Informal employment in India: voluntary choice or a result of labor market segmentation?*

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Abstract

This paper uses the National Sample Survey (India) data on Employment and Unemployment for 2011-12 to test for labor market segmentation in the Indian labor market. Results show that workers can freely enter informal employment. However, there is no evidence of self-selection into formal employment. Based on this evidence, we cannot reject the labor market segmentation hypothesis for the Indian labor market. The wage gap decomposition results show that the informal workers earn less than the formal workers not only because they are less skilled, but also because they face discrimination as they receive lower returns to their endowments compared to the formal workers. Thus policies that focus on skill development may be necessary but are not sufficient to increase formal job opportunities and reduce the formal-informal wage gap.

JEL classification: O17; J42
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1 Introduction

In India, as of 2011-12, informal workers comprise 85.8 percent of the total labor force. These workers lack basic social and legal protections and are not eligible for employment benefits. The relatively large share of informal workers in the total labor force is a typical feature of developing

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countries. Interestingly, informal employment is not only a feature of small unregistered and unincorporated enterprises (collectively known as the informal sector), but they comprise a substantial portion of the workforce employed in the formal sector as well. In India, informal employment as a share of formal sector employment increased from 37.8 percent in 1999-2000 to 46.6 percent in 2004-05 and to more than 50 percent in 2011-12. Thus, the formal sector recruits half of the workers informally by not providing them any social security and employment benefits.

The share of informal employment in the Indian labor force, particularly the increase in the share of informal employment in the formal sector posits some important questions that remain unanswered till date. Firstly, what is the wage gap between the formal and informal workers? Secondly, do workers voluntarily choose informal employment or they are forced into informal employment as a result of rationing of formal jobs? Thirdly, what are the differences between formal and informal workers in terms of human capital and individual characteristics? This paper tries to answer to these questions that have not been analyzed yet for the Indian labor market.

Traditionally the informal sector comprises of the disadvantaged workers waiting for employment in the formal sector (Lewis, 1954; Harris and Todaro, 1970). Employers ration the formal jobs that results in a queue for these jobs. Institutional barriers also restrict the workers from entering formal employment. In the absence of entry barriers and subject to the availability of enough formal jobs, a worker would choose the sector that pays him higher wages and other non-wage benefits. In the labor economics literature this line of argument is commonly known as labor market segmentation. A similar line of argument is put forward by the efficiency wage proponents (Stiglitz, 1976; Solow, 1980). According to the efficiency wage argument, formal wages are set higher than the market clearing rate to induce worker productivity and discipline that create segments in the labor market. Burdett and Mortensen (1998) introduced search frictions like simple search costs that may result in labor market segmentation. Ashtenfelter et al (2010) and Manning (2011) investigates the prevalence of monopsonistic power in the labor market. Firms can exercise their monopsonistic power owing to different labor supply elasticities for different groups of workers. Thus monopsonistic discrimination may be a cause for labor market segmentation.

However, Fields (1990) is of the opinion that the informal sector comprises of two segments: the upper tier and the lower tier. The upper tier informal segment comprises of self-employed workers who voluntarily move out of the formal jobs. The lower tier informal segment comprises the disadvantaged workers who do not find formal employment and eventually settle for low paying informal jobs. Maloney (2004) argues that informal employment has desirable non-wage features that attract voluntary movement form formal to informal employment. Thus there are two contrasting viewpoints: one that views informal employment as a competitive choice and the other leans on to the labor market segmentation hypotheses that emphasizes on the entry barriers and rationing of formal jobs.

In this paper, I test for the labor market segmentation hypothesis with respect to formal and informal employment in India. Specifically, I am trying to answer two questions. First, I am measuring the formal-informal wage gap across different quantiles of the wage distribution and decompose the wage gap into coefficient and endowment effects. The coefficient effect explains the contribution of the difference in returns to human capital variables and individual characteristics between formal and informal workers to the wage gap. The endowment effect explains the contribution of the differences in characteristics between formal and informal workers to the wage gap. Second, I analyze whether informal employment is a competitive choice vis-à-vis formal employment as argued by Maloney (2004) and Fields (1990) or it is an outcome of labor market segmentation. I use the micro data on Employment and Unemployment for the year 2011-12 provided by the National Sample Survey Office (India) for the empirical analysis.

Several papers have empirically tested the labor market segmentation hypothesis. Heckman and Hotz (1986), Dickens and Lang (1985), Rosenzweig (1988), Magnac (1991) and Gindling (1991) present different methodologies to test the segmentation hypothesis. The consensus on the methodology is that a near zero returns to human capital variables for informal workers are neither necessary nor sufficient for the segmentation hypothesis to be valid. Bosworth et al (1996) explain that different returns to human capital variables for formal and informal workers are not necessary conditions for market segmentation because the actual wage levels may be different for

the formal and the informal workers. That is, a wage gap between formal and informal workers may exist even if informal workers earn higher returns on a subset of their endowments compared to formal workers. Different returns to endowmwnts are neither sufficient conditions because higher returns to formal workers may be compensated by lower starting salaries. Similarly, different wage determination mechanisms in the two sectors do not imply market segmentation if workers are free to choose the type of employment. Dickens and Lang (1985) emphasized the existence of entry barriers or an evidence of queuing of jobs in formal employment as a necessary precondition for the labor market segmentation hypothesis to be valid. Gindling (1991) argues that if workers were free to choose the type of employment, an observationally identical worker would choose the one that pays him higher wages. Thus labor market segmentation implies a wage penalty for the observationally identical workers.

This paper contributes to the literature in three ways. Firstly, this paper looks at an emerging South Asian economy that has not been studied in earlier works on labor market segmentation. This is important because the share of informal employment in South Asian countries (see figure 1) are quite high compared to the other regions of the world. Secondly, this paper will provide insights to policy prescriptions by identifying the channels through which the share of informal employment can be reduced. Thirdly, this paper follows the definition of informal employment adopted by the International Labor Organization (ILO) that gives an opportunity for cross country comparisons in the future. This study bridges these gaps by using the 68th round of National Sample Survey Organization (India) data on Employment and Unemployment. The data set is very rich in terms of the information it provides on individual characteristics, household characteristics and job characteristics. It allows the identification of formally and informally employed workers. To the best of my knowledge, no study has analyzed these questions for India using this data set as of now.

[Figure 1 about here]

I use Machado and Mata (2005) technique that uses the quantile regression framework to de-

compose the formal-informal wage gap across the wage distribution. Then I use the polychotomous choice model developed by Lee (1983) to test for labor market segmentation. The methodology is an extension to Heckman (1979) that allows for multiple labor market choices. In the first stage, I use the the multinomial logit to estimate the participation decision that includes four labor market choices: formal employment, informal employment, self-employment and staying out of the labor force. In the second stage, I estimate the wage equations for formal and informal workers taking into account the sample selection bias resulting from self-selection of workers into formal and informal employment. Gindling (1991) argues that a non-random selection of workers into a particular sector that does not affect wages in that sector implies that workers do not have full access to that sector.

The results presented here support the labor market segmentation hypothesis for the Indian labor market. First of all, I find a significant wage gap between formal and informal workers across the wage distribution. Formal workers earn higher returns to human capital and individual characteristics compared to informal workers. At the lower end of the distribution, differences in returns to human capital and individual characteristics between formal and informal worker explain a major part of the wage gap. The informal workers at the lower end of the wage distribution may be identified as the disadvantaged workers who earn lower returns to their skills compared to their formal counterparts. A the higher end of the distribution, the major part of wage gap is explained by the differences in characteristics between formal and informal workers. So, at the upper end of the distribution, informal workers earn less than their formal counterparts may be because they are less skilled. When corrected for sample selection bias, the wage equation estimates show positive returns to schooling for male formal and informal workers. In fact, the returns to education are almost the same for formal and informal workers. Female informal workers, however, receive positive returns to additional years of schooling, but the returns are not statistically significant for formal workers. Overall, these results are not quite consistent with the notion that informal workers receive zero or near zero returns to human capital variables. As discussed above, near zero returns to education for informal workers do not imply labor market segmentation. I find no evidence of

workers being able to self select into formal employment if they wish to. Thus, we cannot reject the labor market segmentation hypothesis. The counterfactual wages show that 85 percent of the male and 83 percent of the female informal workers, would have earned higher wages if they were formal workers. It may be argued that the informal employment has other non-wage benefits, but this argument is not plausible enough in this case because by definition the informal workers do not receive any employment benefits.

The remainder of this paper is organized as follows. Section 2 reviews the literature on labor market segmentation focusing on the developing countries. Section 3 provides the definitions of informal employment and informal sector. Section 4 discusses the data and summary statistics and more importantly the identification of formal and informal workers. Section 5 sets out the empirical models. The results are presented in Section 6. Section 7 concludes.

2 Literature review

I will discuss the the relevant literature for this paper in two parts. First, I will discuss a few seminal papers that proposed the formal tests for the segmentation hypotheses. Since the main objective of this paper is to test for labor market segmentation with respect to formal and informal employment in India, in the second part of the literature survey, I will discuss the empirical literature on segmentation focusing on the developing countries. I will restrict the sample of papers to the ones that test for labor market segmentation in the formal and informal context. The literature uses different empirical approaches to test the labor market segmentation and the competitive labor market hypotheses. Heckman and Hotz (1986) test for labor market segmentation based on the earnings of Panamanian males. They test for labor market segmentation in the following way: if the fitted earnings functions are different for different groups (separated either geographically or by income) and if the differences between the selection corrected estimates are significantly different then it would imply that the labor market is segmented. They find strong regional differences

in estimated earnings functions and claim that Panamanian labor markets are geographically segmented. They also find differences in the functional forms of the earnings equation for the samples of high-earning and low-earning workers. However, they argue that there is little robust behavioral content to imply dual labor markets in Panama.

Dickens and Lang (1985) propose a "switching model" to test of labor market segmentation. They simultaneously estimate two separate wage equations and a third equation that predicts sector attachment. Using log likelihoods they test whether two equations fit better than one. If workers were free to choose the sector, the coefficients in the switching equation should be equal to the difference between the coefficients of the wage equations in the two sectors. A rejection of this test would imply the existence of entry barriers. Using data from the Panel Study on Income Dynamics for the year 1980, they provided evidence for the dual market hypothesis.

Magnac (1991) tests for labor market segmentation for married women in Columbia. He develops a microeconomic model derived from a labor supply model in a four-sector labor market with explicit demand constraints. The empirical strategy is similar to a sample selection model but he uses the cost of entry to the formal sector to test whether the labor market is strongly or weakly competitive. The paper finds evidence of comparative advantages for individuals between the various economic sectors are more important compared to segmentation. Acknowledging the deficiencies of the segmentation test procedures the paper claims that unobserved characteristics of the workers determine the choice between the sectors as a matter of tastes and not as a matter of individual ability or productivity.

Now I discuss the empirical literature on labor market segmentation for the developing countries. The main focus of this discussion is to provide evidence for and against the segmentation hypothesis in the context of formal and informal employment in the developing countries. Most of the studies on labor market segmentation mainly focus on Latin American countries. Maloney (1999) provides evidence of comparative advantage for working in the informal sector using a dynamic panel data on the Mexican labor market. He concludes that earnings differentials do not offer compelling evidence in favor of the segmentation hypothesis because of the difficulty of

quantifying unobservable variables. Navarro & Schrimpf (2004) uses a discrete choice model to test for segmentation in the Mexican labor market. They find no evidence of rationing of jobs in the formal sector and thus reject the segmentation hypothesis. The evidence is consistent with a market in which comparative advantage determines who goes to which sector.

Pratap and Quintin (2006) test for segmentation hypothesis on the Argentinean labor market. Specifically, they test for the hypothesis that observably similar workers earn higher wages in the formal sector than in the informal sector in developing nations. The paper semi parametrically controls for individual and establishment characteristics arguing that this approach gives robust estimates of wage differentials compared to parametric approaches. They find no evidence of a formal sector wage premium in Buenos Aires and its suburbs. Although wages are higher on average in the formal sector, this apparent premium disappears after semi parametrically controlling for individual and employer characteristics. Although they do not perform a formal test on whether informal sector workers voluntarily choose informal sector over the formal sector , the near zero wage gap between formal and informal sector workers insinuates that workers are indifferent between the formal and informal sectors.

Pianto and Pianto (2002) tests for the segmentation hypothesis on labor market data from Brazil. They use quantile regressions to test for sample selection bias at different quantiles of income. They find that earnings gap between formal and informal workers are wider at the lower quantiles than at the high ones. Returns to attributes explain around 30 percent of the earnings at low quantiles. At high quantiles the earnings gap is completely explained by their individual characteristics. Informal workers in the lower quantiles receive lower returns to their skills compared to their formal counterparts. Based on this observation they cannot reject the hypothesis of labor market segmentation. On the other hand, Carneiro & Henley (2001) provide evidence in favor of the competitive hypothesis in the Brazilian labor market.

Some studies look into the labor markets in African countries that also feature a huge share of informal employment. For example, Günther and Launov (2012), based on data from Côte d'Ivoire, rejects the hypothesis of fully competitive labor markets. They use an augmented two step

Heckman procedure to correct for sample selection bias to estimate the number of segments within the informal sector. Their results show that the informal sector comprises of two segments: the upper tier and the lower tier. The lower tier informal sector is a result of labor market segmentation. However, they conclude that comparative advantage considerations is the cause for the existence of the upper tier informal sector. Grootaert and Mundial (1988) analyze the formal and informal systems of acquiring vocational and technical training in Cote d'Ivoire and their effect on wages and the sector of employment. They find the difference in returns to formal and informal training to be merely 4 percent. Based on this estimate they cannot conclude that informal training is an inferior mode of training. The study, however, does not make any specific claims on the choice of sector allocation. In summary, findings from for the Latin American countries are heavily skewed in favor of competitive labor markets validating the voluntary informal employment hypothesis. I have come across only two studies that focuses on African countries. It wont be right to arrive at any conclusions based on this scarce evidence on African countries.

Due to data constraints there is a dearth of research that analyzes the segmentation hypothesis for the South Asian countries (like India, Bangladesh, Sri Lanka, Pakistan). However the questions are rather important for a country like India because 84 percent of the labor force (see Figure 1) in India is informally employed-largest amongst the emerging economies. Another point of concern that has challenged policy makers lately is the growing informalization of jobs. Over the last decade Indian economy has experienced strong economic growth and an increase in employment opportunities in the formal sector. However, as Mehrotra et al (2013) shows, the share of informal employment in the formal sector has increased from 32 percent in 1999-2000 to 54 percent in 2004-05 to 67 percent in 2011-12. This informalization of formal employment is a result of an increase in contractual jobs within the formal sector in which the firms do not pay any employment benefits to the workers. Mehrotra et al (2012) argues that the increasing prevalence of informal employment in the formal sector poses a tough challenge to policy makers in achieving inclusive growth and sustainable development in the future. Recent public policies in India focus on skill development as the main instrument to increase the employability of the workforce. The basic

assumption behind these policies is the direct link between skill level and better pay, and hence better living and working conditions for the workers. However, King (2012) argues that, although the relative wages of workers with general secondary education have increased over the years, but the same trend is not seen for the workers with technical training and vocational education. Given the huge share of informal employment in India, the pertinent question is whether these policies play a positive role in reducing the share of informal employment. Data from the Employment and Unemployment Survey, conducted by the National Sample Survey Organization show that, 28.2 percent and 29.2 percent of the workers having some technical education are distributed across formal and informal employment respectively. Amongst those who received formal vocational training, only 21 percent are formally employed and 30 percent are informally employed. Thus, present policy initiatives assume that the worker characteristics are the sole determinant of job choices. The policies do not take into account entry barriers to formal employment or rationing of formal jobs by the employers. The National Skill Development Corporation, which was recently set up pays attention to the informal workers, but the whole point of developing skills may be ineffective if we find that informal workers with similar characteristics as formal workers face discrimination in the labor market.

Khanderkar (1990) is the only study that looks into labor market segmentation for India. He uses survey data for urban slum dwellers and finds evidence of labor market segmentation resulting not from sample selection bias on the part of workers but selectivity bias by firms. The study differentiates between protected wage segments, unprotected wage segments and self employment that are not consistent with the modern definitions of formal and informal employment. Moreover, the scope of the study is limited to urban slum dwellers that do not represent the different cohorts of the labor force. Thus no study, prior to this one has ever tested for the segmentation hypothesis for the Indian labor market in the context of formal and informal employment. As discussed in the literature review section, evidence from the Latin American countries show that informal employment is a competitive choice for workers vis-à-vis formal employment. It needs to be seen whether these predictions hold for the Indian labor market as well.

3 Definitions and conceptual framework

This paper uses the following definitions for informal sector and informal employment:[1]

Definition 1: The *informal sector* consists of small-scale, self-employed activities (with or without hired workers but less than 10 workers), typically at a low level of organization and technology, with the primary objective of generating employment and income. The activities are usually conducted without proper recognition from the authorities, and escape the attention of the administrative machinery responsible for enforcing laws and regulations.

Defintion2: *Informal employment* is a job-based concept and encompasses those jobs that generally lack basic social or legal protections or employment benefits and may be found in the formal sector, informal sector or households.[2]

Table 1 below illustrates this categorization.[3]

[Table 1 about here]

4 Data and summary statistics

The National Sample Survey Organization (NSSO) in India collects data on employment and unemployment every five years. Data are collected on a number of individual characteristics, job characteristics, working conditions and social security benefits. This paper uses individual level data for the year 2011-12 (latest year available) provided by the NSSO to answer the questions outlined in the previous sections.

The 2011-12 Employment and Unemployment Survey, studies 101,724 households that include

[1]These definitions were adopted by the International Conference of Labour Statisticians (ICLS). The International Labor Organization has implemented them based on the ICLS resolutions. The NCEUS (2007) restricts the informal sector to the proprietary and partnership firms that have less than 10 workers.

[2]I use workers in informal employment and informal workers interchangeably in the text.

[3]The 17th International Conference on Labor Statisticians (ICLS) provides the definition of the informal sector and informal employment based on the enterprise types and job characteristics pertaining to the non-agricultural sector. As far as the agricultural sector is concerned, no consistent definition is followed across countries. The International Labor Organization has adopted these definitions based on the ICLS resolutions. The statistical office in India does not provide a formal definition of informal sector that includes the agricultural sector, and therefore I focus on the non-agricultural sector. See http://ilo.org/public/englisg/bureau/stat/download/papers/def.pdf

456,999 individuals. The sector of employment for each working individual is recorded according to the 2-digit National Industrial Classification (NIC, 2008) codes. I restrict the sample to the primary working age population (15 to 59 years) in the non agricultural sector.[4] Subject to available data on all covariates, the final sample has 109,219 observations for males and 118,620 observations for females. A detailed description of the sample selection process is provided in the Appendix.

4.1 Identification of informal sector and informal employment

4.1.1 Informal sector

The 17th ICLS provides the definition for informal sector based on the enterprise type (firm). The type of enterprise is recorded for all workers. It is not recored for the unemployed persons and the persons who are not in the labor force because these workers were not working at the time of the survey. Table 2 shows the distribution of the individuals across different enterprise types. Categories 1-4, 8 and 9 make up the informal sector[5] and 5-7 comprise the formal sector. In the sample, 77.5 percent of the workers are employed in the informal sector and 22.5 percent of the workers are employed in the formal sector.[6]

[Table 2 about here]

4.1.2 Informal employment

The definition of informal employment is based on the job categories outlined in the 17th ICLS. The identification of informal workers is done in steps. First, the workers are separated based on their job types: self employed and employees. As we will see, the self employed workers are by definition categorized as informal workers. For the employees working in the firms, those who do

[4]Since unemployed persons do not have any NIC-2008 classification, I include them in the non-agricultural labor force. It is not possible to distinguish agricultural and non-agricultural unemployment.

[5]The 17th ICLS treats households as a separate category outside the formal and the informal sector. However, all workers employed by the households are classified as informal workers. For brevity, 'employer's households' are classified as informal sector enterprises in Table 2. This classification is innocuous since those workers are anyway treated as informal workers in the final classification.

[6]All figures in tables 2-7 are census-adjusted

not receive any employment benefits are categorized as informal workers and the rest as formal workers. Tables 3-5 illustrates this identification process.

As discussed, first we need to identify the different categories of the workers based on the job types. In the data, the job categories are recorded based on the principal activity status for the last 365 days from the date of the survey. The job type of the workers is independent of the sector they work in. Table 3 shows the distribution of job categories based on the principal activity status. Majority of the workers are regular salaried wage employees (14.4 percent), followed by self employed (own account workers) (11.5 percent). In the sample, 62 percent of all the individuals (categories 7-12 in table 3) are not in the labor force.[7]

[Table 3 about here]

The information provided in table 3 is insufficient to categorize the workers as formal and informal workers. We need additional information on the benefits received by the workers in each category in order to identify them as formal and informal workers. Workers are classified into self-employed and employees who are employed by other persons or firms. The employees comprise of the regular/ salaried wage employees, casual wage laborers in public works and other types of work. These workers are found both in the formal and the informal sectors. As per the definition, informal workers do not receive any social security, job security and other employment benefits such as paid leave. This information on employee benefits is recorded only for the employees (categories 4-6 in Table 3) and not for the self employed workers (categories 1-3 in Table 3). Workers who receive all of the benefits above are identified as formal workers. Table 4 shows the percentage of workers receiving each category of benefits (social security, job contract and paid leave). The last column in table 4 shows that only 17.4 percent of the workers receive social security, has written job contracts and are eligible for paid leave. The rest (82.6 percent) do not receive any of these benefits.[8]

[7]Note that the total number of observations are different in Table 2 and Table 3. This is because, enterprise type is recorded only for the working individuals while principal activity status is recorded for all individuals in the sample (including those who are unemployed and those who are not in the labor force).

[8]Again, note that the total number of observations reported in Table 5 is different from Table 2 and Table 3. This

[Table 4 about here]

Tables 3 and 4 give us the information on the job types and the employment benefits received by the workers. Combining these two information sets, we now identify the formal and informal workers. Table 5 reports the measures of formal and informal employment treating self employment as a separate category.[9] The formal and informal employment categories in Table 5 comprise of the wage earners only. The categories reported in Table 5 are the final categories used in this paper. Further, Table 5 reports the figures separately for males, females and for the entire sample. Overall, 14.2 percent of the workers in the labor force are formally employed and 44.3 percent of the workers are informally employed. If we employ the broader definition of informal workers that includes the self employed workers, informal workers comprise 85.8 percent (treating the 41.5 percent of the self employed workers in table 5 as informal workers) of the total labor force. However, we treat self employed workers as a separate category for the reasons noted in footnote 9.

[Table 5 about here]

Table 5 shows that 29.4 percent of the working age males are out of the labor force while 88.8 percent of the working age females are out of the labor force. Labor force participation rate varies significantly for males and females across all states of India. For this reason, the empirical results in this paper are reported separately for males and females. For the entire analysis in the

is because, information on benefits is recorded only for wage employees (Category 4,5 and 6 in Table 3). Information on benefits is not available for self employed workers.

[9] Wages are reported only for the wage earners that include regular salaried employees and casual laborers. Since it is difficult to identify the the profit and wages components from the earnings of the self employed, data on earnings of self employed persons are not collected in the survey. Although, self employed workers are categorized into formal and informal employment as per the ILO definition, in this paper I consider them as a separate category from formal and informal employment because estimation of a wage equation is not possible for the self employed workers. Furthermore, the share of self employment (14.7 percent of the working age population) is quite large in the sample representing systematically different types of jobs than the wage earners. This difference in job types compared to wage earners, and the unavailability of earnings information for the self employed workers makes the treatment of self employed workers as a separate category (from formal and informal employment) a plausible assumption.

paper, I have treated unemployed persons as not in the labor force. This assumption is necessary because the empirical model I use does not allow unemployment as a separate category. Moreover, only 1.9 percent (category 7 in table 3) of all individuals in the sample reports to be involuntarily unemployed that makes this assumption innocuous to the results reported in this paper.

4.1.3 Formal and informal employment in formal and informal sectors

In this subsection, I break up the formal and informal workers into the formal and informal sectors. Although this classification is not directly significant for the analysis, it would give us some useful insights on the nature of informal employment. Specifically, this classification measures the share of workers who do not receive any employment benefits in spite of working in the formal sector. Table 6 presents the framework for the identification of formal and informal employment in the formal and the informal sectors. The cells with 'NE' refer to non-existent. Own account workers in the formal sector are identified as formal workers in the formal sector (cell A). Since all own account workers in the informal sector are identified as informal workers, so, there does not exist any formal own account workers in the informal sector. All own account workers working in the informal sector are identified as informal workers (cell F). Employees who run their own informal household enterprises by hiring employees are identified as informal workers (cell G). Some employers may be working in the formal sectors that are identified as formal workers. Unpaid family members who contribute to the production processes are considered as informal workers regardless of which sector they work in.

[Table 6 about here]

Applying the definition of informal employment on regular and casual workers based on the employment benefits, and treating self employed workers as shown in table 6, the following categories (Table 7) of employment are identified. Each category in Table 7 is derived by aggregating the cells in Table 6. For example, the category formal employment in the formal sector comprise

of own account workers in the formal sector (cell A in table 6), employers who work in the formal sector (cell B in Table 6) and those employees who work in the formal sector but do not receive any employment benefits (cell D in table 6).[10] 85.6 percent of the workers in the labor force are informally employed. Also, the formal sector employs 51 percent of its workers as informal workers which is a growing point of concern for policy makers, as argued in section 2.

[Table 7 about here]

4.2 Summary Statistics

Table 8 reports the mean and standard deviations of all the variables used in the analysis for males. Table 9 reports the summary statistics for females. In both the tables 8 and 9, the summary statistics are reported separately for the following categories of employment: formal employment, informal employment, self employed and not in the labor force.

[Table 8 and 9 about here]

4.2.1 Wages and Consumption expenditure

Weekly nominal wages for formal male workers (Rs 4966) are significantly higher than the informal male workers (Rs 1771). The mean formal-informal wage gap is Rs 3195 for males and Rs 2963 for females. [11] The monthly per capita consumption expenditure (MPCE) is also significantly less for informal workers (Rs 1714 for males and Rs 2007) compared to formal workers (Rs 2902 for males and Rs 3651 for females).[12] Male self employed workers report slightly higher MPCE (Rs 1806) than the informal workers, but female self employed workers report lower MPCE (Rs 1756) than informal workers. These evidences insinuates that on average informal workers maintain poor living conditions compared to the formal workers.

[10] The letters in parentheses following each category in Table 5 are the references to the cells in Table 4.

[11] The average official exchange rate during the period 2011-12 was Rs 50/$ (World Development Indicators).

[12] The MPCE is used only to highlight the difference between the different categories. This variable is not used for the analysis that follows.

4.2.2 Demographics

Informal workers are on average younger (34.2 years for males and 34.9 years for females) than formal workers (42.1 years for males and 39 years for females) for both males and females. The average age of females not in the labor force (32 years) are significantly higher than their male counterparts (20.1 years). Majority of the females who are not in the labor force may comprise housewives which is a common feature in households in India, both in rural and urban areas. During 2009-10, 40 percent of the rural females and 48 percent of urban females were engaged in domestic duties.[13]

The number of dependents is an important factor that influence the labor market participation decision and the sectoral choice of a worker.[14] Dependents are divided into two separate categories: children under 15 years of age and elderly members greater than 60 years of age. Formal workers have on average fewer dependents than their informal counterparts and self employed workers, for both males and females. The significant variation of number of dependents across the different sectors implies that number of dependents may play a role in sector selection.

Other demographic control variables include religion, caste and marital status. Hindus comprise roughly 80 percent of the workers in all categories followed by Muslims. In India, caste is an important demographic characteristic. The category 'others' include the higher castes. Majority of the formal employment comprise of higher castes (40 percent) and Other Backward Classes (OBC). 90 percent of all males and 70 percent of all females in the sample in all categories are married.

[13] Source: NSS report on "Participation of Women in Specified Activities Along with Domestic Duties", 2013.
[14] See Section 5.3 for a detailed discussion.

4.2.3 Human capital

General education is reflected by the years of schooling.[15] Formal workers are on average more educated (12.5 years of schooling for males and 13 years of schooling for females) than informal workers (7.4 years of schooling for males and 7.3 years of schooling for female). Male self employed workers (8 years of schooling) are slightly more educated than informal male workers and but the same does not hold true for female self employed workers. Men who are not in the labor force are more educated than informal workers (10.1 years of schooling), but less educated than formal workers. These men may have chosen to stay out of the labor force to gain a few years of education before joining the labor force. However, this is not true for the females in the sample.

Technical education and vocational training are regarded as important attributes that contribute significantly towards the employability of workers and wages offered.[16] Roughly 14 percent of formal male workers have some technical education compared to 5 percent of informal workers. 28.2 percent and 29.2 percent of the workers having some technical education are distributed across formal and informal employment respectively. Amongst those who received formal vocational training, only 21 percent are formally employed, 30 percent are informally employed, 23 percent are self employed and the rest are not in the labor force. Females follow roughly the same pattern for technical education and vocational training as males. These facts provide preliminary evidence that technical education and vocational training may be necessary, but not sufficient to increase the chances of being formally employed and earn more wages.

[15] I have used NCEUS (2007) to compute the mean years of schooling. The following classification is considered: Illiterate-0, literate below primary-1, primary-4, middle-8,) secondary-10, higher secondary-12, diploma/ certificate course - 14, graduate - 15, postgraduate and above -17.

[16] A person has some sort of technical education if he holds a degree, diploma or certificate in engineering and technology, agriculture, medicine and all other technical fields. Vocational training means some sort of expertise in the field of trade. Examples of vocational training are book binding, handicraft, medical transcriptions etc. Vocational training is more focused towards the type of job and can be formal and informal. If a worker acquires skills for a particular job from, say, family heredity then it is regarded as informal vocational training. But if a worker enrolls in a formal institution to acquire vocational training that is regarded as formal vocational training. Both technical and vocational training captures the skill level of a worker, whereas years of schooling reflect the general level of education of the workers.

4.2.4 Regional variables

Regional variables include whether a worker resides in an urban or rural area and the the region of residence – south, north, central, east, north-east and west. Workers (both male and females) in all categories are almost evenly distributed across urban and rural areas. The distribution is even across the region of residence as well.

5 Empirical methods

The first objective of this paper is to measure the wage gap between formal and informal workers. Measuring the formal-informal wage gap on the average may not provide adequate information on what happens across the whole wage distribution. Pratap and Quintin (2006) showed that the wage gap between formal and informal workers decreases at the higher quantiles of the wage distribution. Thus to reveal useful information on the wage gap, I use quantile regressions that estimate the formal-informal wage gap at different quantiles of the wage distribution. I use the empirical technique proposed by Machado and Mata (2005) to decompose the wage gap into endowment and coefficient effects. The dependent variable is the weekly wage earnings. The independent variables include years of schooling, whether or not received technical education and vocational training and a number of individual characteristics like age sex, religion, caste and region of residence. However, due to empirical complexity I am not able to control for sample selection bias in the quantile regression framework that may produce spurious results. Nonetheless, the estimates give a preliminary idea of the wage penalty faced by informal workers. I discuss the empirical strategy in section 5.1.

The second objective of this paper is is to test for labor market segmentation. We estimate two wage equations for formal and informal workers accounting for sample selection bias. There are four labor market choices: formal employment, informal employment, self employment and not in the labor force. I use a polychotomous choice model developed by Lee (1983) which is

an extension of the binary choice model developed by Heckman (1979). I lay out the model in section 5.2. The identification of the model is achieved by including at least one variable in the selection equation that is excluded from the wage equation. I use two variables for this purpose: the number of dependents less than 15 years of age and the number of dependents more than 60 years of age. I discuss the rationale for this identification strategy in section 5.3. The test for labor market segmentation is based on a careful interpretation of the results from the polychotomous choice model. I follow Gindling (1991) in interpreting the results. Basically, if worker's selection into formal employment is non random and if that non randomness does not affect formal wages, then it implies that workers cannot self select into formal employment and that entry barriers exist. I discuss this interpretation and the different hypotheses in detail is section 5.4.

5.1 The formal-informal wage gap

In this section I discuss the decomposition technique proposed by Machado and Mata (2005).[17] The objective is to estimate the wage gaps between formal and informal workers at different quantiles of the wage distribution and decompose the wage gap into coefficient effects and endowment effects. The Machado and Mata (MM) technique can be seen as generalization of the Oaxaca-Blinder decomposition method for quantile regressions. The first step of the estimation process involves estimating the conditional quantile functions for both sets of workers. Let w_i denote the log weekly wage and $\mathbf{X_i}$ denote the set of covariates for each individual i that includes age, education, caste, religion, marital status, and regional dummies. ε_i is a disturbance term independent of the explanatory variables. The conditional quantile function for formal workers can be specified as a linear function:

$$q_\tau^F(w_i^F \mid \mathbf{X_{F,i}}) = \mathbf{X_{F,i}^{'}}\beta^{\mathbf{F}}{}_\tau \quad \tau \in (0,1) \tag{1}$$

[17] See Albrecht et al (2009) and Arulampalam et al (2007) for applications of this technique.

and for informal workers:

$$q^I_\tau(w^I_i|\mathbf{X_{I,i}}) = \mathbf{X^{'}_{I,i}}\beta^{\mathbf{I}}{}_\tau \quad \tau \in (0,1) \tag{2}$$

where $q_\tau(w_i|\mathbf{X_i})$ specifies the conditional quantile (τ^{th}) of the log weekly wage distribution and the set of coefficients (β_τ) are interpreted as the estimated returns to the covariates at the specified quantile. F and I denote formal and informal workers respectively. The conditional quantile regression function is then estimated using the Koenker and Bassett (1978) approach that minimizes the weighted least absolute deviations. The wage gap (G) between formal and informal workers can be specified as:

$$G_\tau = q^I_\tau(w^I_i|\mathbf{X_{I,i}}) - q^F_\tau(w^F_i|\mathbf{X_{F,i}}) = X^{'}_{I,i}\beta^{\mathbf{I}}{}_\tau - X^{'}_{F,i}\beta^{\mathbf{F}}{}_\tau \quad \tau \in (0,1) \tag{3}$$

The next step is to decompose the wage gap into coefficient effect and the endowment effect. Equation 3 can be written as:

$$G_\tau = [(X^{'}_{I,i}\beta^{\mathbf{I}}{}_\tau - X^{'}_{I,i}\beta^{\mathbf{F}}{}_\tau)] + [(X^{'}_{I,i}\beta^{\mathbf{F}}{}_\tau - X^{'}_{F,i}\beta^{\mathbf{F}}{}_\tau)] \quad \tau \in (0,1) \tag{4}$$

The first term on the right hand side of expression (4) refers to the coefficient effect. This term shows how much of the wage gap is explained by the differences in the returns to covariates for formal and informal workers if the informal workers had retained their characteristics. The second term calculates the contribution of the differences in characteristics between formal and informal workers to the overall wage gap. The decomposition technique involves the construction of the counterfactual unconditional wage distribution $X^{'}_{I,i}\beta^{\mathbf{F}}{}_\tau$, that is, how much the informal workers would earn if they were paid the same returns as the formal workers. However, in case of quantiles the unconditional quantile is not the same as the integral of conditional quantiles. Machado and Mata (2005) address this problem using a simulation based technique. The following steps summarizes the MM technique:

1. Sample u from a standard uniform distribution.

2. Estimate the different quantile regression coefficients, $\beta^{\mathbf{I}}{}_\tau(u)$ and $\beta^{\mathbf{F}}{}_\tau(u)$ for informal and formal workers respectively.

3. Generate a random sample with replacement from the empirical distribution of the covariates ($X_{I,i}$ and $X_{F,i}$) for each group.

4. Compute the counterfactual $X'_{I,i}\beta^{\mathbf{F}}{}_{\tau}(u)$.

5. Repeat steps 1 to 4 M times[18]

5.2 Polychotomous choice model with selectivity bias

The quantile regression technique works well in estimating the wage gap between the formal and informal workers given that the sectoral allocation of workers is exogenous. In other words, the model discussed above assumes that the allocation of workers into formal and informal employment is completely random.[19] However, if sectoral allocation and labor force participation are non random, then the estimates from the models 1 and 2 are biased. This problem, commonly known as sample selection bias, was first proposed by Heckman (1979). In his original model, workers faced a binary decision to enter the labor force or stay out of the labor force. The decision is based on an underlying latent variable, such as the utility of the worker. If the utility from working is less than the utility from not working, the worker stays out of the labor force. Since utilities are not observed and offered wages are only observed for the workers who are in the labor force, estimating a standard Mincerian wage equation would yield biased estimates, since the decision to enter the labor force is an endogenous choice. Heckman proposed a two stage method to circumvent this problem. In the first stage, a probit model is estimated with the participation decision as the dependent variable. This participation equation is also known as the selection equation. In the second step, the inverse Mill's ratio is constructed using the predicted probabilities from the first stage that is included in the standard wage equation in the second stage. This method produces consistent coefficient estimates of the wage equation. To identify the model and to avoid large standard errors in the second step, it is necessary to include at least one variable in the selection

[18] I have used the Stata command 'mmsel' recently released by Soubani (2012). The command implements the MM technique as mentioned above. The standard errors are calculated using a bootstrapping procedure.

[19] Albretcht et al (2009) extends the Machado and Mata (2005) technique to allow for sample selection bias. However, the model only allows a bivariate choice in the underlying selection choice is not appropriate in this case.

equation that is excluded from the wage equation.

The problem I am analyzing in this paper is slightly more complex. A potential worker faces the decision to enter or stay out of the labor market. If he decides to enter the labor market, he has three choices : start his own business (self employed), start working as an informal worker, or start working as a formal worker. So in the aggregate, a worker faces four potential outcomes: stay out of the labor force, accept informal employment, accept formal employment, or become a self employed worker. He chooses the outcome that gives him the maximum utility. For example, if a worker gains the maximum utility working as an informal worker compared to all other choices that he has, he chooses informal employment. Whether a worker actually faces these choices or whether the endogenous decision making on the part of the workers actually holds is an empirical question. This paper tests the hypothesis of endogenous sectoral allocation. If the evidence suggests that workers choose sectors that gives them the maximum utility, then we can infer that sectoral selection is endogenous. The Heckman model discussed above is not well suited to tackle the problem of polychotomous choices such as those described above. In this paper I use a polychotomous choice model developed by Lee (1983).[20] Hay (1980) proposes a similar model that deals with multiple choices with stronger assumptions than the Lee model. I use the Hay model as a robustness check for my results. Both approaches are discussed below.

Let there be M categories and one potential wage equation in each category.

$$w_{ji} = \mathbf{x_{ji}}\boldsymbol{\beta_j} + u_{ji} \;\; j = (1,...M) \;\; i = (1,...N) \tag{5}$$

$$I^*_{ji} = \mathbf{z_{ji}}\boldsymbol{\gamma_j} + \eta_{ji} \;\; j = (1,...M) \; i = (1,...N) \tag{6}$$

[20] See Trost and Lee (1984), Gyourko and Tracy (1988), Cohen and House (1986), Hilmer (2001), Zhang (2004) and Packard (2007) for applications of this model. Bourguignon et al (2007) perform Monte carlo simulations to compare three methods used in the literature for selection bias correction using multinomial logit model, namely Dubin and McFadden (1984), Lee (1983) and Dahl (2002). Their results show that the semi-parametric alternative proposed by Dahl (2002) is to be preferred to Lee (1983). However, the semi-parametric approach by Dahl (2002) does not provide a robust interpretation of the coefficient on the selection term that is useful to identify the underlying selection process. One of the objective of this paper is to identify whether the workers can self select into formal and informal employment. The Lee (1983) approach allows us to interpret the coefficient on the selection term in a way to fulfill this objective. Nonetheless I have tested my results using the Dahl (2002) model but I did not find any significant differences in the estimates and the standard errors. However, in the robustness check section I have only reported the Hay (1980) model because it's interpretation is similar to the Lee (1983) model.

where w_{ji} is the log weekly wage in sector j for individual i. $\mathbf{x_{ji}}$ is the vector of explanatory variables that affect wages and $\beta_\mathbf{j}$ the respective coefficients. u_{ji} is the error that captures all unobserved characteristics of the workers not in $\mathbf{x_{ji}}$. I^*_{ji} is the utility derived from choosing sector j which is a function of $\mathbf{z_{ji}}$ is the vector explanatory variables and $\gamma_\mathbf{j}$ the coefficient vector. η_{ji} is the error term in the latent equation. The variables in x_{ji} and $z_{ji}$are exogenous such that, $E(u_j|\mathbf{x_1}, \mathbf{x_2}, ...\mathbf{x_M}, \mathbf{z_1}, \mathbf{z_2}, ...\mathbf{z_M}) = 0$ and $E(\eta_j|\mathbf{x_1}, \mathbf{x_2}, ...\mathbf{x_M}, \mathbf{z_1}, \mathbf{z_2}, ...\mathbf{z_M}) = 0$.

w_{ji} is observed only if the j^{th} category is chosen. Let I_j be the indicator function such that $I_j = j$ if the j^{th} category is chosen. The model can be formulated by an underlying utility maximization exercise in the following way :

$$I = j \ \ iff \ I^*_j > MaxI^*_s (s = 1, ...4; \ j \neq s) \tag{7}$$

Let us define

$$\varepsilon_j = MaxI^*_s - \eta_j (s = 1, ...4; \ j \neq s). \tag{8}$$

So we can write the sectoral choice as :

$$I = j \ \ iff \ \varepsilon_j < \mathbf{z_j}\gamma_\mathbf{j} \tag{9}$$

Assume that $\eta_j s$ are independently and identically distributed with type I extreme value distribution:

$$F(\eta_j < c) = exp[-exp(-c)] \tag{10}$$

Then, as shown by McFadden (1973) and Domenich and McFadden (1975), the probability that sector j is chosen is given by:

$$Pr(I = j) = Pr(\varepsilon_j < \mathbf{z_j}\gamma_\mathbf{j}) = F(\mathbf{z_j}\gamma_\mathbf{j}) = \frac{exp(\mathbf{z_j}\gamma_\mathbf{j})}{\sum_{j=1}^{M} exp(\mathbf{z_j}\gamma_\mathbf{j})} \tag{11}$$

The distribution of ε_j is given by,

$$F_j(\varepsilon) = Prob(\varepsilon_s < \varepsilon) = \frac{exp(\varepsilon)}{exp(\varepsilon) + \sum_{j=1, j\neq s}^{M} exp(\mathbf{z_j}\gamma_\mathbf{j})} \tag{12}$$

Since wages are observed for the particular sector that the worker chooses, the conditional wage equation then becomes,

$$E(w_{ji}|I=j) = E(w_{ji}|\ \varepsilon_j < \mathbf{z_j}\gamma_\mathbf{j}) = \mathbf{x_{ji}}\beta_\mathbf{j} + E(u_{ji}|\ \varepsilon_j < \mathbf{z_j}\gamma_\mathbf{j}) \tag{13}$$

Equation (12) shows that if $E(u_{ji}|\ \varepsilon_j < \mathbf{z_j}\gamma_\mathbf{j}) \neq 0$, the coefficient estimates from OLS will be inconsistent. If the underlying latent equation has two outcomes, we are in the standard Heckman selection world where the correction term (the inverse Mill's ratio) is included in the wage equation that yields consistent coefficient estimates. In the case where the selection equation is estimated using a multinomial logit, we run OLS on the wage equation (12) including an analogue of the inverse Mill's ratio (λ_j) as given below :

$$E(w_j|I=j) = \mathbf{x_j}\beta_\mathbf{j} + \delta_j\lambda_j + \vartheta_j \tag{14}$$

where,

$$\lambda_j = -\phi[\Phi^{-1}[F_j(\mathbf{z_j}\gamma_\mathbf{j})]]/F_j(\mathbf{z_j}\gamma_\mathbf{j}) \ \ and \ \ \delta_j = \sigma_j\rho_j$$

and σ_j is the variance of u_j and ρ_j is the correlation between u_j and $\varepsilon_j^*(=\Phi^{-1}(F_j(\varepsilon))$. The error term ϑ_j has a zero mean and uncorrelated with u_j. Since parametric form of the variance and covariance matrix is difficult to derive, the standard errors are calculated by bootstrap methods.

Hay (1980) develops a similar approach for the polychotomous choice model where the conditional expectation of u_j conditional on the disturbances in the selection equation are assumed to linear. This linearity of the conditional expectation is a stronger assumption imposed on the model. By contrast, the Lee model does not impose such restrictions. When the linearity assumption is imposed, the analogue of the inverse Mill's ratio becomes :

$$\lambda_j = 6/\pi^2(-1)^{j+1}[\sum_{k\neq j}(1/J).(\frac{p_k}{1-p_k}).logp_k + (J-1)/Jlogp_j] \tag{15}$$

where $p_j = F_j(\mathbf{z_j}\gamma_\mathbf{j})$. Consistent estimates of the wage equation is derived by running OLS on (13) by replacing λ_j in (14). [21]

[21] See Hill (1990) and Khanderkar(1992) for applications of this approach.

5.3 Identification strategy

The identification of the model is achieved by correctly specifying the selection equation and including at least one variable in the selection equation that is excluded from the wage equation. So we need to find at least one variable that affects sectoral choice but does not affect wages in that sector. I use two variables for identification purposes: number of children in the household less than 15 years of age and number of non earning elderly members in the household greater than 60 years of age. Grootaert and Mundial (1988) and Gunther and Luanov (2012) have used number of dependents for the identification of their model.

Theoretically, dependents do play a role in determining the sectoral choice of a worker, however the question on how it affects the sectoral decision is an empirical one. A worker with many dependents may be more likely to prefer formal employment because he values benefits like social security and job security more compared to workers with fewer dependents. So higher the number of dependents, greater is the probability of accepting formal over informal employment. On the other hand, higher the number dependents, more desperate the worker is to accept a job and earn his livelihood. In such as scenario the worker reduces his search time for formal employment and settle for informal employment. Thus the question on how the number of dependents affects sectoral choice is an empirical question that cannot be ascertained a priori. Further, children and elderly may have differential effects on the sectoral employment choice. To exploit this extra variation in the sample, I have included separate variables for children and elderly dependents rather than including the total number of dependents.

Pratap and Quintin (2006) have used the presence of a relative in the formal sector as the exclusion restriction. Since the share of formal workers in the entire labor force is very small, the variation obtained by including a dummy variable for a relative in the informal sector is negligible. In fact, every worker in the sample I use, has at least one relative who is an informal worker. For this reason, I chose the number of dependents over a relative who is an informal worker for identification purposes.

5.4 Test for labor market segmentation : interpretation of δ_j

In equation 13 the coefficient on the selection correction term λ_j in the wage equation for the j^{th}sector is δ_j. The coefficient δ_j has the same sign as ρ_j (since $\delta_j = \sigma_j \rho_j$ and $\sigma_j > 0$), which is the correlation coefficient between the errors in the original wage equation (u_j) and the transformed variable ε_j^*. Further since, ε_j^* is the standardized transformation of ε_j, they are directly proportional to each other. This proportionality implies that the correlation coefficient ρ_j (between $u_j$and ε_j^*), have the same sign as the correlation coefficient between u_j and ε_j. However, from equation (7) we know that ε_j and the error term in the selection equation (η_j) are negatively correlated. Thus a negative ρ_j implies a positive correlation between the errors in the wage equation (u_j) and the errors in the selection equation (η_j). A negative sign on δ_j (that has the same sign as ρ_j) means a positive correlation between u_j and η_j. The economic interpretation of the correlation between u_j and η_j is discussed below. [22]

Hypothesis 1: Sectoral choice is voluntary

The error terms u_j and η_j include unobservable characteristics of a worker. A positive (negative) correlation between between u_j and η_j (i.e $\delta_j < 0$) implies that unobserved worker characteristics that increases the worker's probability of choosing sector j, increases his wage in that sector. Worker's innate ability or productivity can be thought of as one of the unobserved factors that cannot be controlled by any observed variable. In that case, a positive correlation means that a more productive worker (in terms for unobserved innate ability) who has higher probability of selecting into sector j (controlling for observed characteristics) also earns higher wages in that sector. This implies that productive workers competitively selects sector j that offers them higher wages.

Another interpretation of δ_j is the wage difference between the workers who self select into sector j, and a randomly chosen worker in that sector. Since λ_j is negative by construction, a negative δ_j (i.e $\delta_j \lambda_j > 0$) means that a worker who self selects into sector j earns higher wages than a randomly chosen worker in that sector. Thus a negative sign on δ_j implies that workers

[22] I follow Gindling (1991), Gootaert and Mundial (1988), Khanderkar (1992) and Zhang (2004) for the economic interpretation.

competitively choose sector j that pays them higher rewards for their unobserved productivity reflected by higher wages in that sector.

Hypothesis 2: Adverse selection

On the other hand, a negative correlation implies that a higher productive worker (in terms of innate ability) who has a higher probability of selecting into sector j earns lower wage in that sector. Alternatively, a lower productive worker who has a lower probability of selecting sector j earns higher wages in that sector. Thus a negative correlation implies adverse selection in sector j, where lower productive workers who select sector j earns higher wages and higher productive workers earn lower wages.

In case of a negative correlation, the term self selection is not quite appropriate because the selection mechanism is not competitive. If a more productive worker knows that he has increased probability of entering sector j and will earn lower wages in that sector, then it may not be rational for the worker to self select into that sector. Thus a negative correlation can only happen if there is information asymmetry between the employers and the workers. Since the employers in sector j do not have perfect information on the worker's productivity, they offer lower productive workers higher wages and the higher productive workers lower wages leading to adverse selection in that sector. This argument is based on the assumption that worker's utility is linear in wages that may not be the case. A worker may receive better non-wage benefits even though receiving lower wages in a particular sector. This adverse selection argument is put forward by Grootaert and Mundial (1988).

Alternatively, a positive sign on δ_j (i.e $\delta_j \lambda_j < 0$) means that a worker who self selects into sector j earns lower wages than a randomly selected worker in that sector. Thus a positive sign on δ_j means that self selection into sector j is not a rational choice for the workers as they do not receive higher rewards for their unobserved productivity reflected by lower earnings. This can only happen if there is information asymmetry about the worker's productivity between the employers and the workers as argued in the previous paragraph.

Hypothesis 3: Entry barriers exist and sectoral allocation is involuntary

A third possibility arises if δ_j is statistically insignificant that implies three things. First, a statistically insignificant $\delta_j$means no evidence of self selection in that sector. Second, it could be the case the the the selection process is not well identified. And lastly, as Gindling (1992) suggests, an insignificant δ_j means that worker's unobserved ability that affects his probability of choosing sector j does not affect his wages. If the coefficients of the sector allocation model are significantly different from zero as a group, then sector allocation is non random. If workers were free to choose the sectors, then they would choose the sector that pays higher rewards for their unobserved productivity. But in this case, the non random allocation of workers into sector j does not affect the wages in that sector. In other words, productivity of workers that affects the probability of a worker choosing sector j does not affect wages in that sector. Thus, there is no sample selection bias even though the sector allocation mechanism is non random. Thus, in our context if the coefficient on the selection correction term for the formal sector is statistically insignificant but the sector allocation is non random (the coefficients of the sector allocation model are significantly different from zero as a group) it means that workers do not have full access to formal employment. Evidence from counterfactual wages that show expected formal wage are higher than informal wages will further corroborate this explanation. A higher expected formal wage relative to the informal wage along with the evidence that sector allocation is non random, will provide definitive evidence of restricted entry into formal employment.

6 Results

6.1 The formal-informal wage gap

In the first model, I estimate the wage gap between formal and informal workers at different quantiles of income. I have used the MM technique to decompose the wage gap into coefficient and endowment effects. The underlying assumption of this model is that workers are randomly selected into formal and informal employment, hence there is no selectivity bias.

[Tables 10 and 11 about here]

Tables 10 and 11, report the formal-informal wage gap estimates for males and females respectively. For both males an females, significant wage gap exists between formal and informal workers across the wage distributions. The wage gap increases between the 10th and 40th quantiles and decreases thereafter. For males, coefficient effects explain the major part of the wage gap between the 10th and the 40th quantiles. At higher quantiles, the endowment effect explains major part part of the wage gap. For females, the endowment effect explains the major part of the wage gap across the whole distribution. However, the contribution of coefficient effect cannot be ignored because even at the 90th quantile it explains around 40 percent of the formal-informal wage gap for males (47 percent for females). Two things can be inferred from these results. First, informal workers face a significant wage penalty across the wage distribution. The persistent wage gap across the wage distribution show that informal employment may not be a voluntary choice even for the upper tier informal workers as argued by Fields (1990).[23] Second, both coefficient and characteristic effects play significant roles in explaining the formal-informal wage gap. The contribution of the coefficient effects show that informal workers earn less wages because they receive lesser returns on their human capital and individual characteristics than their formal counterparts. This coefficient effect insinuates to some form of discrimination because informal workers receive lower returns to their skills just by the virtue of being informal workers. The contribution of endowment effect shows that informal workers are significantly different from formal workers. Basic education and skill level may be important factors that give rise to these differences. In the next section I discuss the results of the polychotomous choice model.

[23] A literature survey by Chen, Vanek and Carr (2004) provides evidence of informal wage penalties for Egypt, El Salvador and South Africa. Marcouiller et al (1997) find significant wage premiums for formal sector workers in El Salvador and Peru, but find wage premiums for informal workers in Mexico. Using, Brazilian labor market data, Pianto and Pianto (2002) showed that the earnings gap between formal and informal workers are wider at the lower quantiles than at the high ones. Thus, the results presented here conform to the evidence from other developing countries.

6.2 Selection corrected estimates

The results presented in Section 7.1 are based on the assumption that sector allocation of workers is random. So, it will not be correct to base our predictions based on this specification because it does not take into account self-selection on the part of the workers. The self selection issue may bias the estimates reported in tables 10 and 11. To derive consistent estimates of the wage equation, we correct for sample selection bias. The estimation process is done in two stages. First, a multinomial logit equation is estimated for the selection equation. In the second stage, the wage equation is estimated separately for formal and informal workers including the selection correction term. The first stage and second stage results are reported separately in the following two subsections.

6.2.1 Multinomial logit estimates of the sectoral allocation equations

Tables 12 and 13 report the multinomial logit estimation for males and females respectively. In this model a worker faces four choices : formal employment, informal employment , self employment and to stay out of the labor force.

[Tables 12 and 13 about here]

To achieve identification and circumvent the problem of large second stage standard errors I include two variables in the selection equation that are excluded from the wage equation: children under 15 years of age and non earning-elderly persons more than 60 years of age. All other control variables that are included in the wage equation are also included in the selection equation. The coefficient estimates for each category reported in the tables 12 and and 13 are the log odds with respect to formal employment ,which is the base category. The marginal effects of each variable are also reported in the tables. A first look at the tables tells us that allocation of workers to the segments is non-random. A χ^2 test rejects the null hypothesis that coefficients are jointly equal to zero.

For men, an additional year of schooling increases the probability of formal employment by 1.1 percent and decreases the probability of informal employment by 2.3 percent.[24] Having some technical education increases the chances of formal employment by 1.9 percent, however, it also increases the chances of informal employment by 9.2 percent. But a person having technical education is less likely to be self employed or stay out of the labor force. Formal vocational training increases the probability of formal employment by 2 percent but increases the chances of informal employment by only 0.6 percent. Like technical education, a person having formal vocational training decreases the probability of self employment or staying out of the labor force. For women (see table 13), an additional year of schooling does not have a significant effect on the sector allocation. Technical education increases the chances of informal employment by 6.5 percent but increases the chances of formal employment by only 0.6 percent. Formal vocational training increases the chances of informal employment by 3.8 percent, but increases the chances of formal employment by 0.5 percent. Thus, technical education and vocational training seems to have a greater favorable effect on the likelihood of informal employment than formal employment. These results, particularly with respect to technical education and vocational training may seem counter-intuitive at first, but they provide useful insights to the central idea of the paper. First, it means that skill development programs (technical education and vocational training) are ineffective in making workers employable for formal employment. Second, it insinuates to entry barriers and rationing of formal jobs that restricts even those workers with the adequate skills from entering formal employment. It is is because of rationing of formal jobs and entry barriers that workers having technical education and vocational training are not able to enter formal employment. The formal workers with technical education and vocational training may be considered as the lucky ones, a term commonly used in the segmentation literature.

For men, an additional child in the household decreases the likelihood of formal employment by only 0.5 percent and informal employment by 1 percent. However, the probability of self employment increases by 2 percent for a person having one more child. Having one more elderly

[24]Results for men refer to table 12. Results for women refer to table 13

dependent in the household decreases the probability of formal employment by 0.5 percent and informal employment by 3.8 percent, but increases the probability of self employment by 2.8 percent. Thus, both categories of dependents seem to have a larger negative effect on informal employment than formal employment. So, a person with greater number of dependents is more likely to be formally employed. As was discussed earlier, the role of dependents on the sectoral choice is an empirical question. Greater number of dependents may increase the likelihood of formal employment because the workers would value the employment benefits accompanying formal employment. On the other hand, greater number of dependents may increase chances of informal employment because the worker would be more likely to reduce search length and avoid long spells of unemployment. Since the results show that workers with more dependents are more likely to be formally employed, it conforms to the hypothesis that workers with more dependents value benefits of formal employment. For women, number of dependents have lesser effects on the sectoral choice.

The control variables include a number of individual characteristics like religion, caste, marital status and the region of residence. Religion plays an important role in sector allocation for males compared to females. Muslim men are 1.1 percent less likely to be formally employed and 4.3 percent less likely to be informally employed than Hindus. However, Muslim men are 6.5 percent more likely to be self employed than Hindus. Caste is an important attribute that can be used for discrimination and hence may play an important role in sector allocation. Amongst men, scheduled tribes are 5.2 percent more likely to be formally employed, 8.7 percent more likely to be informally employed and 14.9 percent less likely to self employed than other higher castes. Scheduled castes are 1.8 percent more likely to be formally employed, 12.9 percent more likely to be informally employed and 14 percent less likely to be self employed than other higher castes. For females, however, caste is a comparatively less significant factor in sector allocation than men. Marital status also plays an important role in sectoral allocation. For men, those who are currently married compared to those who never married are 1.5 percent less likely to be formally employed, 3 percent less likely to be informally employed and 9 percent less likely to be self employed. For females,

those who are currently married compared to those who are never married are 0.2 percent less likely to be formally employed, 6.5 percent less likely to informally employed and 4 percent less likely to be self employed. Thus, sector allocation of workers is not independent of the worker's background characteristics.

Sectoral allocation may depend on whether a worker resides in rural or urban areas. Males living in urban areas, are 0.9 percent less likely to be formally employed and 2.7 percent more likely to informally employed compared to those who live in rural areas. For females also, living in the urban area proves unfavorable for formal employment. Rural to urban migration may be one of the factors that may produce this kind of result. Since, the data set does not allow us to distinguish between the migrant and non-migrant workers it is hard to substantiate these results based on migration patterns.

6.2.2 Selection corrected estimates of the wage equations for formal and informal workers

Table 14 presents the formal and informal wage equation estimates for males. Columns 1 and 4 report the OLS estimates for formal and informal workers respectively. Columns 2 and 5 report the selection corrected estimates for formal and informal wages respectively.[25]

[Table 14 about here]

Selection corrected returns to schooling are similar for formal and informal workers. An additional year of schooling increases the weekly formal and informal wage by 4.6 percent. Technical education has a higher return for informal workers than formal workers. Formal vocational training has no statistically significant effect on formal wages, but has a positive significant effect on informal wages. Informal vocational training has no statistically significant effect on formal wages but has a negative and significant effect on informal wages. Although returns to general education as measured by years of schooling are similar for formal and informal workers, returns to any

[25] Estimates reported in Columns 3 and 6 correspond to Hay's methodology that will be discussed in the next section under robustness check.

specialized training like technical education and vocational training are significantly different for formal and informal workers. These results are consistent with the segmentation literature because similar returns to human capital variables in the two sectors are neither necessary nor sufficient for the segmentation hypothesis (Dickens and Lang, 1995). Here similar returns to general education do not mean that informal workers earn as much as formal workers because the quantile regression estimates show significant wage gap between formal and informal workers at all quantiles of the wage distribution. However, higher returns to technical education for informal workers than formal workers may seem an aberration at first, but this result can be explained by the fact that the government and public sector employ majority of the formal workers. The eligibility criteria for government jobs is based on general education levels. Thus a worker qualifying for a government job based on the basic eligibility criteria, does not earn higher returns for technical education and vocational training.[26] Returns to experience (measured by age) are almost the same for formal and informal workers.

Religion does not play a significant role in determining the formal wage, but is important for the informal wage. Scheduled castes and other backward classes face wage penalties for both formal and informal workers compared to other higher castes. Marital status does not have any significant effect on the formal wage. But married informal workers earn 15 percent more compared to unmarried informal workers. Formal workers located in the urban regions earn 14 percent more than formal workers located in the rural regions. Informal workers located in the urban region earn 10.2 percent more than informal workers located in rural regions.

Table 15 reports the formal and informal wage estimates for female workers. As in Table 14, columns 1 and 4 report the OLS estimates for formal and informal wages respectively. Columns 2

[26]Duraisamy (2002) estimated returns to education for workers in wage employment using NSSO data for the years 1983 and 1993. He finds that men receive 6.4 percent, 15.7 percent and 8.9 percent returns on middle, secondary and higher secondary levels. Women received 10.3 percent , 33.7 percent and 11.8 percent returns for the same levels of education. Azam (2012) used NSSO data for the years 1983, 1993 and 2004 to estimate the returns to education. He uses quantile regression techniques and finds that returns to education have increased during the period 1983-2004. Both the studies do not make a distinction between formal and informal workers. The estimates reported in this paper are slightly different from the earlier studies because, I use years of schooling as a measure of education and they use dummy variables for each level of education.

and 5 report the selection corrected estimates for formal and informal wages respectively.[27]

[Table 15 about here]

Selection corrected returns to schooling has no significant effect on the formal wage. However, returns to schooling for informal workers are 6.7 percent. Technical education has no significant effect on formal workers but has positive and significant returns for informal workers. Formal vocational training has a negative premium attached with respect to formal wage while it has no significant effect on informal wage. The same argument follows as with men that the government jobs cover majority of formal employment, where the minimum eligibility criteria is based on general education levels. The negative premium on formal vocational training for formal workers seems to be an aberration. However, it can be argued that the quality of the training programs in the formal vocational training institutes is not good enough to provide workers higher returns on their training. Experience (as measured by age) has no significant effect on formal wage, but the returns to experience is positive for informal workers.

Religion is not a significant factor that affects the formal wage. However, female Muslim informal workers earn less than Hindus. On the other hand, Christian informal workers earn more than Hindus. Schedules castes and other backward classes face a wage penalty compared to other higher castes in both formal and informal employment. Martial status has no significant effect on formal wage. But married informal workers earn less compared to unmarried informal workers. Urban formal workers earn 37.7 percent more than rural formal workers. Urban informal workers earn 22.8 percent more than rural informal workers.

The wage estimates show that significant difference exists between the formal and informal wage determination mechanisms. However, two different wage determination mechanisms do not mean that the labor market is segmented. If workers can freely move between the types of employment i.e if there are no entry barriers, they will choose the sector that pays them higher

[27] As in table 14, estimates reported in Columns 3 and 6 correspond to Hay's methodology that will be discussed in the next section under robustness check.

wages. We have already seen that informal workers earn significantly less than formal workers across the wage distribution. Thus, the situation where workers choose informal employment because it pays them higher wages is less likely. The next section provides evidence of entry barriers and rationing of formal jobs that substantiates the segmentation hypotheses.

6.2.3 Evidence for labor market segmentation

Section 5.4 discussed the implications of the sign and the statistical significance of the estimated coefficients on the selection correction terms (λ_{Formal} and $\lambda_{Informal}$) in the wage equations. For the formal wage equation (for both males and females in tables 14 and 15 respectively) the estimated coefficient on λ_{Formal} is positive but statistically insignificant. A statistically insignificant coefficient on λ_{Formal} implies no evidence of self selection in the formal sector. In other words, a worker's unobserved productivity that increases his chances of formal employment does not affect his wages. Also there is no difference between a randomly selected formal worker and a worker who self selects into formal employment. No evidence of self selection into formal employment insinuates to the fact that entry barriers may be present in the formal sector. However, it could also be the case that the model is not identified properly that would require some further testing of the model with alternative identification strategies. Decomposition of the wage gap into characteristics and coefficient effects may give further insights to labor market segmentation hypothesis. I discuss the results in the next section.

The coefficient on $\lambda_{Informal}$ is negative and statistically significant. A negative coefficient on $\lambda_{Informal}$ implies that informal employment is a competitive choice for the worker. Workers can self select into informal employment and increase the informal wage. Also, a worker self selecting into informal employment earns higher wages than a randomly selected informal worker.

Based on these two findings we cannot reject the hypothesis that the labor market is segmented. This is because there is no evidence of self selection into formal employment. If on the contrary we had found that workers can self select into both formal and informal employment we could have

safely rejected the labor market segmentation hypothesis. Since in that case, the workers would be free to choose between formal and informal employment. They would choose the sector that maximizes his utility. Decomposition of the wage gap into coefficient and characteristic effect may provide further insights to this argument. However, I have to constrain myself to the decomposition at the mean. The underlying self selection model is a polychotomous choice model that does not allow the implementation of the MM decomposition technique across the quantiles of the wage distribution. I have used the Oaxaca-Blinder technique to decompose the formal-informal wage gap into coefficient and characteristics effect.

6.2.4 Wage gap decomposition adjusting for self selection (Oaxaca-Blinder)

Table 16 shows the wage gap decomposition into coefficient and and endowment effects. The first column shows the results for males and the second column for females. For both males and females, the formal-informal wage gap is higher when corrected for self selection. For males, the coefficient effect explains 66 percent of the wage gap and the endowment effect explains the rest 34 percent. For females, the coefficient effects explain 84 percent of the formal informal wage gap. So, at the mean, the informal workers face a wage penalty because they receive lower returns on their human capital and individual characteristics. So formal workers enjoy higher returns on their human capital and individual characteristics. This finding is compatible with the efficiency wage theory in the sense that firms pay higher wages to formal workers that is set higher than than the market clearing wage to incentivize the worker. So, formal workers who receive higher returns to their skills and individual characteristics have less incentivize to move elsewhere. On average they could also be more productive than the informal workers because they receive higher returns.

A significant part of the wage gap is explained by the differences in characteristics of the formal and informal workers. These differences may stem from skill differences, age and other individual characteristics. So, if workers with different characteristics have different labor supply elasticities, firms can exploit to opportunity to exercise their monopsonistic power. This line of argument is

also compatible with labor market segmentation because firms having monopsonistic power can now pay different wages to the workers with different labor supply elasticities. In our case, it may be optimal for the firms to pay different wage to formal and informal workers because they have differ in skills and individual characteristics and hence have different labor supply elasticities.

Figures 2 and 3 are the kernel density plots of the predicted formal wage and the observed informal wage for the informal male workers and informal female workers respectively. The counterfactual is based on the differences in returns to human capital and individual characteristics. That is, how much the informal workers would have earned if they had received similar returns on human capital and individual characteristics as the formal workers. For males, we see that predicted mean and median formal wage is higher than the observed informal wage. Also, 85 percent of the male informal workers (83 percent of female informal workers) would have earned higher wages in formal employment than their observed informal wage. Given that informal workers do not receive any non-wage benefits as formal workers, the result shows the majority of the informal workers would choose formal employment over informal employment.The other 15 percent of the male informal workers (17 percent of the female informal workers) would have earned less as formal workers. These few people could be regarded as voluntary informal workers who would have chosen informal employment even if they had full access to formal employment. No discernible differences in observed characteristics can be found between the involuntary informal workers and the voluntary informal workers. But majority of the voluntary informal workers are employed by the proprietary and the government enterprises. So, it could be the case that these enterprises pay a higher wage to informal workers instead of providing defined employment benefits to the workers. These individuals could also posses entrepreneurial skills that are rewarded by the proprietary enterprises that compensates for the employment benefits that accompany formal employment.

[Figures 2 and 3 about here]

6.2.5 Robustness check

I conducted the robustness check for my results by employing the selection correction strategy proposed by Hay (1980). This methodology imposes stronger restrictions on the model by assuming linearity of the conditional expectation of the error terms in the wage equation conditional on the errors in the selection equation. But the results should not be different from our baseline model. The selection correction terms constructed from the first stage multinomial logit estimates are given by equation 14 in section 6.2. Columns 3 and 6 in Table 14 and 15 report the wage estimates employing Hay's method. For both males and females, the results are similar to the baseline model. The coefficients on $\lambda_{Formal_{Hay}}$ are statistically insignificant that provides evidence for entry barriers in the formal employment. The coefficients on $\lambda_{Informal_{Hay}}$ are negative and significant that implies informal employment is a competitive outcome given that workers cannot self select into formal employment. Moreover, the coefficient estimates from both models are almost the same. Thus, the results presented in this paper are robust and invariant to the other polychotomous choice models used in the literature.

7 Conclusions

The results in this paper show that the Indian labor market is segmented between formal and informal employment. Evidence does not support the hypothesis of a fully competitive labor market and that workers choose informal employment as the last resort. This finding is in strong contrast to the empirical evidence from some Latin American countries that show informal employment is a competitive choice for workers over formal employment. The paper shows that majority of the workers would have earned more as formal workers than their current informal wage if they had full access to formal employment. Also, informal workers earn significantly less than formal workers as reflected by the wage gap between the two sets of workers at all quantiles of the wage distribution. Thus, the finding refutes the hypothesis of voluntary informal employment for

majority of the workers that is propounded by Maloney (1999) and Fields (1990). The current empirical and theoretical literature on informal employment is mainly based on Latin American countries. Evidence amassed in this paper show that the Indian labor market is systematically different from Latin American countries providing the platform for further research on both empirical and theoretical grounds focusing on South Asian countries.

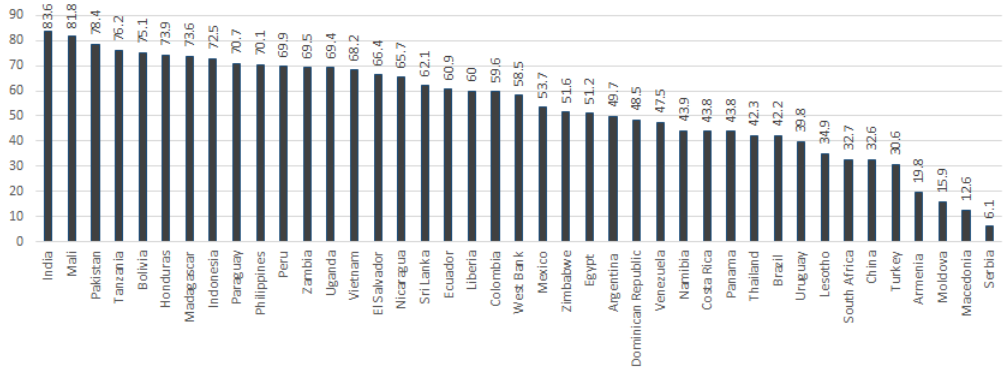
The wage gap decomposition results show that both coefficient and endowment effects explain significant portion of the formal-informal wage gap at all quantiles of the wage distribution. This evidence suggests that informal workers earn less than formal workers not only because they have different human capital attainments and individual characteristics, but also because they face discrimination in terms of lower returns to their characteristics than their formal counterparts. Recent policies focus on skill development to address the problem of informal employment. However, policies should also address the problem of discrimination faced by informal workers as firms pay lower returns to their skills and characteristics. Moreover, results also show that workers having technical education and vocational training do not have a clear advantage to enter formal employment.Thus skill development policies are necessary to make workers employable as formal workers but they are not sufficient to bring down the formal-informal wage gap. The Unorganized Sector Worker's Social Security Bill passed in 2007 was an important and directed step towards reducing informal employment. However, the efficacy of this initiative can be questioned. This is because, 85.8 percent of the labor force still continues to be informally employed even after four years since the bill was passed.

This paper finds no evidence of self selection into formal employment. However, it will be interesting to see what kinds of entry barriers that workers face. Monopsonistic discrimination, efficiency wages and search frictions are some of probable causes that may give rise to the discrimination and entry barriers that workers face. Ito (2009) finds that transaction costs in the Indian labor market (that includes actual expenditure and time spent traveling for finding employment) are higher for socially backward classes. On the other hand, he finds no evidence of wage discrimination in regular employment that implies caste based discrimination takes the form of job based

discrimination. This job based discrimination limits the range of available jobs to some groups of people. Social norms may also play an important role on the labor market outcomes. Besley and Burgess (2004) show that labor regulations in India have significant effect on informal sector activity that hints at institutional barriers in the labor market. This paper provides the groundwork for further research on the specific types of entry barriers and their impact on informal employment. Identifying and analyzing these entry barriers would help to implement directed policy initiatives to reduce informal employment.

Figures

Figure 1: Share of informal employment in the non agricultural sector, by countries



Source: Women and men in the informal economy: a statistical picture (second edition), International Labour Office, 2013[28]

Figure 2 : Predicted formal wage for informal workers (Males)

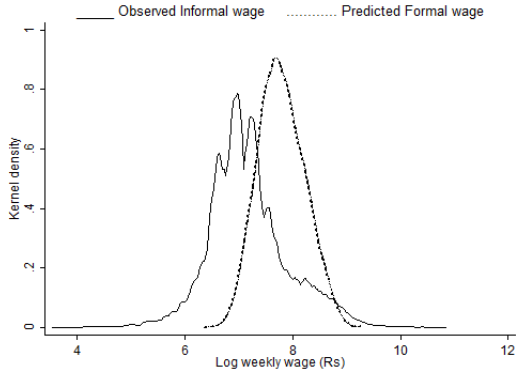
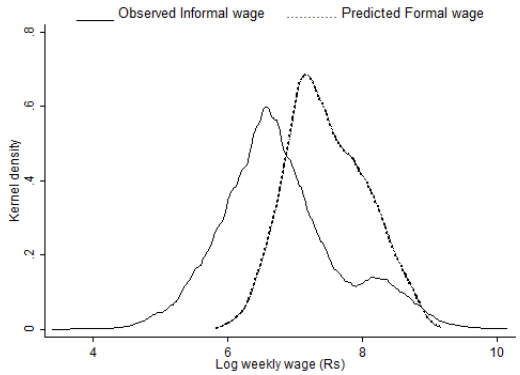


Figure 3 : Predicted formal wage for informal workers (Females)



[28]The figures represent the latest data available for each country.

Tables

Table 1: Classification of informal employment and informal sector

Production Units	Informal jobs	Formal Jobs
Informal sector enterprises	A	B
Other units of production	C	D

A+C = Persons in Informal Employment

A+B = Persons Employed in the Informal Sector

C = Informal Employment outside the Informal Sector

B = Formal Employment in the Informal Sector

Table 2 : Identification of formal/informal sector, by type of enterprise

Enterprise type	Frequency	%
Informal sector		
1. Proprietary (male)	55702	62.3
2. Proprietary (female)	4318	4.7
3. Partnership (members from same hh)	1833	1.9
4. Partnership (with members from different hh)	1265	1.6
8. Employer's households(i.e., private households)	1290	1.6
9 . Others	4826	5.3
Formal sector		
5. Government/public sector	18591	12.8
6. Public/Private limited company	5902	8.5
7. Co-operative societies/trusts	1198	1.2
Total	94639	100.0

Source: Author's calculation based on NSSO 68th Round Employment-Unemployment data

Table 3 : Identifying broad categories of employment, by principal activity status

Principal activity status	Frequency	%
Self employed		
1. Self-employed (own account worker)	30807	11.5
2. Self-employed (Employer)	1320	0.5
3. Self-employed (unpaid family member)	7232	2.6
Employees		
4. Regular salaried/ wage employee	37329	14.4
5. Casual wage labor (public works)	902	0.4
6. Casual wage labor (other types)	17219	8.5
Not in the labor force		
7. Did not work but was seeking for work	5508	1.9
8.Attended educational institution	42415	18.5
9. Attended domestic duties only	48902	21.9
10. Attended domestic duties & other activities	33378	18.3
11. Rentiers, pensioners, remittance recipients	1263	0.6
12. Others (begging, prostitution,etc.)	1564	0.8
Total	227839	100

Source: Author's calculation based on NSSO 68th Round Employment-Unemployment data

Table 4 : Percentage of workers receiving employment benefits

Employment benefits	Social security	Job contract	Paid leave	All benefits
	%	%	%	%
No	69.4	77.1	32.0	82.6
Yes	30.6	22.9	68.0	17.4
Total	100	100	100	100
Observations			55,450	

Source: Author's calculation based on NSSO 68th Round Employment-Unemployment data

Table 5: Formal and informal employment (treating self employed as a separate category)

	Male		**Female**		**All**	
Categories	Frequency	%	Frequency	%	Frequency	%
Formal employment	11087	7.4	2377	1.3	13464	4.1
Informal employment	34921	35.9	7065	5.6	41986	19.3
Self employed	33307	27.3	6052	4.3	39359	14.7
Not in labor force	29904	29.4	103126	88.8	133030	62.0
Total	109219	100.0	118620	100.0	227839	100.0

Source: Author's calculation based on NSSO 68th Round Employment-Unemployment data

Table 6: Identification of formal and informal sector and employment based on enterprise type and activity status

	Self employed						
	Own account worker (Activity Status:1)		Employers (Activity Status:2)		Contributing family members (Activity Status:3)	Employees (Activity Status:4,5,6)	
	Formal	Informal	Formal	Informal	Informal	Formal	Informal
Formal sector (Enterprise types :5,6,7)	A	NE	B	NE	C	D	E
Informal sector (Enterprise types :1,2,3,4,8,9)	NE	F	NE	G	H	I	J

Source: Sastry, N. S. (2004) and own calculation

Table 7 : Formal and informal employment in the formal and informal sectors

Employment type, by sector	Frequency	%
Formal employment		
1. Formal employment in formal sector (A+B+D)	12770	4.4
3. Formal employment in informal sector (I)	737	0.1
Informal employment		
2. Informal employment in formal sector (C+E)	12797	8.7
4. Informal employment in informal sector (F+G+H+I+J)	68505	24.8
5. **Not in labor force**	133030	62.0
Total	227839	100.0

Source: Author's calculation based on NSSO 68th Round Employment-Unemployment data

Table 8: Summary statistics all covariates (Males)

	Formal		Informal		Self employed		Not in labor force	
	mean	sd	mean	sd	mean	sd	mean	sd
Wages and Consumption								
Weekly Wage (Rupees)	4966.4	3363.4	1771.4	1889.2	.	.	.	.
Log weekly wage (Rupees)	8.3	0.6	7.2	0.7	.	.	.	.
MPCE (Rupees)	2902.5	2621.5	1714.4	1420.8	1806.4	1585.1	1970.2	1859.1
Log MPCE	7.8	0.6	7.3	0.6	7.3	0.6	7.4	0.6
Age	42.1	9.6	34.2	10.5	37.2	10.3	20.1	7.4
Education								
Years of Schooling	12.5	4.0	7.4	5.2	8.0	4.9	10.1	3.2
Technical education	0.2	0.4	0.05	0.2	0.03	0.2	0.04	0.2
No vocational training	0.8	0.4	0.8	0.4	0.8	0.4	0.9	0.2
Vocational training: formal	0.1	0.3	0.05	0.2	0.04	0.2	0.05	0.2
Vocational training: informal	0.07	0.3	0.2	0.4	0.2	0.4	0.01	0.1
Dependents								
No of Children in the hhd (<15 years)	1.1	1.2	1.3	1.4	1.5	1.5	0.9	1.3
No. of elders (>60 years)	0.2	0.5	0.2	0.5	0.3	0.6	0.3	0.5
Caste								
Scheduled tribe	0.06	0.2	0.06	0.2	0.03	0.2	0.07	0.3
Scheduled caste	0.1	0.4	0.2	0.4	0.1	0.3	0.2	0.4
Other backward class	0.3	0.5	0.4	0.5	0.4	0.5	0.4	0.5
Others	0.5	0.5	0.3	0.5	0.4	0.5	0.3	0.5
Marital status								
Never married	0.1	0.3	0.3	0.4	0.2	0.4	0.9	0.3
Currently married	0.9	0.3	0.7	0.5	0.8	0.4	0.06	0.2
Widowed	0.009	0.10	0.01	0.1	0.01	0.1	0.005	0.07
Divorced/separated	0.002	0.04	0.004	0.06	0.002	0.05	0.0009	0.03
Regional variables								
Urban	0.7	0.5	0.5	0.5	0.5	0.5	0.4	0.5
North	0.2	0.4	0.2	0.4	0.3	0.4	0.3	0.4
West	0.3	0.4	0.2	0.4	0.2	0.4	0.2	0.4
East	0.2	0.4	0.2	0.4	0.2	0.4	0.2	0.4
North-East	0.03	0.2	0.03	0.2	0.04	0.2	0.04	0.2
Central	0.07	0.3	0.06	0.2	0.06	0.2	0.07	0.3
South	0.2	0.4	0.3	0.4	0.2	0.4	0.2	0.4
Observations				109219				

Notes: The summary statistics for religion dummies are not reported in this table due space constraint.

See section 3.2.2 for the discussion on the distribution of religious groups.

Table 9: Summary statistics all covariates (Females)

	Formal		Informal		Self employed		Not in labor force	
	mean	sd	mean	sd	mean	sd	mean	sd
Wages and Consumption								
Weekly Wage (Rupees)	4330.9	2956.7	1367.6	1741.4	.	.	.	.
Log weekly wage (Rupees)	8.1	0.8	6.8	0.9	.	.	.	.
MPCE (Rupees)	3651.7	3559.2	2007.2	2164.2	1756.4	1599.2	1794.4	1662.4
Log MPCE	8.0	0.7	7.4	0.6	7.3	0.6	7.3	0.6
Age	39.0	9.9	34.9	10.4	36.2	10.8	32.0	12.1
Education								
Years of Schooling	13.0	4.1	7.3	6.2	5.6	5.1	6.7	5.1
Technical education	0.2	0.4	0.06	0.2	0.03	0.2	0.01	0.1
No vocational training	0.8	0.4	0.8	0.4	0.7	0.5	1.0	0.2
Vocational training: formal	0.2	0.4	0.07	0.3	0.06	0.2	0.02	0.1
Vocational training: informal	0.04	0.2	0.09	0.3	0.2	0.4	0.03	0.2
Dependents								
No of Children in the hhd (<15 years)	1.0	1.1	1.1	1.3	1.3	1.3	1.4	1.5
No. of elders (>60 years)	0.4	0.6	0.2	0.5	0.2	0.5	0.3	0.6
Caste								
Scheduled tribe	0.06	0.2	0.09	0.3	0.05	0.2	0.06	0.2
Scheduled caste	0.1	0.4	0.2	0.4	0.2	0.4	0.2	0.4
Other backward class	0.3	0.5	0.4	0.5	0.5	0.5	0.4	0.5
Others	0.5	0.5	0.3	0.4	0.3	0.5	0.3	0.5
Marital status								
Never married	0.2	0.4	0.2	0.4	0.2	0.4	0.2	0.4
Currently married	0.7	0.5	0.6	0.5	0.7	0.5	0.7	0.4
Widowed	0.2	0.4	0.1	0.4	0.1	0.3	0.03	0.2
Divorced/separated	0.02	0.1	0.03	0.2	0.02	0.1	0.003	0.05
Regional variables								
Urban	0.7	0.5	0.5	0.5	0.5	0.5	0.3	0.5
North	0.2	0.4	0.1	0.3	0.1	0.4	0.3	0.4
West	0.3	0.4	0.2	0.4	0.2	0.4	0.2	0.4
East	0.2	0.4	0.1	0.3	0.2	0.4	0.2	0.4
North-East	0.03	0.2	0.02	0.1	0.03	0.2	0.04	0.2
Central	0.05	0.2	0.07	0.3	0.05	0.2	0.07	0.3
South	0.3	0.5	0.4	0.5	0.4	0.5	0.2	0.4
Observations	118620							

Notes: The summary statistics for religion dummies are not reported in this table due space constraint.

See section 3.2.2 for the discussion on the distribution of religious groups.

Table 10: Wage gap decomposition (Males)

Quantiles	Wage gap (raw)	Wage gap (predicted)	Endowment effect	Coeffcient effect
10	-1.101	-1.155	-0.536	-0.619
		(0.025)	(0.024)	(0.034)
20	-1.299	-1.245	-0.592	-0.652
		(0.018)	(0.022)	(0.028)
30	-1.338	-1.278	-0.638	-0.640
		(0.015)	(0.022)	(0.027)
40	-1.325	-1.284	-0.673	-0.611
		(0.014)	(0.022)	(0.026)
50	-1.288	-1.267	-0.692	-0.574
		(0.015)	(0.021)	(0.025)
60	-1.273	-1.229	-0.693	-0.536
		(0.015)	(0.020)	(0.025)
70	-1.247	-1.169	-0.672	-0.497
		(0.016)	(0.021)	(0.027)
80	-1.170	-1.077	-0.632	-0.445
		(0.010)	(0.022)	(0.029)
90	-0.788	-0.929	-0.558	-0.372
		(0.024)	(0.025)	(0.034)
Observations		46008		

Table 11: Wage gap decomposition (Females)

Quantiles	Wage gap (raw)	Wage gap (predicted)	Endowment effect	Coefficient effect
10	-1.153	-1.278	-0.668	-0.610
		(0.032)	(0.028)	(0.043)
20	-1.440	-1.431	-0.713	-0.718
		(0.027)	(0.026)	(0.0381)
30	-1.579	-1.520	-0.749	-0.771
		(0.022)	(0.026)	(0.035)
40	-1.573	-1.549	-0.786	-0.763
		(0.019)	(0.026)	(0.033)
50	-1.661	-1.543	-0.814	-0.728
		(0.019)	(0.026)	(0.033)
60	-1.545	-1.497	-0.813	-0.684
		(0.019)	(0.026)	(0.0317)
70	-1.453	-1.413	-0.775	-0.638
		(0.021)	(0.026)	(0.033)
80	-1.342	-1.277	-0.688	-0.589
		(0.023)	(0.026)	(0.034)
90	-0.823	-1.049	-0.551	-0.497
		(0.028)	(0.028)	(0.040)
Observations		9442		

Table 12: Multinomial logit estimates of the sectoral allocation equations (Males)

	Coefficient Estimates			Marginal effects			
	Informal	Self employed	Not in labor force	Formal	Informal	Self employed	Not in labor force
Education							
Years of Schooling	-0.251***	-0.214***	-0.000	0.0111	-0.0232	-0.0046	0.0166
	(0.003)	(0.003)	(0.005)				
Technical education	-0.123**	-0.567***	-0.585***	0.0197	0.0928	-0.0914	-0.0211
	(0.045)	(0.047)	(0.060)				
Vocational training: formal	-0.334***	-0.419***	-0.398***	0.0237	0.0066	-0.0277	-0.0026
	(0.047)	(0.048)	(0.060)				
Vocational training: informal	0.275***	0.631***	-2.100***	-0.0149	-0.0207	0.1336	-0.0980
	(0.044)	(0.043)	(0.077)				
Age	-0.135***	-0.099***	-0.967***	0.0104	0.0224	0.0325	-0.0653
	(0.011)	(0.011)	(0.013)				
Age^2	0.001***	0.001***	0.011***	-0.0001	-0.0004	-0.0004	0.0008
	(0.000)	(0.000)	(0.000)				
Dependents							
No of Children (<15 years)	0.072***	0.142***	0.065***	-0.0051	-0.0107	0.0183	-0.0025
	(0.011)	(0.010)	(0.014)				
No. of elders (>60 years)	0.022	0.178***	0.283***	-0.0056	-0.0386	0.0286	0.0156
	(0.023)	(0.022)	(0.029)				
Caste							
Scheduled tribe	-0.516***	-1.136***	-0.609***	0.0526	0.0871	-0.1491	0.0094
	(0.048)	(0.049)	(0.064)				
Scheduled caste	-0.043	-0.713***	-0.380***	0.0182	0.1292	-0.1410	-0.0063
	(0.040)	(0.041)	(0.052)				
Other backward class	0.089**	0.048	-0.014	-0.0031	0.0138	-0.0046	-0.0061
	(0.031)	(0.030)	(0.039)				
Marital status							
Currently married	-0.215***	-0.025	-1.657***	-0.0150	-0.0301	-0.0946	0.1398
	(0.050)	(0.050)	(0.059)				
Widowed	-0.178	-0.183	0.424**	-0.0196	-0.157	-0.1716	0.3419
	(0.135)	(0.135)	(0.157)				
Divorced/separated	-0.050	-0.091	0.484	-0.0230	-0.1352	-0.1690	0.3272
	(0.231)	(0.234)	(0.282)				
Regional Variables							
Urban	0.138***	0.082**	-0.159***	-0.0089	0.0272	0.0077	-0.0260
	(0.026)	(0.025)	(0.032)				
Regional dummies	Yes	Yes	Yes				
Religion dummies	Yes	Yes	Yes				
Constant	8.512***	6.515***	19.582***				
	(0.207)	(0.207)	(0.224)				
χ^2	110089.51	8727.92	14897.18				
Log likelihood		-93745.166					
N				109219			

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes : The reference category is formal employment.

Omitted category for Vocational training is 'No vocational training',

for Caste is 'others' (that includes higher castes) and for Marital status is 'never married'.

Coefficients on religion dummies are not reported due to space constraint.

χ^2 is the test statistic for the null hypothesis that coefficients are jointly equal to zero.

Table 13: Multinomial logit estimates of the sectoral allocation equations (Females)

	Coefficient estimates			Marginal Effects			
	Informal	Self employed	Not in labor force	Formal	Informal	Self employed	Not in Labor force
Education							
Years of Schooling	-0.319***	-0.381***	-0.327***	0.0013	0.0004	-0.0019	0.0001
	(0.007)	(0.007)	(0.007)				
Technical education	-0.034	-0.770***	-1.085***	0.0064	0.0653	0.0088	-0.0805
	(0.087)	(0.116)	(0.075)				
Vocational training: formal	-0.140	0.424***	-0.978***	0.0049	0.0385	0.0830	-0.1265
	(0.084)	(0.093)	(0.074)				
Vocational training: informal	0.419***	1.629***	-0.789***	0.0022	0.0499	0.2144	-0.2664
	(0.120)	(0.117)	(0.114)				
Age	-0.027	-0.128***	-0.438***	0.0016	0.0157	0.0098	-0.0270
	(0.021)	(0.021)	(0.019)				
Age^2	-0.001*	0.001**	0.005***	0.0000	-0.0002	-0.0001	0.0003
	(0.000)	(0.000)	(0.000)				
Dependents							
No. of Children (<15 years)	0.021	0.043	0.071**	-0.0002	-0.0019	-0.0009	0.0030
	(0.023)	(0.024)	(0.021)				
No. of elders (>60 years)	-0.088*	-0.003	0.005	0.0000	-0.0037	-0.0001	0.0038
	(0.043)	(0.044)	(0.037)				
Caste							
Scheduled tribe	-0.362***	-0.840***	-0.991***	0.0052	0.0290	0.0035	-0.0377
	(0.098)	(0.102)	(0.088)				
Scheduled caste	-0.079	-0.551***	-0.639***	0.0029	0.0263	0.0018	-0.0309
	(0.086)	(0.092)	(0.080)				
Other backward class	0.045	0.234***	0.022	-0.0002	0.0005	0.0073	-0.0076
	(0.066)	(0.067)	(0.059)				
Marital status							
Currently married	-0.653***	-0.389***	0.628***	-0.0020	-0.0645	-0.0393	0.1060
	(0.095)	(0.100)	(0.087)				
Widowed	-0.784***	-1.106***	-1.632***	0.0134	0.0451	0.0189	-0.0774
	(0.123)	(0.130)	(0.114)				
Divorced/separated	-0.119	-0.585**	-1.099***	0.0066	0.0583	0.0183	-0.0832
	(0.208)	(0.224)	(0.203)				
Regional Variables							
Urban	0.599***	0.407***	0.174***	-0.0008	0.0185	0.0086	-0.0263
	(0.054)	(0.055)	(0.049)				
Regional dummies	Yes	Yes	Yes				
Religion dummies	Yes	Yes	Yes				
Constant	7.166***	8.644***	15.978***				
	(0.373)	(0.379)	(0.347)				
χ^2	2904.47	3777.8	5075.33				
Log likelihood		-51015.008					
N				118620			

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes : The reference category is formal employment.

Omitted category for Vocational training is 'No vocational training',

for Caste is 'others' (that includes higher castes) and for Marital status is 'never married'.

Coefficients on religion dummies are not reported due to space constraint.

χ^2 is the test statistic for the null hypothesis that coefficients are jointly equal to zero.

Table 14: Selection corrected wage estimates for formal and informal workers (Males)

	(1)	(2)	(3)	(4)	(5)	(6)
		Formal			**Informal**	
Education	OLS	Selection (Lee)	Selection (Hay)	OLS	Selection (Lee)	Selection (Hay)
Years of Schooling	0.054***	0.046***	0.062***	0.050***	0.046***	0.044***
	(0.002)	(0.006)	(0.004)	(0.001)	(0.001)	(0.001)
Technical education	0.207***	0.191***	0.217***	0.313***	0.321***	0.325***
	(0.017)	(0.020)	(0.018)	(0.021)	(0.021)	(0.021)
Vocational training: formal	0.038*	0.022	0.050**	0.042*	0.042*	0.042**
	(0.017)	(0.019)	(0.019)	(0.017)	(0.017)	(0.016)
Vocational training: informal	0.003	0.017	-0.010	-0.031***	-0.028***	-0.025**
	(0.021)	(0.024)	(0.022)	(0.009)	(0.009)	(0.009)
Age	0.042***	0.033***	0.051***	0.025***	0.032***	0.036***
	(0.005)	(0.008)	(0.007)	(0.002)	(0.003)	(0.003)
Age^2	-0.000***	-0.000*	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Caste						
Scheduled tribe	-0.020	-0.052	0.006	-0.023	-0.009	-0.005
	(0.019)	(0.027)	(0.024)	(0.013)	(0.013)	(0.013)
Scheduled caste	-0.094***	-0.108***	-0.082***	-0.110***	-0.089***	-0.083***
	(0.017)	(0.019)	(0.018)	(0.010)	(0.011)	(0.011)
Other backward class	-0.069***	-0.066***	-0.071***	-0.095***	-0.093***	-0.092***
	(0.013)	(0.013)	(0.014)	(0.009)	(0.009)	(0.009)
Marital Status						
Currently married	0.061*	0.045	0.077**	0.140***	0.149***	0.152***
	(0.025)	(0.027)	(0.027)	(0.010)	(0.010)	(0.010)
Widowed	0.060	0.060	0.063	-0.046	-0.035	-0.032
	(0.063)	(0.064)	(0.065)	(0.035)	(0.033)	(0.035)
Divorced/separated	0.147	0.140	0.156	-0.089	-0.080	-0.078
	(0.112)	(0.117)	(0.116)	(0.049)	(0.049)	(0.049)
Regional Variables						
Urban	0.139***	0.140***	0.137***	0.096***	0.102***	0.104***
	(0.011)	(0.011)	(0.010)	(0.007)	(0.007)	(0.007)
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Religion dummies	Yes	Yes	Yes	Yes	Yes	Yes
Selection Correction terms						
λ_{Formal}		0.097				
		(0.060)				
$\lambda_{Formal_{Hay}}$			-0.099			
			(0.056)			
$\lambda_{Informal}$					-0.107***	
					(0.019)	
$\lambda_{Informal_{Hay}}$						-0.231***
						(0.026)
Constant	6.115***	6.627***	5.699***	6.106***	5.934***	5.881***
	(0.109)	(0.328)	(0.250)	(0.041)	(0.052)	(0.048)
N	11087	11087	11087	34921	34921	34921
R^2	0.278	0.278	0.278	0.326	0.326	0.327

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Bootstrap standard errors in parenthesis.

Notes : Omitted category for Vocational training is 'No vocational training',

for Caste is 'others' (that includes higher castes) and for Marital status is 'never married'.

Coefficients of religion dummies are not reported due to space constraint.

Table 15: Selection corrected wage estimates for formal and informal workers (Females)

	(1)	(2)	(3)	(4)	(5)	(6)
		Formal			**Informal**	
Education	OLS	Selection (Lee)	Selection (Hay)	OLS	Selection (Lee)	Selection (Hay)
Years of Schooling	0.081***	0.033	0.036	0.067***	0.066***	0.067***
	(0.004)	(0.025)	(0.021)	(0.002)	(0.002)	(0.002)
Technical education	0.205***	0.064	0.100	0.348***	0.567***	0.528***
	(0.037)	(0.076)	(0.061)	(0.040)	(0.054)	(0.052)
Vocational training: formal	-0.048	-0.159*	-0.140*	-0.070	0.083	0.061
	(0.040)	(0.073)	(0.060)	(0.038)	(0.049)	(0.046)
Vocational training: informal	-0.131	-0.159*	-0.161*	-0.041	0.136**	0.113*
	(0.071)	(0.073)	(0.071)	(0.031)	(0.043)	(0.044)
Age	0.028*	-0.026	-0.021	0.029***	0.119***	0.112***
	(0.012)	(0.029)	(0.025)	(0.007)	(0.018)	(0.017)
Age^2	-0.000	0.001	0.000	-0.000*	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Caste						
Scheduled tribe	0.059	-0.074	-0.057	0.130***	0.270***	0.252***
	(0.051)	(0.084)	(0.075)	(0.033)	(0.041)	(0.040)
Scheduled caste	-0.127*	-0.206**	-0.194**	-0.058*	0.074	0.059
	(0.052)	(0.064)	(0.059)	(0.027)	(0.038)	(0.035)
Other backward class	-0.159***	-0.152***	-0.154***	-0.103***	-0.103***	-0.103***
	(0.038)	(0.038)	(0.038)	(0.025)	(0.025)	(0.025)
Marital status						
Currently married	-0.008	0.057	0.054	0.090**	-0.213***	-0.185**
	(0.047)	(0.053)	(0.053)	(0.029)	(0.062)	(0.059)
Widowed	0.091	-0.107	-0.062	0.068	0.231***	0.179***
	(0.059)	(0.118)	(0.093)	(0.038)	(0.052)	(0.043)
Divorced/separated	0.003	-0.097	-0.076	-0.032	0.153*	0.090
	(0.105)	(0.119)	(0.114)	(0.053)	(0.065)	(0.057)
Regional Variables						
Urban	0.341***	0.377***	0.371***	0.149***	0.228***	0.238***
	(0.031)	(0.034)	(0.034)	(0.018)	(0.027)	(0.024)
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Religion dummies	Yes	Yes	Yes	Yes	Yes	Yes
Selection correction terms						
λ_{Formal}		0.382				
		(0.196)				
$\lambda_{Formal_{Hay}}$			0.331*			
			(0.155)			
$\lambda_{Informal}$					-0.603***	
					(0.115)	
$\lambda_{Informal_{Hay}}$						-0.555***
						(0.105)
Constant	5.810***	8.397***	7.916***	5.428***	2.947***	3.490***
	(0.228)	(1.321)	(0.984)	(0.108)	(0.484)	(0.384)
N	2377	2377	2377	7065	7065	7065
R^2	0.353	0.354	0.354		0.336	0.340

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Bootstrap standard errors in parenthesis.

Notes : Omitted category for Vocational training is 'No vocational training',

for Caste is 'others' (that includes higher castes) and for Marital status is 'never married'.

Coefficients of religion dummies are not reported due to space constraint.

Table 16: Oaxaca-Blinder decomposition

	Males	Females
Overall wage gap	-1.1449	-1.337
	(0.008)	(0.022)
Adjusted wage gap	-1.3699	-3.087
	(0.0901)	(0.436)
Coefficient effect	-0.906	-2.557
	(0.091)	(0.433)
Endowment effect	-0.464	-0.530
	(0.006)	(0.016)
Observations	46008	9442

Appendix

Sample selection

The survey covered 101724 households and 456999 individuals. In this study I focus on the principal activity status recorded for each person based on their activity in the last 365 days. I deleted those individuals from the sample who were not able to work due to disability and children zero to six years of age. Persons with disabilities and children are identified by the codes 95 and 99 under 'principal activity status code'. 41981 observations are dropped.

I restrict my sample to the working age population of 15 to 59 years. This is primarily done to avoid critical issues like child labor. Moreover, empirical literature on labor markets tends to focus on the working age population. This restriction brings down the sample to 294,044 observations.

The International Labor organization provides the definition for informal sector ad informal employment for the non-agricultural sector. The classification of individuals into agricultural and non-agricultural is done on the basis of 2-digit National Industrial Classification (NIC 2008) code that is recorded for each person. NIC codes 1, 2 and 3 are classified as agricultural sector and the rest non-agricultural sector Since the NIC code is not recorded for unemployed persons and persons who are not in the labor force, they are retained in the sample and treated as a part of the non-agricultural sector. 47,499 observations are deleted in the process.

Information on employee benefits (social security, paid leave and job contract) is recorded only for the regular workers and casual workers in public and other types of works. Information on benefits is missing for 170 workers. I decided to delete these workers from the sample because they cannot be classified as formal or informal workers. The type of enterprise which is the main identifier for formal and informal sector is missing for 363 workers. I classified these workers into formal and informal workers in the formal and informal sector respectively based on the benefits information. This classification is innocuous because I eventually sum up the formal and informal employment regardless of which sector they belong to. 206 workers out of 363 workers are assigned formal-informal worker status by this process. I delete the rest 157 workers who cannot be classified because neither benefits information nor the information on the type of

enterprise is available.

In the NSSO survey, wages are collected only for the regular salaried workers and the casual workers. Wages for self employed workers are not recorded because it is difficult to separate the profit and wage components from the earnings of the self employed workers. Wages for the regular salaried and casual workers are recorded for each activity performed during the reference week. A person may engage in more than one activity in a week. The primary activity is identified by the activity serial number '1' in the data. But wages are recorded against the weekly activity status the reference period of which is the last 7 days. So weekly activity status may not match up with the principal activity status (reference period is 365 days) recorded for some workers. It turns out that 12,678 observations do not report the same weekly and principal activity status. I delete these observations and keep only those observations that report the same weekly and principal activity status. This restriction is necessary to avoid any discrepancy in the classification of formal and informal workers and the wages reported for these workers. Moreover, this restriction allows me to focus on the long term informal employment because principal activity status is based on the worker's activity in the last 365 days. I drop two observations that reported Rs 703000 and Rs 125000 as weekly wages because they were distinct outliers in the sample. I dropped the Zoroastrians (7 observations) from the sample because they were causing perfect predictability problems in the multinomial logit estimation. Further I drop 5384 observations that have no information on the relevant variables: age, sex, religion, social group, marital status, general education, technical education and vocational training. The final sample has 227,839 observations.

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