Big\{ UU, UN, NU, NN \Big\} - EU(w_m, h_m) \Big) + \\
\alpha_f s_f \Big(\int_w \max \Big\{ EU(w_m, h_m), EE(w_m, h_m, w, h), UE(w, h), NE(w, h) \Big\} - EU(w_m, h_m) \Big) dF_f(w, h) \Big\}.
\end{aligned}
$$

where

$$
\begin{aligned}
\mathcal{I} &= w_m h_m, \\
hp_m &= 1 - h_m - l_m, \\
hp_f &= 1 - s_f - l_f.
\end{aligned}
$$

EN Household

$$
rEN(w_m, h_m) = \max_{l_m, l_f} \Big\{ u\Big(\mathcal{I}, \mathcal{H}(hp_m, hp_f, \mathcal{I}), l_m, l_f\Big) + \delta_m \Big(\max \Big\{ UN, NN \Big\} - EN(w_m, h_m) \Big) \Big\}
$$

where

$$
\begin{aligned}
\mathcal{I} &= w_m h_m, \\
hp_m &= 1 - h_m - l_m, \\
hp_f &= 1 - l_f.
\end{aligned}
$$

UE Household

$$rUE(w_f,h_f) = \max_{l_m,l_f} \Big\{ u\Big(\mathcal{I},\mathcal{H}(hp_m,hp_f,\mathcal{I}),l_m,l_f\Big) + \delta_f\Big(\max\Big\{UU,UN,NU,NN\Big\} - UE(w_f,h_f)\Big) +$$
$$\alpha_m s_m\Big(\int_w \max\Big\{UE(w_f,h_f),EE(w,h,w_f,h_f),EU(w,h),EN(w,h)\Big\} - UE(w_f,h_f)\Big)dF_m(w,h)\Big\}.$$

where

$$\begin{aligned}\mathcal{I} &= w_f h_f,\\ hp_m &= 1-s_m-l_m,\\ hp_f &= 1-h_f-l_f.\end{aligned}$$

UU Household

$$rUU = \max_{l_m,l_f} \Big\{ u\Big(\mathcal{I},\mathcal{H}(hp_m,hp_f,\mathcal{I}),l_m,l_f\Big) +$$
$$\alpha_m s_m\Big(\int_w \max\Big\{UU,EU(w,h),EN(w,h),\Big\} - UU\Big)dF_m(w,h) +$$
$$\alpha_f s_f\Big(\int_w \max\Big\{UU,UE(w,h),NE(w,h),\Big\} - UU\Big)dF_f(w,h)\Big\}$$

where

$$\begin{aligned}hp_m &= 1-s_m-l_m,\\ hp_f &= 1-s_f-l_f.\end{aligned}$$

UN Household

$$rUN = \max_{l_m,l_f} \Big\{ u\Big(\mathcal{I},\mathcal{H}(hp_m,hp_f,\mathcal{I}),l_m,l_f\Big) + \alpha_m s_m\Big(\int_w \max\Big\{UN,EN(w,h)\Big\} - UN\Big)dF_m(w,h)\Big\}$$

where

$$\begin{aligned}hp_m &= 1-s_m-l_m,\\ hp_f &= 1-l_f.\end{aligned}$$

NE Household

$$rNE(w_f,h_f) = \max_{l_m,l_f} \Big\{ u\Big(\mathcal{I},\mathcal{H}(hp_m,hp_f,\mathcal{I}),l_m,l_f\Big) + \delta_f\Big(\max\Big\{NU,NN\Big\} - NE(w_f,h_f)\Big)\Big\}$$

where

$$\begin{aligned} \mathcal{I} &= w_f h_f, \\ hp_m &= 1 - l_m, \\ hp_f &= 1 - h_f - l_f. \end{aligned}$$

NU Household

$$rNU = \max_{l_m, l_f} \left\{ u\Big(\mathcal{I}, \mathcal{H}(hp_m, hp_f, \mathcal{I}), l_m, l_f\Big) + \alpha_f s_f \Big(\int_w \max \Big\{ NU, NE(w,h) \Big\} - NU \Big) dF_f(w,h) \right\}$$

where

$$\begin{aligned} hp_m &= 1 - l_m, \\ hp_f &= 1 - s_f - l_f. \end{aligned}$$

NN Household

$$rNN = \max_{l_m, l_f} \left\{ u\Big(\mathcal{I}, \mathcal{H}(hp_m, hp_f, \mathcal{I}), l_m, l_f\Big) \right\}$$

where

$$\begin{aligned} hp_m &= 1 - l_m, \\ hp_f &= 1 - l_f. \end{aligned}$$

C. Additional Results

C.1 All India

Table C1: Wage Distribution under Equal Offers

	Benchmark		Counterfactual		Offers	
	Male	Female	Male	Female	Male	Female
Part-time						
Mean	4.57	3.53	4.57	4.39	3.30	3.30
Std dev	0.59	0.67	0.59	0.75	1.03	1.03
Full-time						
Mean	3.83	3.22	3.84	3.73	2.05	2.05
Std dev	0.55	0.70	0.53	0.65	0.99	0.99

Note: Benchmark represents the estimates of wage distribution calibrated to match the moments from Periodic Labour Force Survey (PLFS 2018-19) and Time Use Survey (TUS 2019). Counterfactual denotes the accepted wages when both males and females face the same offer distribution as given in the offers column.

Table C2: Wage Distribution under 2005 Wages

	Data (Accepted)		Model (Accepted)		Model (Offers)	
	Male	Female	Male	Female	Male	Female
Part-time						
Mean	3.95	3.47	3.87	3.32	1.85	1.76
Std dev	0.46	0.49	0.63	0.62	1.27	0.91
Full-time						
Mean	3.24	2.63	3.18	2.98	1.29	1.40
Std dev	0.54	0.56	0.57	0.58	1.05	0.94

Note: Lognormal estimates of wage distribution for male and female, working part-time and full-time. Those working less than 40 hours a week are considered part-time and greater than 40 hours to be full-time. Data moments are for the year 2005 and are constructed from Employment and Unemployment Survey (EUS 2004-05). Corresponding model moments are obtained from model simulations at the calibrated parameter values.

C.2 Rural

Table C3: Rural Household Distribution and Labour Force Participation

	Data			Model		
	E	U	N	E	U	N
Employed (E)	26.71	0.39	71.6	26.0	0.37	72.26
Unemployed (U)	0.12	0.03	0.9	0.91	0.015	0.45
Out of labour force (N)	0.05	0	0.21	0	0	0
Unemployment rate – Male		1.05			1.38	
Unemployment rate – Female		1.58			1.41	
Share of part-time workers – Male		17.41			15.97	
Share of part-time workers – Female		32.7			24.21	
Labour Force Participation (LFPR) – Male		99.74			100	
Labour Force Participation (LFPR) – Female		27.29			27.29	

Note: Distribution of households based on the labour market status of husbands and wives. Rows represent the status of the male in the family while the columns represent the female. Data moments are for the year 2019 and are constructed from Periodic Labour Force Survey (PLFS 2018-19). Corresponding model moments are obtained from model simulations at the calibrated parameter values.

Table C4: Rural Wage Distribution

	Data (Accepted)		Model (Accepted)		Model (Offers)	
	Male	Female	Male	Female	Male	Female
Part-time						
Mean	4.41	3.76	4.53	3.53	3.29	2.04
Std dev	0.39	0.44	0.58	0.71	1.004	1.003
Full-time						
Mean	4.0	3.03	3.79	3.23	2.03	1.61
Std dev	0.41	0.42	0.56	0.70	0.99	1.05

Note: Lognormal estimates of wage distribution for male and female, working part-time and full-time. Those working less than 40 hours a week are considered part-time and greater than 40 hours to be full-time. Data moments are for the year 2019 and are constructed from Periodic Labour Force Survey (PLFS 2018-19). Corresponding model moments are obtained from model simulations at the calibrated parameter values.

Table C5: Rural Time Disposition

Activity	Data		Model	
	Male	Female	Male	Female
Market work				
– part-time	20.9	19.67	20.49	
– full-time	42.28	38.98	41.83	
Leisure	35.0	31.24	52.56	29.68
Home Production	6.98	54.25	9.31	60.41

Note: Average time spent by male and female on various activities as a share of total time available. Data moments are for the year 2019 and are constructed from Time Use Survey (TUS 2019). Corresponding model moments are obtained from model simulations at the calibrated parameter values.

Table C6: Rural Wage Distribution under 2005 Wages

	Data (Accepted)		Model (Accepted)		Model (Offers)	
	Male	Female	Male	Female	Male	Female
Part-time						
Mean	3.98	3.73	4.15	3.50	3.57	2.15
Std dev	0.43	0.46	0.51	0.73	0.75	0.97
Full-time						
Mean	3.41	2.71	3.28	3.03	1.77	1.56
Std dev	0.50	0.46	0.51	0.62	0.88	0.86

Note: Lognormal estimates of wage distribution for male and female, working part-time and full-time. Those working less than 40 hours a week are considered part-time and greater than 40 hours to be full-time. Data moments are for the year 2005 and are constructed from Employment and Unemployment Survey (EUS 2004-05). Corresponding model moments are obtained from model simulations at the calibrated parameter values.

C.3 Urban

Table C7: Urban Household Distribution and Labour Force Participation

	Data			Model		
	E	U	N	E	U	N
Employed (E)	18.58	0.99	78.33	19.02	0.3	79.27
Unemployed (U)	0.42	0.07	1.09	0.85	0.025	0.54
Out of labour force (N)	0.13	0	0.39	0.005	0	0
Unemployment rate – Male	1.59			1.42		
Unemployment rate – Female	5.30			1.61		
Share of part-time workers – Male	6.21			4.58		
Share of part-time workers – Female	13.43			15.57		
Labour Force Participation (LFPR) – Male	99.48			99.995		
Labour Force Participation (LFPR) – Female	20.19			20.20		

Note: Distribution of households based on the labour market status of husbands and wives. Rows represent the status of the male in the family while the columns represent the female. Data moments are for the year 2019 and are constructed from Periodic Labour Force Survey (PLFS 2018-19). Corresponding model moments are obtained from model simulations at the calibrated parameter values.

Table C8: Urban Wage Distribution

	Data (Accepted)		Model (Accepted)		Model (Offers)	
	Male	Female	Male	Female	Male	Female
Part-time						
Mean	4.25	3.41	4.49	3.59	3.23	1.98
Std dev	0.44	0.52	0.58	0.70	1.04	0.97
Full-time						
Mean	3.73	3.05	3.79	3.14	2.03	1.68
Std dev	0.52	0.60	0.54	0.74	1.006	1.05

Note: Lognormal estimates of wage distribution for male and female, working part-time and full-time. Those working less than 40 hours a week are considered part-time and greater than 40 hours to be full-time. Data moments are for the year 2019 and are constructed from Periodic Labour Force Survey (PLFS 2018-19). Corresponding model moments are obtained from model simulations at the calibrated parameter values.

Table C9: Urban Time Disposition

Activity	Data		Model	
	Male	Female	Male	Female
Market work				
– part-time	20.9	19.67	20.49	
– full-time	42.28	38.98	41.83	
Leisure	32.99	37.29	53.12	32.41
Home Production	4.93	53.67	6.32	59.89

Note: Average time spent by male and female on various activities as a share of total time available. Data moments are for the year 2019 and are constructed from Time Use Survey (TUS 2019). Corresponding model moments are obtained from model simulations at the calibrated parameter values.

Table C10: Urban Wage Distribution under 2005 Wages

	Data (Accepted)		Model (Accepted)		Model (Offers)	
	Male	Female	Male	Female	Male	Female
Part-time						
Mean	4.42	3.69	4.29	3.48	2.13	1.40
Std dev	0.51	0.53	0.69	0.68	1.36	1.16
Full-time						
Mean	3.21	2.41	3.61	2.79	1.50	1.70
Std dev	0.57	0.72	0.53	0.74	1.08	0.82

Note: Lognormal estimates of wage distribution for male and female, working part-time and full-time. Those working less than 40 hours a week are considered part-time and greater than 40 hours to be full-time. Data moments are for the year 2005 and are constructed from Employment and Unemployment Survey (EUS 2004-05). Corresponding model moments are obtained from model simulations at the calibrated parameter values.