

Sectoral Wage Gaps and Gender in Rural India*

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Abstract

Using detailed monthly panel data from rural India, this paper analyzes sectoral wage gaps for men and women. I document three important findings. First, there is clear evidence of sorting into sectors, with very large differences in worker human capital across the farm and non-farm sectors and much higher wages in the latter. Second, while these wage gaps are substantial in the cross-section, the wage gap within individuals is decidedly smaller, consistent with worker sorting. Third, the wage gap for women is much larger than it is for men, with the latter exhibiting almost no within-individual gap in wages across sectors. Women work fewer hours and are less likely to work outside of their own village in the non-farm sector, yet the wage gap is driven by higher-caste and married women. I find no evidence of non-pecuniary benefits of agricultural employment relative to non-farm employment being responsible for this gap. These results are consistent with a lack of local non-farm employment opportunities interacting with barriers to labor mobility for women but not men.

Keywords: Agriculture, Gender, Labor, Non-Farm, Wages

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1 Introduction

Does a household's reallocation of labor from the farm sector to the non-farm sector lead to increased productivity and output? A growing body of evidence shows that the non-farm sector is substantially more productive than the farm sector, especially in developing countries (Gollin et al., 2014; McCullough, 2017; Herrendorf and Schoellman, 2018). Nonetheless, this does not necessarily mean that an individual moving to the non-farm sector will increase her income. It could be the case that selection drives the entirety of the gap, and individuals or households moving from one sector to another will see modest changes to income, as recent evidence suggests (Alvarez, 2020; Hamory et al., 2020). On the other hand, economy-wide barriers to labor mobility may prevent movements of labor from agricultural employment to other sectors, leading to a gap across sectors (Hayashi and Prescott, 2008). More generally, it seems likely that both explanations hold some explanatory power, which would be consistent with the somewhat contradictory evidence.

Importantly, insofar as barriers to labor mobility are an important determinant, women may be at a larger disadvantage than men. Throughout the world, men are much more likely than women to participate in the labor force in some manner (Jayachandran, 2020; World Bank, 2020). While poverty is an important predictor of women's labor force participation (Boserup, 1970; Goldin, 1986; Bandiera et al., 2017), norms related to gender and expectations of women's behavior are also consistent explanations offered in the literature for differences in women's labor force participation across, and even within, countries (Jayachandran, 2020; Fletcher et al., 2018).¹ In particular, expectations that women perform domestic chores (Sudarshan and Bhattacharya, 2009; Sudarshan, 2014; Fletcher et al., 2018), earn less than their husbands (Bertrand et al., 2015), and restrict their movements outside of the household (Andrabi et al., 2013; Chatterjee et al., 2015; Heath and Tan, 2018; Fletcher et al., 2018) lead to lower labor supply than might otherwise occur

¹It is worth noting, however, that poverty and social norms do not work independently of one another. They interact differentially depending on the context, but together help shape women's – and men's – labor supply decisions.

in the absence of such expectations. These barriers to labor mobility may lead to different wage gaps for women if, for example, farm and non-farm employment are located in different areas.

In this paper, I focus on sectoral wage gaps in rural India. Using 60 months of individual-level panel data from the Village Dynamics in South Asia project,² I first explore sectoral wage gaps in the cross-section. I find large wage gaps, consistent with previous literature on sectoral productivity gaps (Gollin et al., 2014; McCullough, 2017). It is important not to conflate wages with productivity, however, so this is not an apples-to-apples comparison. As such, exploring wage gaps is related, but not equivalent, to the sectoral productivity gap literature. In the cross-section, non-farm wages are around 30 percent higher than agricultural wages without any controls, and around 17 percent higher after controlling for age, gender, and education.

Given the richness of the panel data, I am able to explore selection into different types of wage labor in depth. While previous research has used individual fixed effects to quantify the extent of sectoral productivity gaps (Alvarez, 2020; Hamory et al., 2020), I am also able to look at individuals who work in both sectors simultaneously. This could be a salient consideration if, for example, the agricultural cycle is correlated with both wages and the propensity to work in one sector or the other. Importantly, there are large differences in individuals who work only in non-farm wage employment and individuals who work only in agricultural employment or work in both. Restricting the sample to individuals who work in both sectors at some point in the sample or in both sectors in the same month, even without individual fixed effects, decreases the estimated gap by almost half. Moreover, the sectoral wage gap does not completely disappear even when including person-by-year-by-month fixed effects, remaining around nine percent.

This gap, however, hides important heterogeneity. Results show that the gap completely disappears for men when including person fixed effects and explicitly controlling for tim-

²<http://vdsa.icrisat.ac.in/vdsa-index.htm>

ing, using either household-by-year-by-month or person-by-year-by-month fixed effects. For women, however, the gap remains large and significant, at more than 16 percent. Importantly, this gap cannot be explained by norms governing women's labor force participation alone, since the gap is conditional on being an active labor force participant. Moreover, common explanations for gender gaps – like occupational sorting or differential productivity – cannot explain this differential gap by gender. Perhaps men are, on average, employed in higher-paying occupations. This does not explain why women allocate labor to lower-paying agricultural wage employment and higher-paying non-farm wage employment simultaneously. Specifically, why do they not just allocate all of their wage employment time to non-farm employment if it pays more? Any explanation must account for an inability to reallocate labor from agricultural wage employment to non-farm wage employment.

Additional results point to the interaction of a lack of local non-farm wage employment opportunities and norms restricting women's mobility, which have already been shown to affect labor and human capital decisions of women in South Asia (Andrabi et al., 2013; Chatterjee et al., 2015; Heath and Tan, 2018). First, men are significantly more likely – in both quantitative and qualitative terms – than women to perform their non-farm wage employment outside of their village of residence. Second, when they work in both sectors, women allocate much less time to non-farm wage employment than agricultural wage employment, while men allocate similar hours to both. This is consistent with women falling back on lower-paid wage opportunities due to a lack of non-farm options. These patterns are seen only among married women; having children in the household in and of itself does explain the wage patterns. This aligns with previous research showing that marriage is one of the most important predictors of the labor force status of women, perhaps even more important than childbearing status (Fletcher et al., 2018). Finally, these patterns are significantly stronger for higher-caste women, but this is not true for higher-caste men, consistent with caste status being an important driver of gender norms,

including norms related to mobility (Mahajan and Ramaswami, 2017).

I consider one last possible explanation of the wage gap: that non-pecuniary benefits are higher in the agricultural wage employment than non-farm wage employment for women, but not for men. A simple additive non-pecuniary benefit implies that agricultural and non-farm wages should still be correlated within individuals. However, while this is the case for men, it is not the case for women; agricultural wages for women are quite flat, regardless of non-farm wage, and this is true both within and across individuals. This is more consistent with a cap of some kind on non-farm wage employment.

To contextualize these gaps, the last analysis looks at seasonality in wage employment and sectoral wage gaps. There are three key takeaways. First, sectoral wage gaps are much more variable across months for women than for men. Second, agricultural wage employment is much more seasonal than non-farm wage employment. Third, there is very little variation in the probability of being employed in any wage work for men relative to women. This, in conjunction with results showing that agricultural wages are more seasonal than non-farm wages, indicates that sectoral productivity gaps can be difficult to interpret more generally, since labor productivity and the probability of employment in different sectors appear to vary across months.

The rest of this paper is organized as follows. First, section 2 provides a brief description of the data and the methodology, which is straightforward. Then, section 3 presents summary statistics as well as the results before section 4 concludes.

2 Data and Empirical Strategy

2.1 Data

I use data from ICRISAT's Village Dynamics in South Asia (VDSA) project.³ The VDSA was started several decades ago, but I use the most recent data from 2010 to 2015. The data include monthly labor allocation for all household members present in a given year, from July 2010 to June 2015, for a sample of households from eight different Indian States: Andhra Pradesh, Bihar, Gujarat, Jharkhand, Karnataka, Madhya Pradesh, Maharashtra, and Orissa. From these eight states, the data comprise information on households living in 29 different villages across 17 districts. All reported wages and income are in (July) 2015 Indian rupees.

It is important to note that the data are not nationally representative and in fact over-sample larger landholders. This raises concerns about generalizability, not just to other countries, but also to other parts of India. However, its rich panel data, following households monthly for five years, allow for a more robust treatment of sectoral wage gaps.

2.2 Methodology

I first estimate sectoral wage gaps using simple cross-sectional regressions. I estimate regressions of the form

$$w_{ihvt} = \alpha_t + \delta X_{ihvt} + \phi NF_{ihvt} + \varepsilon_{ihvt}, \quad (1)$$

where w_{ihvt} is the wage for individual i in household h in village v at time t . α_t is year-by-month fixed effects, X_{ihvt} is a vector of individual-level characteristics – age, age squared, education, and gender – NF_{ihvt} is a dummy denoting whether a given wage job is located in the non-farm sector (as opposed to the agricultural sector), and ε_{ihvt} is a mean-zero

³<http://vdsa.icrisat.ac.in/vdsa-index.htm>

error term. The data are at the individual-month-sector level, so individuals that work in both sectors in the same month will have two observations in that month. Individuals who work in a single sector in a given month will have only one observation in that month. For this reason, I cluster all standard errors at the individual level.

I then take advantage of the panel nature of the data. Though I estimate several different fixed effects regressions, the most restrictive regressions I estimate employ individual-by-year-by-month fixed effects, or

$$w_{ihvt} = \alpha_{it} + \phi NF_{ihvt} + \varepsilon_{ihvt}, \quad (2)$$

where α_{it} is now a vector of individual-by-year-by-month dummies. In other words, this specification focuses only on individuals who work in both sectors in a given month. To examine sectoral wage gaps by gender, I estimate this regression separately for men and women. Since this specification focuses within individuals and uses just a single sector dummy, estimating a pooled regression has no effect on the estimated coefficient of interest.

2.3 Identification

The individual-by-year-by-month fixed effects specification removes most concerns regarding identification. Any individual-level covariates are collinear with the fixed effects and are thus not included in the regression. The comparison is within individuals who work in both sectors in a given month. This means that selection into sectors will not bias the coefficient. Instead, most of the concerns regarding identification relate to the exact effect being identified. However, since the results for the individual-year-month fixed effects are so similar for results for the individual fixed effects specifications, most of the additional analyses focus on the individual fixed effects specification

It is important to note that the individuals who engage in both sectors in the same

month are a select group of people. Of the 93,378 individual-month-sector observations with non-missing control variables, only 6,304 observations are from people who work in both sectors in the same month.⁴ This is less than seven percent of all wage observations. Many more individuals are observed at least once in each sector. For women, almost 36 percent of all observations belong to women observed at least once in each sector, while for men it is more than half. For this reason, the additional analyses focus on this group.

3 Results

Given the focus on sectoral productivity gaps, I first present summary statistics and descriptive figures of the data. Table 1 breaks down wages and several individual characteristics across three different groups. Each observation is an individual-sector-month observation. The first two columns are for individuals who are only ever observed in a single sector. The farm column is for individuals who only ever work for wages in an agricultural enterprise (during the five years of the data), while the non-farm column is for individuals who only ever work for wages in a non-agricultural enterprise. Total income, daily wages, and hourly wages are substantially higher for non-farm wage employment than for farm wage employment. Moreover, the number of hours and days appears to vary across the two sectors, pointing to the importance of taking hours worked into account when comparing wage gaps (Gollin et al., 2014; McCullough, 2017). Naïve comparisons of the total income variables lead to quite different conclusions than comparisons with the daily wage or hourly wage variables.

Consistent with higher wages in the non-farm sector, single-sector non-farm worker are much more likely to be male than wage farm workers. They are also much more educated and younger than farm-only wage workers. The education gap is especially large, with those in the non-farm sector having more than 40 percent more years of education than

⁴Approximately 41 percent of observations are from individuals who work in both sectors at some point in the data. Of these, about 16.5 percent are the main subsample.

those in the farm sector. Finally, around 12 percent of non-farm employment months for non-farm-only workers are months with employment provided by NREGS, the national workfare program. Dropping NREGS workers, however, does not qualitatively change any of the conclusions presented here.⁵

The middle two columns are for individuals that are observed to work in both sectors at some point in the data. This group of observations does not include any months in which those individuals worked in both sectors (which are presented separately in the last two columns). Compared to the “single-sector” wage workers in the first two columns, “both-ever” non-farm workers bring home slightly less money during the month, which results in lower wages at both the daily and hourly level. These non-farm workers are also more likely to be female, have less education, and are slightly older than the single-sector non-farm workers. Both-ever farm workers, on the other hand, have slightly *higher* wages and are slightly less likely to be female, but are also slightly less educated. It is also noteworthy that the size of this subsample is relatively large compared to the first two columns. While specialization in one of the two sectors seems to be the norm, a not insignificant proportion of workers engage in wage labor in both sectors at some point.

The last two columns present statistics for workers during the months in which these workers engage in wage employment in both sectors simultaneously. While this is a rather select group, it also allows for an apples-to-apples comparison across sectors; since we are comparing within individuals in the exact same month, there are fewer concerns related to selection across sectors. Non-farm wage workers here have only a slightly lower hourly wage than those of the both-ever workers. However, farm workers in this category apparently have slightly higher hourly wages than farm wage workers in either of the other two categories. These workers have less education, are slightly older, and are more likely to have worked in NREGS during the month.⁶ Notably, almost half of all workers

⁵Results available upon request.

⁶The individual characteristics are identical across the two sectors because a person in one sector necessarily has an observation in the other sector.

engaged in both farm and non-farm wage labor in the same month are female.

Figure 1 shows the evolution of sectoral wages over time, broken down by single-sector workers (the first two columns of Table 1) and others (the last four columns of Table 1). It is striking to compare the two graphs side-by-side. There is a clear difference in non-farm wages between the two groups, with those who only ever work in the non-farm sector having wages around 40 log-points higher than non-farm wages for the both-sector workers. Agricultural wages, however, are very similar for the two groups. Apparently, the majority of the selection is happening in the non-farm sector. This comparison points to some of the difficulties in equating economy-wide sectoral productivity gaps with misallocation (Herrendorf and Schoellman, 2018), though it is important not to conclude anything about overall sector productivities using only wages (and wages from just rural areas, at that).

Though not the principal finding of the paper, it is worth exploring Figure 1 quantitatively. Table A1 presents cross-sectional wage gaps related to those shown in Figure 1, controlling for just year-by-month fixed effects in the first three columns. The last three columns also include three common demographic variables: age (and its square), male, and years of education. Column one presents gaps using total monthly income. In terms of total income, non-farm wage employment appears significantly more remunerative, around two-times higher than farm wage employment. However, columns two and three underline the importance of taking time worked into account. When using hours worked and turning income into an hourly wage, the gap drops to just 31 log points. Including the demographic characteristics decreases the estimated gap by around half, at least when focusing on hourly wages. After controlling for age, gender, and education, non-farm wages are only 18 percent higher than farm wages.

There are several other patterns of interest in Table A1. First, the importance of considering actual time worked looms large when comparing across sectors in the last three columns, as well. The raw totals in column one and four decrease markedly after taking

into account time worked. Comparing across the last three columns, the daily wage difference is less than 17 percent as large as the raw difference. The hourly wage increases slightly, implying that those in the non-farm (wage) sector work more days, but fewer hours per day, than those in the agricultural sector. Since the hourly wage contains the most information about time worked, I focus on that variable for the rest of the paper.

Also note that the gender wage gap is large across all three columns and that it is relatively similar in columns four and five. However, it decreases slightly in column six, implying men and women work quite different hours per day. In fact, men and women work similar hours in agricultural wage work, but men work substantially more hours in the non-farm sector, by around 50 percent (results not shown). Finally, education is also positively correlated with hourly wages. Perhaps not surprisingly, though not shown here, that relationship is also stronger in the non-farm sector than it is in the wage sector.

Table 2 presents estimates of sectoral wage gaps. The first column presents similar estimates to the last column in Table A1, but this time with household-by-year-by-month fixed effects instead of simply year-by-month fixed effects. This addition takes into account idiosyncratic household situations in a given month, such as seasonality and household-specific shocks, as well as any shared variation in human capital within households. This decreases the gap by approximately a quarter – from around 17 percent in Table A1 to around 13 percent – but the gap remains qualitatively and statistically significant.

Columns two and three go back to year-by-month fixed effects, but restrict the sample in different ways. The second column restricts the sample to only individuals who reported working in both sectors at least once. This restriction is important and again points to the importance of selection in explaining sectoral wage gaps; simply restricting the sample decreases the estimated gap by half, compared to the same estimate in Table A1. We might think of this coefficient as a similar estimate of an individual “switching” from one sector to the other, as in Hamory et al. (2020). Further restricting the sample to those individuals who work in both sectors in the same month has no further effect on the estimated gap,

which remains around nine log points.

Column four adds person fixed effects and column five person-by-year-by-month fixed effects. This last column removes a substantial amount of possible selection concerns, as it compares across sectors, but within individuals in the same month. It also removes possible explanations related to individuals working in different sectors seasonally.⁷ Surprisingly, the estimated gap remains consistent across these columns. The estimates are also surprisingly similar to recent estimates using panel data in Hamory et al. (2020), who use longitudinal data from Kenya and Indonesia.

Table 3 presents the main results of the paper, breaking down the sectoral wage gaps by gender. Panel A, at the top of the table, presents estimated sectoral wage gaps for women, while Panel B presents the same gaps but for men. The first column includes only year-by-month fixed effects. The estimated sectoral wage gap is similar in magnitude for both men and women, though it is slightly larger for women. The second column includes household-by-year-by-month fixed effects. The gap for women is unchanged, but the gap for men decreases substantially, to less than half the estimated gap for women. This suggests that a substantial proportion of the wage gap for men is explained by differences across households, not differences across individuals within households. However, these do not explain the gap for women.

Column three adds person fixed effects to the year-by-month fixed effects. The gap for women decreases by about half, but the gap for men changes only slightly. Column four then adds household-by-year-by-month fixed effects. The coefficient for women increases slightly while the coefficient for men decreases even more, such that we can only just reject no difference in sectoral wage. Column five moves to person-by-year-by-month fixed effects, the most compelling specification from an internal validity perspective. The estimated gap for women is unchanged, but it decreases to just 0.015 for men. In other words, sectoral wage gaps completely disappear for men but not for women when we

⁷I discuss seasonality below.

focus on individuals who participate in both sectors simultaneously.

While column five presents the cleanest test for sectoral wage gaps, the sample is quite selective. In each column, the total number of observations refers to non-singletons (with respect to the fixed effects). For women, this number is just 10.7 percent of the size of the sample in column one. For men, it is even more selective, at just 4.6 percent. Column four, which includes a slightly different set of fixed effects but results in very similar estimated wage gaps, is decidedly less selective. For women, the sample is 35.6 percent of the column one sample, while for men it is more than half the size. As such, I use the specifications in column four in the remainder of the paper.

3.1 Explaining female-specific wage gaps

Previous literature has pointed to the importance of norms for female labor force participation, including recent empirical evidence (Sudarshan, 2014; Bernhardt et al., 2018; Heath and Tan, 2018). However, while this can explain women's entrance into the labor force or into certain jobs, it alone cannot explain a sectoral wage gap among women who are already working in both sectors. Instead, there must be additional constraints interacting with these norms that limit women's ability to reallocate labor. Previous work has suggested that some rural households in this exact sample may lack off-farm wage opportunities (Merfeld, 2020), which could also explain the pattern seen here.

Importantly, common explanations for gender wage gaps cannot explain the differential gaps we see here, at least under common economic assumptions. For example, consider the possibility that men and women work in different types of jobs, either in the agricultural sector, the non-farm sector, or both. This could, of course, explain different average wages – perhaps men work in higher-paying positions than women for some reason – either in aggregate or even within a single sector. This could also explain possible differences in average wages across castes, since workers sort into different sectors at least partially based on caste identity (Oh, 2020).

However, an important nuance is that these empirical regularities cannot explain within-individual sectoral wage gaps. Consider someone who sorts based on gender and caste. While this might explain the fact that they have a lower wage than someone else, it cannot explain why they choose to work two jobs that pay different wages. There must be some restriction on them choosing to work only in the higher-paying job. Oh (2020) finds that individuals are less likely to take up a job if the job is usually associated with castes higher than their own. While this explains take up, it cannot explain individuals who take up both types of jobs, despite differential wages.

Restrictions on mobility, on the other hand, offer one possible explanation. Women's mobility is often limited in South Asia (Heath and Tan, 2018). As such, if there are limited non-farm wage opportunities within an "acceptable" distance, then women may have to instead work in lower-paid agricultural wage opportunities, despite working in the higher-paying non-farm job when it is available. Men, on the other hand, would be free to travel to other locations to engage in more remunerative wage employment, taking only local agricultural wage opportunities that pay similar wages. Table A2 presents some suggestive evidence of this possibility. In all columns, the dependent variable is a dummy equal to one if the job is located outside of the individual's village of residence. For women, non-farm jobs are only slightly more likely to be located outside of the village than farm wage jobs. This difference is almost five-times larger for men, however. This is also true if we restrict the sample to just individuals that worked in both sectors at least once.⁸ In other words, men are significantly more likely to travel outside of the village for non-farm wage opportunities.

If this story is true, we would also expect women to work fewer hours in non-farm employment than men, even conditional on working in both sectors. Table A4 confirms this. Across all columns and specifications, women spend significantly less time in non-

⁸Unfortunately, data issues prevent me from looking at individuals who engaged in both activities in the same month. The data records the exact same distance for almost all observations in the same-month subsample, even when that distance is not zero.

farm wage employment than in agricultural wage employment. Men, on the other hand, spend significantly more time in non-farm wage employment than in agricultural wage employment, relative to women. In other words, despite earning lower wages in the agricultural sector, women are still working more hours in that sector. This is again consistent with a lack of local non-farm wage opportunities, as well as similarly-paid agricultural wage opportunities.

If this pattern is indeed driven by social norms, there are still questions surrounding which norms drive the results. I consider two possibilities here. First, I consider the possibility that women are simply expected to perform other household tasks (Sudarshan and Bhattacharya, 2009), leading to an inability to work far from home. Second, I consider the possibility that married women, specifically, have less mobility (Fletcher et al., 2018). Table 4 presents several additional specifications related to these two possible explanations. All regressions include only women. The first column is unmarried women only and the second column is married women only. Apparently, the entirety of the sectoral wage gap among women is explained by married women. This does not rule out either explanation, however.

The second and third columns restrict the sample to unmarried women only. The third column includes only women who live in households with no children (less than 15 years of age) and the fourth column includes only women who live in households with children. Although the smaller sample and person-by-year-by-month fixed effects decrease precision markedly, neither coefficient is significant and, in fact, both are negative. The last two columns, on the other hand, present the same breakdown for married women. The sectoral wage gap persists for married women, regardless of the presence of children. This evidence is more consistent with married women, specifically, facing specific norms regarding mobility. If this were driven more by domestic responsibilities, we might expect to observe heterogeneity based on the presence of children in the household, at least insofar as having children increases the amount of household tasks.

Given the small sample sizes – I drop singletons in the analysis to give an accurate representation of the number of observations contributing to identification of the key variable – Table A5 presents the results using year-month fixed effects instead of household-year-month fixed effects. This greatly increases the number of observations. While overall conclusions for specific columns differ, the two main patterns remain. First, children do not increase the gap for unmarried or married women. In fact, in the new results, the gap is actually smaller for women with children in the household. Second, married women have much higher gaps than unmarried women, regardless of child status.

Table 5 breaks down these effects by caste. In particular, it classifies men and women into lower castes⁹ and higher castes. In India, among Hindus – who make up more than 93 percent of the sample – women in higher castes traditionally have lower rates of labor force participation and face more restrictive social norms across a range of behaviors, including mobility (Das, 2006; Field et al., 2010; Eswaran et al., 2013; Mahajan and Ramaswami, 2017; Fletcher et al., 2018). As such, if the mobility story is true, we should see larger sectoral wage gaps for higher caste women than for lower caste women. However, we should not see any differences across men, who are free to move regardless of caste.

The first two columns present results for women, with lower-caste women in the first column and higher-caste women in the second. Consistent with expectations, there is a much larger gap for higher-caste women than for lower-caste women. For men, on the other hand, we do not see this pattern. For both upper- and lower-caste men, the gaps are quantitatively small. In other words, the bigger driver of the sectoral wage gap appears to be higher-caste women, which is consistent with an argument that social norms on mobility are preventing women from reallocating from lower-paid agricultural wage employment to higher-paid non-farm wage employment.

Another possible explanation that might account for the differential sectoral wage gap across genders is that women prefer some non-pecuniary benefit of agricultural wage

⁹Lower caste here includes scheduled castes, scheduled tribes, and other backwards castes.

employment relative to non-farm wage employment. For example, it seems clear that non-farm wage employment is more likely to be located farther from the home. If this closer location affords additional flexibility, this may explain the gap.¹⁰ If this non-monetary benefit is additive, we might have something that looks like:

$$w_{nf} = w_{ag} + \phi_{ag},$$

where w_{nf} is the non-farm wage, w_{ag} is the agricultural wage, and ϕ_{ag} is the monetary equivalent of some non-pecuniary benefit. One clear prediction of this setup is that the non-farm wage should be positively correlated with the agricultural wage within an individual.

We can test this prediction with the data. Figure 2 presents correlations between non-farm and agricultural wages for individuals that work in both non-farm and agricultural wage employment simultaneously. There is a clear positive correlation between wages in the two sectors for men, but not for women. This is not consistent with a story of compensating differentials for women but not for men. However, the graph is comparing both within and across individuals. Table A3 presents three regressions to add to the graph. The first column presents results within individuals while the last two columns present results without person fixed effects, taking a simple median wage for each individual/sector so that the sample is not limited to only individuals who work in both sectors simultaneously. In all columns, the correlation between sectoral wages is significantly less for women than for men. In other words, both within and across individuals, non-farm and agricultural wages are correlated less for women than for men. This is not consistent with a compensating differentials story, in which a non-farm wage job is somehow less desirable for women than an agricultural wage job.

¹⁰Insofar as this preference for the flexibility is driven by cultural norms – like the expectation that women take care of children – it is not clear if this is really any different from the previous argument regarding constraints on mobility.

Again, it is important to note that norms alone cannot explain the sectoral wage gap for women. A norm on mobility may prevent women from traveling outside of the village for work, but it should not, in and of itself, prevent women from reallocating labor from lower-paid agricultural wage employment to higher-paid non-agricultural wage employment in the same location, particularly for women already engaged in both. Comparative advantage, likewise, cannot explain the gap. While comparative advantage could explain selection across individuals, it cannot explain an apparent misallocation within individuals. Previous research has found clear evidence of norms preventing women from earning more than men (Bertrand et al., 2015). However, this cannot explain the current results, either. Women are earning much less than men overall, because women's wages are significantly lower than men's wages. As such, this is not an absolute income story. Rather, it is a relative wage story, within individuals and across sectors. In absolute terms, men in earn more than 40 percent more per hour than women in the same subsample of individuals who work in both sectors simultaneously and 35 percent more than women in the subsample of individuals who ever work in both sectors. In terms of total monthly wage income, men earn even more than women in both subsamples

3.2 Wage gaps and seasonality

One difficulty with the sectoral productivity gap literature, especially in developing countries, is that the composition of employment may change throughout the year due to the seasonal nature of agricultural production. This causes two issues. First, it could be that the productivity gap itself differs by month. Second, comparisons across sectors could be comparing across months, which somewhat muddies the interpretation of the gap. Consider, for example, that to calculate productivity on one's own farm, it is necessary to aggregate all labor over the agricultural season, despite the fact that returns to that labor are only realized at harvest. Insofar as labor productivity differs within the season and that non-farm work may be correlated with those productivity changes, it is easy to see

how difficult it can be to interpret these gaps, at least for individuals/households. While the sample of individuals in this data who work in both sectors simultaneously is quite small, it nonetheless allows for a temporal apples-to-apples comparison of wage gaps. We can also look at how these gaps differ, by gender, across the calendar year.

Figure 3 presents estimates of seasonality in wage gaps. Panel A has two figures: the first is the difference in the sectoral wage gap in each month, relative to January; the second is the probability of working in both sectors, again relative to January. These are coefficients from simple regressions with individual fixed effects, so the effects are within-individual differences. Since these coefficients are relative to January, they are meant to show the seasonal *changes* in the wage gap, not the levels. This is to make all of the figures in Figure 3 comparable with respect to interpretation.¹¹ For women, the wage gap is highest in May and the surrounding months. For men, the gap is highest in July and August. Comparing this to the timing of working both types of jobs, for both men and women we see that the gaps appear to be highest exactly at the times of the year when individuals are more likely to be working in both sectors (the second graph in Panel A).

Panel B of Figure 3 breaks down these differences by sector and by wage employment in general. Importantly, these figures still present coefficients from regressions of dummy variables (ag wage work, non-farm wage work, and any wage work across the three figures) on 11 month dummies, controlling for individual fixed effects. Interestingly, the highest wage gaps and the highest probability of working in both sectors is actually concurrent with the lowest probability of working in agriculture and the highest probability of working in the non-farm sector (for a wage). For men, we see relatively little variation in the probability of any wage employment, while for women we see a large drop in the probability of any wage work in April, May, and June, exactly where agricultural wage work is lowest. Apparently, these months include the highest probability of working in

¹¹It is possible to present simple averages by month. However, levels for men are sometimes quite different than for women, making presentation difficult. Since the goal here is to evaluate seasonality, looking at changes – which are of similar magnitudes for men and women – helps improve the presentation in the figures.

both sectors *and* the highest probability of not working at all, at least for women. In other words, it appears that some women working in agricultural wage employment stop during these months, while other women continue but also pick up a non-farm wage employment job, as well.

Finally, Figure A1 in the appendix shows changes in average hourly wages in the agriculture and non-farm sectors, separately by gender. There are two things to note. First, there is much more notable seasonal variation in wages in the agricultural sector than the non-farm sector, for both men and women. Second, and perhaps related, the correlation between the male and female average wage across months is much higher in the non-farm sector. One possible explanation is that average productivity in the agricultural sector is much more seasonal than average productivity in the non-farm sector. This again speaks to possible complications of comparing productivity across sectors when production is highly seasonal.

4 Conclusion

This paper argues that an interaction of social norms regarding women's mobility and a lack of local non-farm wage opportunities lead to an apparent misallocation of labor to wage employment among women, but not men, in rural India. Overall sectoral wage gaps for women are about 17 percent, while gaps for men are non-existent. Moreover, all evidence suggests that women are taking local agricultural wage employment – which pays relatively low wages – because they are unable to travel for more remunerative non-farm wage employment. I find gaps for married women, but not unmarried women, and for higher-caste women. These are consistent with a story of social norms restricting their mobility.

While the subsample of individuals working in both sectors is quite small, it nonetheless provides insights into broader patterns. First, there are clear barriers to labor mobility for

women that are not present for men. Take, for example, individuals in this paper who engage in wage labor only in the farm sector or only in the non-farm sector. Among those in the farm sector, more than half of individual-month observations are women. As such, the results presented here suggest many of these women may be prevented from moving into non-farm wage employment due to a lack of local employment options.

Second, more generally, these results point to the importance of constraints as a driving force of sectoral wage gaps. While selection into different sectors may be one of the most important factors, it is also possible that other constraints interact to create a productivity gap across sectors (or across rural and urban areas). For example, liquidity constraints may prevent migration from rural to urban areas, while lack of information may lead many to underestimate the gains. Moreover, government policy can explicitly restrict the movements of labor, with China's *Hukou* system being perhaps the most famous example of this. In any case, this area of research remains a fruitful avenue for future work.

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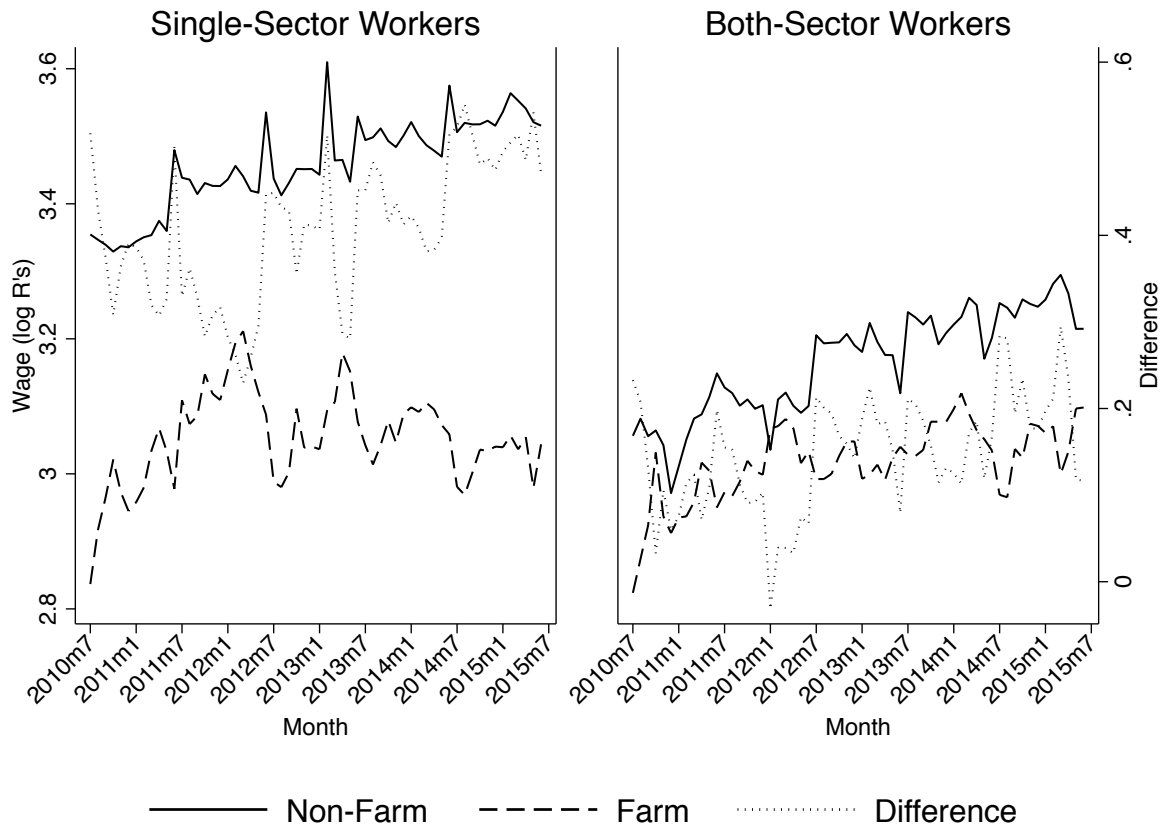
5 Tables

Table 1: Summary Statistics by Sector and Worker Type

	Single Sector		Both Ever		Same Month	
	(1) Farm	(2) Non-farm	(3) Farm	(4) Non-farm	(5) Farm	(6) Non-farm
Total monthly wage income	7.530 (0.672)	8.283 (0.858)	7.622 (0.687)	7.989 (0.740)	7.291 (0.631)	7.274 (0.702)
Daily wage	4.999 (0.422)	5.307 (0.709)	5.019 (0.418)	5.110 (0.577)	5.063 (0.351)	4.923 (0.601)
Hourly wage	3.025 (0.429)	3.356 (0.654)	3.002 (0.428)	3.165 (0.525)	3.045 (0.375)	3.132 (0.481)
Wage days	2.534 (0.535)	2.980 (0.443)	2.608 (0.524)	2.882 (0.464)	2.228 (0.530)	2.378 (0.548)
Wage hours	4.508 (0.578)	4.931 (0.582)	4.625 (0.561)	4.828 (0.585)	4.248 (0.543)	4.157 (0.556)
Female (yes = 1)	0.524 (0.499)	0.132 (0.339)	0.396 (0.489)	0.197 (0.398)	0.484 (0.500)	0.484 (0.500)
Years of education	3.970 (4.262)	7.123 (4.976)	3.670 (4.307)	4.864 (4.604)	3.005 (4.101)	3.005 (4.101)
Age	37.658 (11.390)	34.902 (11.055)	37.186 (11.451)	35.588 (11.197)	37.970 (10.106)	37.970 (10.106)
Work in NREGS		0.119 (0.324)		0.140 (0.347)		0.260 (0.438)
Observations	33,766	59,612	17,432	20,624	3,152	3,152

Standard deviations are in parentheses. The first two columns present summary statistics for individuals who are only ever observed in one of the two sectors. The middle two columns include individuals who we observe in both sectors at least once, but does not include those months they work in both sectors. The last two columns include only months in which individuals work in both sectors.

Figure 1: Evolution of Sectoral Wages over Time, by Worker Type



The figure on the left includes individuals that we observe in only one sector throughout the entire data. The figure on the right includes all individuals who are observed in both sectors at least once (and not necessarily concurrently).

Table 2: Sectoral Wage Gaps - Comparing within Households and Individuals

	(1) All	(2) Both Ever	(3) Both Same	(4) Both Ever	(5) Both Same
Non-farm	0.129*** (0.019)	0.092*** (0.017)	0.086*** (0.018)	0.081*** (0.017)	0.087*** (0.018)
Age	0.025*** (0.005)	0.027*** (0.006)	0.018* (0.011)		
Age squared	0.000*** (0.000)	0.000*** (0.000)	0.000 (0.000)		
Male (yes=1)	0.396*** (0.019)	0.260*** (0.024)	0.321*** (0.037)		
Education (years)	0.005* (0.003)	0.013*** (0.003)	0.006 (0.005)		
Fixed Effects:					
Year-month		X	X	X	
Household-year-month	X				
Person				X	
Person-year-month					X
Sample	All	Both ever	Both month	Both ever	Both month
Observations	74,547	44,296	6,292	26,597	6,300

Standard errors are clustered at the individual level and are in parentheses. The first column includes all wage workers in the data. The second and fourth columns include individuals we observe in both sectors at least once (thought not necessarily concurrently). The third and fifth columns include individuals we observe in both sectors in the same month. All singletons are dropped from the analysis.

* p<0.1 ** p<0.05 *** p<0.01

Table 3: Sectoral Wage Gaps and Gender

	(1)	(2)	(3)	(4)	(5)
Panel A: Female					
Non-farm	0.211*** (0.032)	0.207*** (0.038)	0.115*** (0.018)	0.162*** (0.037)	0.164*** (0.030)
Age	0.032*** (0.007)	0.001 (0.007)			
Age squared	0.000*** (0.000)	0.000 (0.000)			
Education (years)	0.011** (0.005)	-0.012* (0.006)			
Observations	28,602	10,185	28,601	10,178	3,052
Panel B: Male					
Non-farm	0.144*** (0.021)	0.088*** (0.025)	0.073*** (0.014)	0.032* (0.018)	0.015 (0.019)
Age	0.042*** (0.006)	0.034*** (0.007)			
Age squared	0.000*** (0.000)	0.000*** (0.000)			
Education (years)	0.032*** (0.003)	0.012*** (0.004)			
Observations	70,955	38,037	71,026	38,073	3,248
Fixed Effects:					
Year-month	X		X		
Household-year-month		X		X	
Person			X	X	
Person-year-month					X

Standard errors are clustered at the individual level and are in parentheses. The top panel includes only women. The bottom panel includes only men. All singletons are dropped from the analysis.

* p<0.1 ** p<0.05 *** p<0.01

Table 4: Marital Status and Sectoral Wage Gaps for Women

	(1)	(2)	Not Married		Married	
	Not	Married	(3)	(4)	(5)	(6)
	Married		No	Children	No	Children
			Children		Children	
Non-farm	-0.026 (0.130)	0.207*** (0.030)	0.003 (0.164)	-0.072 (0.217)	0.231*** (0.052)	0.196*** (0.038)
Fixed Effects:						
Household-year-month	X	X	X	X	X	X
Individual	X	X	X	X	X	X
Observations	1,560	5,116	893	667	1,380	3,732

Standard errors are clustered at the individual level and are in parentheses. All regressions include only women. Children is defined as having children in the household, not necessarily having one's own children in the household. All singletons are dropped from the analysis.

* p<0.1 ** p<0.05 *** p<0.01

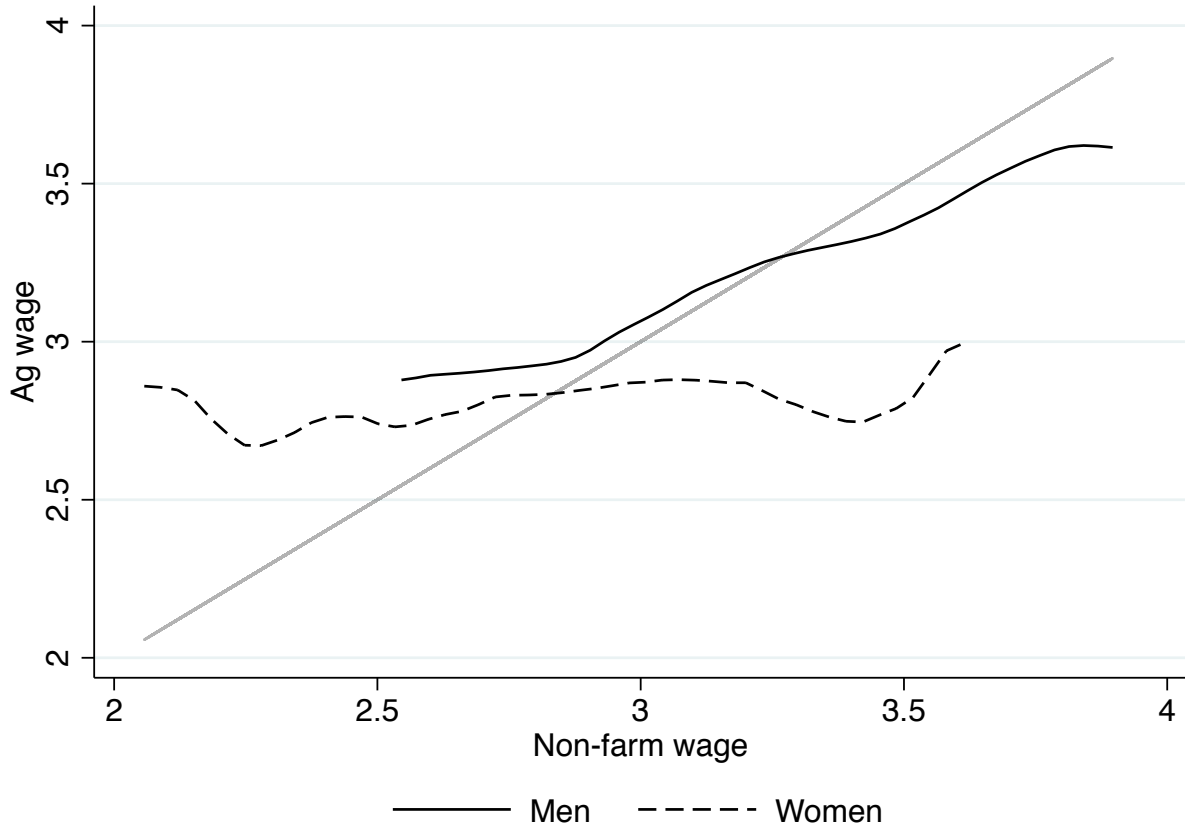
Table 5: Caste and Sectoral Wage Gaps

	Female		Male	
	(1)	(2)	(3)	(4)
	Low caste	High caste	Low caste	High caste
Non-farm	0.091** (0.039)	0.257*** (0.073)	0.039* (0.023)	0.009 (0.051)
Fixed Effects:				
Household-year-month	X	X	X	X
Individual	X	X	X	X
Observations	6,158	1,232	22,606	6,197

Standard errors are clustered at the individual level and are in parentheses. Low caste is defined as scheduled castes, scheduled tribes, and other backwards castes. All singletons are dropped from the analysis.

* p<0.1 ** p<0.05 *** p<0.01

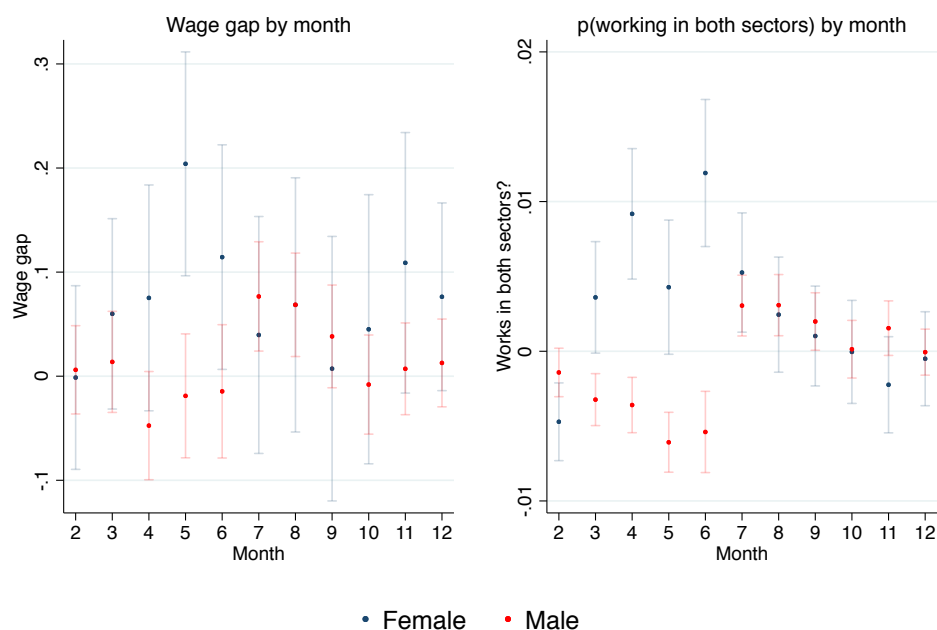
Figure 2: Relationship between Non-Farm and Agricultural Wages



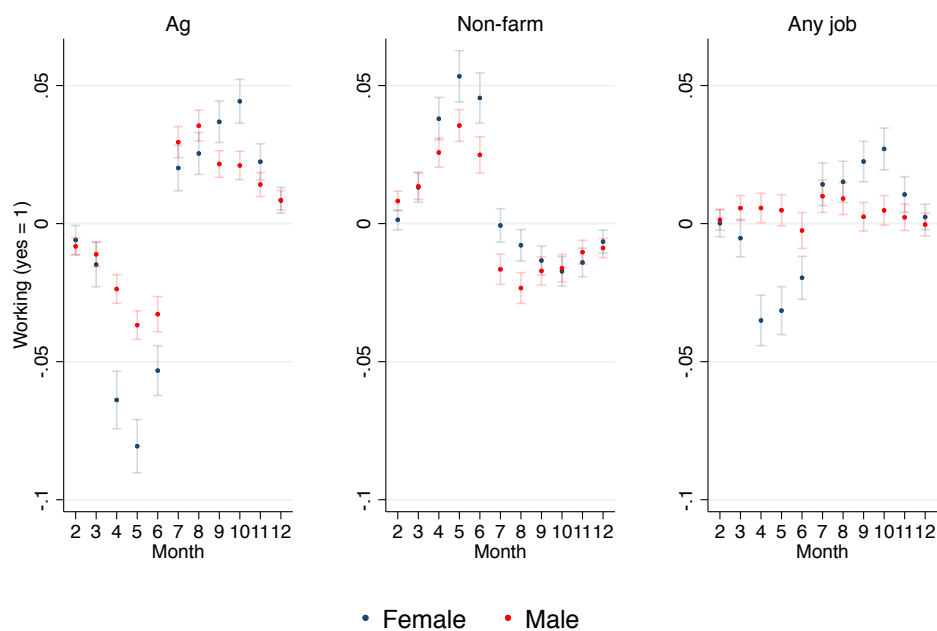
The figure is kernel-weighted local polynomial smoothing of the relationship between agricultural and non-farm wages for individuals that work in both sectors simultaneously.

Figure 3: Gaps, Probability of Working, and Seasonality

Panel A: Wage gaps and working, relative to January



Panel B: Working, relative to January



All markers are coefficients from a regression with individual fixed effects of the outcome variable (listed in the figures) on 11 month dummies. The base month in all figures is January, so the coefficients represent changes relative to January.

Appendix A

Table A1: Sectoral Wage Gaps and Time Worked

	(1) Monthly Income	(2) Daily Wage	(3) Hourly Wage	(4) Monthly Income	(5) Daily Wage	(6) Hourly Wage
Non-farm	0.725*** (0.023)	0.276*** (0.019)	0.313*** (0.018)	0.475*** (0.023)	0.080*** (0.019)	0.164*** (0.017)
Age				0.055*** (0.006)	0.042*** (0.005)	0.043*** (0.005)
Age squared (10s)				-0.006*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
Male (yes=1)				0.380*** (0.029)	0.372*** (0.023)	0.252*** (0.021)
Education (years)				0.043*** (0.003)	0.027*** (0.003)	0.028*** (0.002)
Fixed Effects:						
Year-by-month	X	X	X	X	X	X
Observations	99,925	99,743	99,680	99,802	99,620	99,557

Standard errors are clustered at the individual level and are in parentheses. The first and fourth columns use total sectoral wage income as the dependent variable. The second and fifth columns use a daily wage, created by dividing the total by days worked. The third and sixth columns use an hourly wage, created similarly.

* p<0.1 ** p<0.05 *** p<0.01

Table A2: Gender and Probability of Working Outside of Village

DV: Job located outside village	All			Both Ever	
	(1) All	(2) Female	(3) Male	(4) Female	(5) Male
Non-farm	0.126*** (0.011)	0.033*** (0.010)	0.157*** (0.018)	0.023*** (0.008)	0.116*** (0.018)
Fixed Effects:					
Household-year-month	X	X	X	X	X
Person	X	X	X	X	X
Observations	99,933	28,689	71,244	14,023	30,367

Standard errors are clustered at the individual level and are in parentheses. The dependent variable in all columns is whether the individual works outside of the village in the given sector. The first three columns include everyone, while the last two restrict attention to just those individuals who are observed in each sector at least once. All singletons are dropped from the analysis.

* p<0.1 ** p<0.05 *** p<0.01

Table A3: Correlation of Wages within and across Individuals

	Person-month	Person	
	(1)	(2)	(3)
Female		-0.001 (0.179)	0.753*** (0.213)
Non-farm wage	0.041 (0.027)	0.165*** (0.030)	0.250*** (0.043)
Female times non-farm wage	-0.064** (0.030)	-0.121** (0.058)	-0.363*** (0.067)
Fixed Effects:			
Village-year-month	X		
Village		X	
Household			X
Person	X		
Observations	2,818	1,167	764

Standard errors are clustered at the individual level and are in parentheses. The dependent variable in all columns is the agricultural wage an individual receives in a given month. The first column is at the person-month level, so the regression is identified by only by individuals who work in both sectors simultaneously. The second and third columns take the median farm/non-farm wage across all months for each individual. All singletons are dropped from the analysis.

* p<0.1 ** p<0.05 *** p<0.01

Table A4: Gender and Hours Spent in Each Sector

	(1)	(2)	(3)	(4)
	All Jobs	All Jobs	All Jobs	No NREGS
Non-farm	-0.112*** (0.036)	-0.117** (0.059)	-0.201*** (0.045)	-0.175*** (0.045)
Male times Non-farm	0.394*** (0.042)	0.332*** (0.074)	0.216*** (0.070)	0.254*** (0.060)
Fixed Effects:				
Year-month	X			
Household-year-month		X		
Person-year-month			X	X
Observations	44,529	44,529	44,529	39,964

Standard errors are clustered at the individual level and are in parentheses. The dependent variable in all columns is total hours worked in each sector. The last column drops months in which an individual works in the large Indian workfare program, NREGS. All singletons are dropped from the analysis.

* p<0.1 ** p<0.05 *** p<0.01

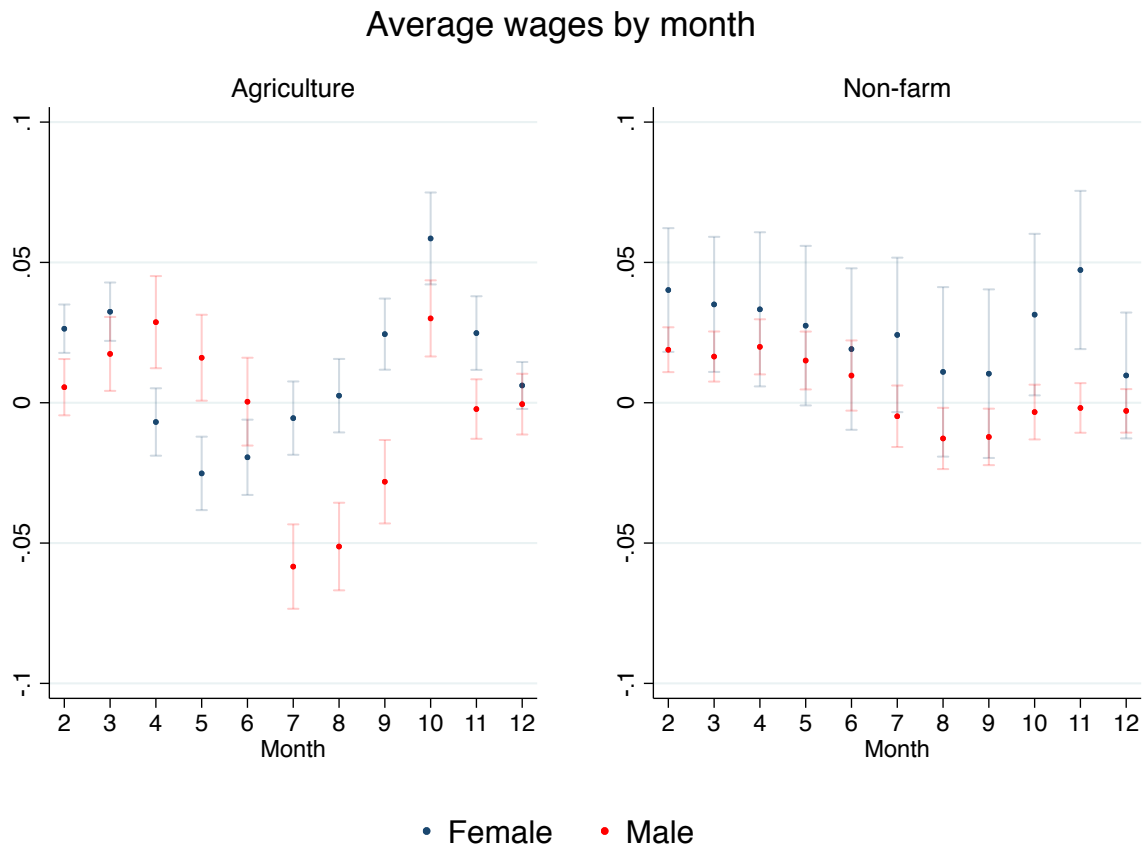
Table A5: Marital Status and Sectoral Wage Gaps for Women II

	(1) Not Married	(2) Married	Not Married		Married	
			(3) No Children	(4) Children	(5) No Children	(6) Children
Non-farm	0.045 (0.054)	0.129*** (0.019)	0.112* (0.065)	-0.033 (0.092)	0.184*** (0.030)	0.103*** (0.023)
Fixed Effects:						
Year-month	X	X	X	X	X	X
Individual	X	X	X	X	X	X
Observations	5,350	23,251	2,942	2,407	8,898	14,348

Standard errors are clustered at the individual level and are in parentheses. The regressions are identical to those in Table 4, except they include year-by-month fixed effects instead of household-by-year-by-month fixed effects.

* p<0.1 ** p<0.05 *** p<0.01

Figure A1: Seasonality in wages



All markers are coefficients from a regression with individual fixed effects of the outcome variable (wage) on 11 month dummies. The base month in all figures is January, so the coefficients represent changes relative to January.