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ABSTRACT

Calorie Consumption and Wages: Evidence from India's Labor Market*

Using nationally representative data from India, this study estimates the effect of calorie intake on wages. To account for endogeneity and heterogeneity, we apply Instrumental Variable and Instrumental Variable Quantile Regression methods. Results suggest that higher calorie consumption positively affects workers' wages. A 10% increase in per capita calorie intake per day leads to a 2.5% increase in daily wages. The wage effect varies by occupation type and across the wage distribution; the marginal effect of calorie intake on wage is higher at lower quantiles of the wage distribution and for non-elementary workers. Our findings highlight the need for nutritional supplementation, particularly for workers at low and median wage levels, to maximize the wage gains from nutritional public policies.

JEL Classification: I14, I15, J24, J31, O15

Keywords: wages, calorie, 2SLS, instrumental variable quantile regression, India

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1 Introduction

Approximately 700 million people live on less than \$2.15 per day in low-income countries, while an estimated 3.5 billion people in upper-middle-income countries subsist on less than \$6.85 per day (World Bank, 2024). Despite notable progress in reducing global poverty over the past two decades, efforts to meet the poverty-related Sustainable Development Goals have slowed considerably. A substantial share of the world's population remains trapped in extreme poverty, with progress uneven across regions and income groups. In this context, it has become critically important for policymakers in resource-constrained countries to identify and address the structural drivers of poverty and to better understand the mechanisms that perpetuate poverty traps.

Among the many factors affecting poverty, the rate and quality of human capital formation are widely recognized as key determinants of economic development and poverty dynamics. Human capital encompasses education, health, on-the-job training, and migration — all of which enhance individual productivity in the labor market (Kiker, 1966; Jorgenson and Fraumeni, 1989; Schultz, 1994; Laroche et al., 1999). Health, in particular, serves both as a dimension of human capital in its own right and as an input into the formation of other forms of human capital, such as education (Bleakley, 2010). Poor health negatively affects labor productivity, reduces incentives to invest in other forms of human capital, and ultimately results in lower income and poverty. Inadequate nutrition and widespread malnutrition further constrain employability and earning potential. Improved nutritional status enhances an individual's ability to work longer hours, increases work intensity, and reduces absenteeism due to illness (Bloom and Canning, 2000).

The relationship between nutrition and labor market outcomes was first formalized by (Leibenstein, 1957) through the "Efficiency Wage Hypothesis" (EWH). Subsequent work by Mirrlees (1975) and Stiglitz (1976) expanded on this framework, arguing that higher calorie intake enables workers to perform more physically demanding tasks, thereby increasing their productivity and wages. At the core of the EWH is the idea that low-income households are trapped in poverty due to inadequate nutritional intake, which limits their capacity to be productive in the labor market.

This paper revisits the empirical relevance of this hypothesis in the context of India, a country that continues to grapple with widespread poverty, low employment rates, low wages, and high levels of malnutrition among both children and adults. Using data from a nationally representative employment survey, we examine the causal relationship between nutritional intake, proxied by calorie consumption, and wages earned by workers in India. We further explore heterogeneity in this relationship by comparing elementary and non-elementary occupations.[1] We examined heterogeneity in this relationship by comparing elementary and non-elementary occupations and by estimating calorie-wage elasticities across different points of the wage distribution for both types of workers (elementary and non-elementary workers).

We use data from the 68th round of the National Sample Survey (NSS), conducted in 2011-12, to estimate the effect of calorie consumption on wages. A key challenge in estimating the causal impact of calorie intake on wages is the potential endogeneity concerns, particularly those stemming from reverse causality, simultaneity, and measurement error. For example, higher wages could enable workers to afford more nutritious, higher-calorie diets, creating a feedback loop that complicates causal inference. Additionally, unobserved district- or state-level characteristics, such as industrial development or political conditions, could simultaneously influence both wages and nutritional intake. For instance, southern states in India tend to have higher average wages and better population health than northern states. If these sources of endogeneity are not addressed, ordinary least squares (OLS) estimates would be biased and would contaminate the true causal impact of calorie intake on wages. To address these issues, we apply the Instrumental Variable (IV) method and estimate the two-stage least squares (2SLS) model, which allows us to estimate the causal effect of calorie consumption on wages while correcting for endogeneity in calorie intake. Following Strauss (1986) and Weinberger (2004), we use the price of calories, the household's monthly per capita expenditure (MPCE), and the household head's education level as instruments for calorie intake.

In addition to addressing endogeneity, it is important to consider heterogeneous effects of nutrition on labor market outcomes because the productivity returns to calorie intake may

[1] According to the International standard classification of occupation (ISCO-2008), elementary occupation consists of tasks that are of a simple and routine nature, mainly entail the use of hand-held tools, some physical effort, little or no previous experience and understanding of the work and limited initiative or judgment (ILO, 2008).

vary across different segments of the workforce. Workers at lower levels of nutrition or lower points in the wage distribution may experience larger marginal gains from improved calorie intake, while effects may taper off at higher levels of income or nutritional adequacy (Strauss and Thomas, 1998; Behrman et al., 1997a; Dasgupta, 1997). To fully capture this heterogeneity, we estimate quantile regression (QR) and instrumental variable quantile regression (IVQR) models, as proposed by Chernozhukov and Hansen (2008). These approaches allow us to explore how the effect of calorie intake on wages varies across the calorie distribution, providing richer insights into the heterogeneous impacts of nutrition on labor market outcomes.

Our findings show that calorie intake has a statistically significant positive impact on wages. For the full sample of currently employed workers, we estimate calorie-wage elasticity of 0.25, implying that a 10% increase in calorie intake leads to a 2.5% increase in wages at the mean of the wage distribution. When disaggregated by occupation types, the estimated elasticity is 0.10 for elementary workers and 0.33 for non-elementary workers. Moreover, we find substantial heterogeneity in the calorie–wage relationship across the wage distribution. For the full sample, the calorie-wage elasticity is 0.25 at the 25th quantile and 0.20 at the 90th quantile, suggesting that lower-wage workers derive relatively larger benefits from improved nutrition. This pattern is consistent across occupation types, with non-elementary workers exhibiting larger wage gains from increased calorie intake at all quantiles compared to elementary workers.

This paper contributes to the existing literature on the nutrition–productivity nexus in several important ways. First, while most prior studies have focused on estimating average effects of nutrition on wages, we provide the first comprehensive evidence on how this relationship varies across the entire wage distribution in India. By documenting these distributional effects, we shed light on whether improved nutrition disproportionately benefits lower-wage or higher-wage workers — a question with important implications for poverty reduction and inclusive growth. Second, we apply the IVQR method, which simultaneously addresses concerns of endogeneity and allows for heterogeneity in the calorie–wage elasticity. In contrast, much of the earlier literature — including Deolalikar (1988) and Jha et al. (2009) — has relied on OLS or 2SLS, or used household religion as an instrument. Our study improves on this by employing more robust instruments: food prices, household head education, and per capita monthly consumption expenditure. Third, we expand the scope of analysis beyond agricultural workers — the focus of many earlier studies — to include both elementary and non-elementary workers across a wide range of sectors, including services, construction, manufacturing, and transport. This broader occupational scope allows us to provide evidence that is more representative of India's evolving labor market. Finally, while some prior studies have either not measured health and nutrition in terms of calorie intake (Deolalikar, 1988), or have provided mixed or dated evidence (Jha et al., 2009), our study offers new, up-to-date estimates of the causal impact of calorie intake on wages using recent nationally representative data from India. Together, these contributions provide new empirical insights on the role of nutrition in shaping labor market outcomes in one of the world's largest and most diverse developing economies.

The remainder of this paper proceeds as follows. Section 2 reviews the existing literature on the calorie-productivity/wage relationship. Section 3 describes the data, while Section 4 explains the econometric framework. Section 5 presents the results, and Section 6 offers conclusions and policy recommendations.

2 Literature Review

The relationship between nutrition and economic outcomes, particularly labor productivity and wages, has been widely studied in both development and health economics literature. Nutrition is often conceptualized as a key component of human capital, enhancing an individual's productivity by improving physical health, cognitive abilities, and stamina (Schultz, 1961). Early theoretical models by Becker (1965) and Strauss (1986) emphasized that nutritional investments yield returns in the form of higher productivity and wages. The Beckerian framework suggests that better nutritional status increases work capacity, reduces absenteeism, and enhances efficiency in work performance. The interdependence between nutrition and income further highlights the bidirectional nature of this relationship: improved nutrition leads to higher wages, while higher income facilitates better dietary intake (Strauss and Thomas, 1998).

Several influential studies have documented the positive effect of improved nutrition on labor productivity. For example, the seminal work by Fogel (1994) highlighted the historical role of nutrition in driving economic growth, showing that better nutritional intake was a key factor in the productivity gains observed during the Industrial Revolution. Similarly, Thomas and Strauss (1997) found a strong association between caloric intake and agricultural productivity in developing countries. In addition to calories, specific micronutrients have also been found to influence productivity. Basta et al. (1979) showed that iron supplementation significantly reduces fatigue and increases productivity among iron-deficient workers in Indonesia. The positive effect of iron supplementation on productivity has also been reported by Pollitt (1997). Similarly, a study by Horton and Ross (2003) quantified the economic losses attributable to micronutrient deficiencies, underscoring the importance of nutritional interventions in enhancing productivity. Several non-experimental studies have also found that better nutritional or health status, measured in terms of calorie intake, height, or BMI, has positive effects on labor productivity per time unit worked and labor supply per adult (Strauss, 1986; Thomas and Strauss, 1997; Strauss and Thomas, 1998; Thomas and Frankenberg, 2002).

A substantial body of empirical research has examined the relationship between nutritional intake and labor productivity, yielding a range of findings across different contexts and populations. Early work by Strauss (1986) in Sierra Leone demonstrated that calorie intake significantly affected farm productivity, with an estimated calorie–output elasticity of 0.33. Subsequent study by Sahn and Alderman (1988) found a positive calorie–wage elasticity of 0.2 for male workers in Sri Lanka, though no effect for women. In Brazil, Thomas and Strauss (1997) showed that multiple nutritional indicators — including calorie and protein intake — had positive impacts on wages, and that the relationship between calorie intake and wages was non-linear, with larger gains for severely malnourished individuals. Positive associations between calorie intake and wages were also reported in Rwanda by Bhargava (1997). However, results from India have been more mixed. Using data on agricultural workers in South India, Deolalikar (1988) found a strong positive effect of weight-for-height on wages and farm output, but no significant effect of calorie intake. Similarly, Haddad and Bouis (1991) reported insignificant effects of calorie intake on wages in the Philippines, but positive effects of height on agricultural wages, indicating that long-term nutritional status, rather than short-term calorie intake, is more impactful on agricultural productivity.

More recent work by Jha et al. (2009) highlighted the heterogeneity of nutrition–wage effects in India, with impacts varying by gender, occupation, and task type — significant only for certain activities performed by female workers. Other studies have further highlighted that the strength of the calorie–wage relationship may depend on labor demand conditions, with higher wage–calorie elasticities observed during peak agricultural seasons (Behrman et al., 1997a; Swamy, 1997). These findings suggest that the relationship between calorie intake and labor productivity is shaped by a range of contextual and behavioral factors, which may vary across income levels, occupations, and stages of economic development. Berha et al. (2021) found a positive farm labor productivity effect of current nutritional status in Ethiopia; however, the effects varied considerably depending on the initial level of diet quality and diversity, with a stronger and positive effect for low-consumption households. In contrast, Custodio et al. (2025) showed that daily micronutrient (haem iron, zinc, folate, calcium, vitamins B2 and A) intakes, rather than calorie intakes, have positive impacts on labour productivity, highlighting the importance of micronutrient intakes over calorie intakes.

Several mechanisms help explain this variation. First, in low-income settings, many workers are engaged in physically demanding manual labor in primary sectors, where greater endurance and stamina — both of which can be improved through higher calorie intake — are critical for productivity (Becker, 1965; Alleyne and Cohen, 2002). Second, as income increases, changes in work–leisure preferences and dietary choices may influence the calorie–wage relationship in complex ways. For example, higher income could lead to greater consumption of processed or convenience foods, or time constraints from longer working hours could alter food preparation and intake patterns (Fogel, 1994; Strauss and Thomas, 1998). Thus, the net effect of income on calorie intake is theoretically ambiguous and context-dependent. Third, the returns to calorie intake are likely to be highest among malnourished workers, whereas protein intake and other quality dimensions of nutrition may become more important as nutritional adequacy improves.

Furthermore, while much of the literature on nutrition and wages emphasizes health and human capital mechanisms, structural and institutional factors also shape individual outcomes in the labor market. For example, Gupta et al. (2018) show that identity-based disparities continue to influence economic alienation in post-reform India, even after controlling for household characteristics and education. Their findings underscore that identity-based disparities persist alongside economic and nutritional constraints, reinforcing the idea that productivity and wage outcomes are jointly determined by both individual capacity (e.g., nutrition) and broader social structures. Kumar et al. (2009) develop a cereal consumption–deprivation index using NSS data, showing rural deprivation declined pre-reform but stagnated in the reform era, especially in urban areas. Their findings highlight persistent nutritional shortfalls that frame our analysis of calorie–wage effects. Rattsø and Stokke (2024) demonstrate how public sector wage compression drives wage inequality across gender and regions. Together, these studies underscore that nutrition-driven productivity gains interact with broader social and institutional determinants of wages.

At low levels of income and nutrition, an increase in calorie intake tends to raise labor productivity and wages, though at a diminishing rate Deolalikar (1988), Strauss and Thomas (1998), and Dasgupta (1997). Improved nutritional status enhances work efficiency, reduces absenteeism due to illness, and boosts overall productivity (Bloom and Canning, 2000). In developing countries, where malnutrition and infectious diseases remain widespread, the marginal productivity of health improvements is typically greater than in more advanced economies (Strauss and Thomas, 1998). Taken together, the findings from the literature suggest that while improved nutrition can enhance productivity and earnings, the magnitude and significance of these effects are likely to vary across contexts, occupations, and points in the wage distribution — a gap this study seeks to address across diverse sectors in the broader Indian labor market. Our study intends to fill this gap by providing up-to-date evidence on the causal effect of calorie intake on wages, disaggregated by occupational type (elementary and non-elementary workers), using recent nationally representative data from India.

3 Data and Variables

3.1 Measurement of Health

In terms of nutrition, health can be envisioned as the physical capacity to work, i.e., maximum work per unit of time someone is capable of doing (Dasgupta, 1997). However, individual health is a multidimensional concept and hence highly susceptible to measurement error (Jamison, 1985). Several studies have used disability-adjusted life years, activities of daily living, instrumental activities of daily living, self-reported health status, and morbidity as measures of individual health status (Strauss and Thomas, 1998; Bhargava, 2001; Weinberger, 2004). However, these measures are likely to suffer from reporting bias, which could lead to either an overestimation or underestimation of the association between health status and labor market outcomes (Murray and Chen, 1992; Sen, 2002). Existing studies in development economics have associated the long-term effect of calorie intake among the nutritionally deficient population with increases in height during infancy and income among adults (Strauss, 1986; Fuentes et al., 2001). As discussed before, considering calorie, protein, iron, and other micronutrient intake as health input, several studies have established positive effects of improved health on labor productivity and wages (Deolalikar, 1988; Fogel, 1994; Strauss and Thomas, 1998; Bhargava, 2001; Weinberger, 2004). Following these important studies, we measure the health and nutritional status of the individual in terms of daily calorie intake.

3.2 Data description

Our study is based on two nationally representative, employment/unemployment and consumer expenditure surveys, conducted by the National Sample Survey Office (NSSO) of India. Both surveys were conducted from July 2011 to June 2012 (68th round). Using a multi-stage stratified sampling design, 456,999 (280,763 rural and 176,236 urban) individuals were enumerated from the 28 states and 7 union territories of India. To capture the seasonal variation in rural employment, food grains availability, and price fluctuation, the total sampled villages/urban blocks were equally divided into four groups, and these were surveyed in four different agricultural seasons. The details of the sampling design, concepts, and definitions followed in the survey can be referred to from the respective survey report (NSSO, 2014).

The employment survey records the socio-economic, demographic, consumption expenditure, and economic activity data for each sampled household's members. All employed members of the household are listed by their industry[2] and occupation[3] of employment. For the currently working member, total wages received in the last seven days preceding the survey are also available in the survey. In addition to employment and wage information, the employment survey also collected information on total monthly and/or yearly consumer expenditure on twelve food groups, consumer durables, medical, education, and other services, but did not collect information on the quantity of food items consumed. Therefore, we cannot calculate the price of food items or the price and quantity of calories consumed in the employment survey.

Therefore, we supplement the employment survey with the 68th round of the NSSO consumer expenditure survey, which was conducted at the same time and has a similar sample design (NSSO, 2014). The consumer expenditure survey collected consumption data for more than 300 food items, which fall into the 12 food groups, identical to the food groups in the employment survey. For each sampled household in the consumer expenditure survey, consumption expenditure and the quantity consumed in the last 30 days were collected for each food item in the 12 food groups – cereals; pulses and pulse products; milk; milk products; edible oil; vegetables; fruits & nuts; egg, fish & meat; sugar; salt & spices; beverages & packaged foods; pan, tobacco & intoxicants were collected. We map the 12 food groups in the employment-unemployment survey with the corresponding 12 food groups in the consumption expenditure survey and use the following formula to calculate calorie consumption in the employment survey.

$$\sum_{i=1}^{12} \text{Calorie}_{\text{emp survey}} = \frac{\sum_{i=1}^{12} \text{Total Expenditure}_{\text{emp survey}}}{\sum_{i=1}^{12} \text{Expenditure per unit calorie}_{\text{consumption expenditure survey}}} \tag{1}$$

[2]Employment status in an industry of a person has been classified as per the National Industrial Classification NIC-2008 in 2011-12.

[3]Occupation of the employment has been classified as per the National Classification of Occupations, NCO-2004 in 2011-12.

We estimate the price of a calorie and total calorie consumption by the respondents in the employment survey in the following ways. First, following the Indian Planning Commission method, we convert the quantity consumed of the 12 food items into calorie intake in the consumer expenditure survey (Planning Commission, 2009). Second, since the consumer expenditure survey collected information on total expenditure on these 12 food items, we divide total consumption expenditure by the total amount of calories consumed to estimate the price of a calorie per unit. Third, assuming that irrespective of the economic status, total calories gained by the households from the expenditure on each food item vary only by NSS regions, rural-urban, and agriculture seasons, using contemporaneous consumer expenditure surveys.[4] We calculate the mean calorie price[5] of each 12 food items in each NSS region by rural-urban and agriculture seasons.[6] Finally, the calculated calorie price from the consumer expenditure survey is merged with the employment-unemployment survey to estimate the total amount of calories consumed by households in the employment-unemployment survey. Total household calorie intake is the sum of calorie intake from each food item, which is equal to the multiplication of the per-rupee value of calories for each food item by the corresponding food expenditure. Since individual calorie intake is seldom collected in household surveys, the household-level calorie variables estimated from food expenditure were converted into per-capita calorie consumption. Singh and Kumar (2004) show that for a given amount of labor per capita calorie requirement varies by age and sex. Hence, taking into account the age and sex structure of the household members, we estimate per adult equivalent calorie intake, which is the main independent variable in our regression model.

Since demand for calories and returns to calorie consumption depend on the nature of labor activities performed, we extend our analysis by the occupational types of the individuals. Based on the International Standard Classification of Occupation (ISCO-2008), we classify workers either as elementary or non-elementary workers (ILO, 2008). Elementary occupations include (1) cleaners, helpers, food preparation, street, and related sales and service workers, refuse workers, and other elementary workers; (2) agricultural, fishery, and

[4]Using the same sampling frame up to the first-stage unit or ultimate stage-units NSS simultaneously conducts the quinquennial rounds of Employment and Unemployment and Consumer Expenditure surveys.

[5]Calorie price is the calorie obtained from one rupee on food items.

[6]There are 88 NSS regions and districts in each region share similar socio-economics and agro-climatic characteristics.

related laborers; (3) laborers in mining, construction, manufacturing, and transport (ILO, 2008). Non-elementary occupations include legislators, senior officials and managers, professionals, associate professionals, clerks, service workers, and shop & market sales workers, skilled agricultural and fishery workers, craft and related trades workers, plant and machine operators, and assemblers.

We classify the workers by occupation type as per the usual principal activity status in the NSS data. There might be a chance that some of the elementary workers would have been employed as per the usual principal activity status, but would not have been employed as per the current daily activity status. One of the strategies would have been to study only the elementary workers who were employed as per the current daily activity status, but it does not consider the agricultural seasons, business cycles, and long-term determinants of employment status. Therefore, we proceed to include and analyze workers who were employed as per the usual principal activity status in the NSS data.

3.3 Outcome and Control Variables

Our main outcome variable, the log of daily wages, is the log of the average wages received in the last 7 days preceding the survey. We converted this into daily wages. Wage information was collected in the employment survey by NSSO. The primary independent variable is the log of calorie intake per consumer unit. The calorie intake per consumer unit is defined as calorie intake per capita adjusted for different calorie needs by gender and age. We used NSSO adjustment parameters to calculate per consumer unit calorie intake. It should be noted that calorie intake per consumer unit is different than calorie intake per capita, which is equal to the total calorie intake at the household level divided by the household size. Since the Government of India focuses on calorie intake per consumer unit, our analysis is based on calorie intake per consumer unit and not on calories per capita. Previous studies on the health and wage relationship identify several socio-demographic factors that may be associated with the wages received in the labor market. Therefore, we control for age, age square, gender, general education, technical education dummy, religion, and caste of the household head, land-holding size, urban dummy, agricultural seasons (sub-round), type of occupations, and agro-climatic regions. We include fixed effects of the NSS agro-climatic region to control for the fixed characteristics of the NSS regions. The NSS surveys define 88 NSS agro-climatic regions sharing similar agro-climatic conditions.

4 Estimation framework

The relationship between calorie consumption and wages can be examined by estimating the following log-log model in the OLS framework:

$$\log(\text{wage})_{ihd} = \alpha_{ihd} + \beta \log(\text{calorie})_{ihd} + \gamma X_{ihd} + \theta D_d + \epsilon_{ihd} \tag{2}$$

where $\log(\text{wage})_{ihd}$ is the wages received by individual i in household h in district d. The main explanatory variable is $\log(\text{calorie})_{ihd}$, the log of calorie consumed per consumer unit in household h, X includes the household and individual level control variables, and D_d is the NSS region fixed effect that controls for time-invariant NSS region characteristics.[7] ϵ_{ihd} is the error term. Standard errors are clustered at the district level to account for intra-class correlations. All regression models are weighted with sampling weights. β in equation (2) can be interpreted as a causal estimate of the effect of calories on wages if there are no omitted variables correlated either with calorie intake or wages, and there is no reverse causality running from wages to calorie intake, conditional on the controls.

By definition, only currently employed workers have reported wages in our sample, whereas unemployed workers have missing wage data. Consequently, analyzing the calorie-wage relationship using only the employed sample introduces an upward bias, as the analysis excludes individuals without wages. Workers who are employed and have received positive wages are more likely to self-select into the labor market, and they differ from unemployed workers in distinctive ways that can make these two groups incomparable. To correct the sample selection bias due to non-random employment and missing wages, we use the Heckman two-step correction model. The first step models the likelihood of being included in the sample (e.g.,

[7] There are 88 NSS regions. The NSS regions are agro-climatic units above districts but below states. Our dataset includes approximately 523 observations across 88 NSS regions, with each region contributing a sufficient number of observations to ensure adequate data variability.

being employed and thus having observed wages). A probit model is used in the first step to compute the Inverse Mills Ratio (IMR). In the second step, the wage equation is estimated, incorporating the IMR to account for selection bias. This method ensures that the calorie-wage elasticity is not upward biased due to the non-random selection of employed workers in the sample (Heckman, 1979).[8] The robustness of the Heckman sample selection model relies on the exclusion restriction—a variable included in the selection equation but not in the outcome equation. In our analysis, we have used "marital status" as the excluded variable. The marital status of the workers is likely to influence the likelihood of employment, but is unlikely to directly affect wages once employment status is controlled for.

However, several reasons can make the causal interpretation β in eq (2) challenging. One major concern is that the primary independent variable, calorie intake, may not be free from endogeneity, raising issues of simultaneity and reverse causality in the calorie-wage relationship. In the case of reverse causality, wages may influence an individual's nutritional status, as measured by calorie intake, which in turn could affect wages (Dasgupta, 1997; Thomas and Strauss, 1997; Jha et al., 2009).[9] As a result, reverse causation would bias the OLS coefficient in the upward direction. Furthermore, simultaneity introduces further bias. Another potential source of bias is omitted variable bias that arises from unobserved individual characteristics, such as innate ability, motivation, work ethic, or time preference, that may influence both dietary behavior and wage outcomes. For example, these unobserved characteristics may influence both nutritional behavior (e.g., higher calorie consumption due to better planning or food access) and wage outcomes (e.g., through higher productivity or job performance). If not properly accounted for, such factors can bias the estimated effect of calorie intake on wages, leading to overestimation of the true causal relationship. Additionally, calorie intake may suffer from measurement error, making it endogenous and potentially correlated with the unobserved error term. Thus, whether due to reverse causality, simultaneity, or measurement error, the OLS coefficient is likely to be upwardly biased, undermining the validity of the causal interpretation of β.

[8] The caveats of the Heckman model discussed by Deaton (1997) remain a concern, such as the Heckman model relies heavily on the assumption that the errors in the outcome and selection equations are jointly normally distributed, particularly in household survey data where error structures may be more complex.

[9] Dasgupta (1997) argued that there is no one-to-one reverse causation between wage and calorie intake as laborers spend no more than 15-20% of their wage on energy requirements.

4.1 Two-stage least square model

We use the IV method to address the concerns regarding endogeneity in the OLS estimation. We estimate the 2SLS estimator of the following form.

First-stage equation:

$$\log(\text{calorie})_{ihd} = \alpha_{ihd} + \beta Z_{ihd} + \gamma X_{ihd} + \theta D_d + \epsilon_{ihd} \tag{3}$$

Second-stage equation:

$$\log(\text{wage})_{ihd} = \alpha_{ihd} + \beta \log\left(\widehat{\text{calorie}}_{ihd}\right) + \gamma X_{ihd} + \theta D_d + \epsilon_{ihd} \tag{4}$$

Where Z in equation (3) is the instrumental variable. In the first-stage, we regress the endogenous variable, calorie intake, on instruments and all exogenous control variables, and in the second stage, the outcome variable is regressed on calorie intake predicted from equation (3) and control variables. We estimate the 2SLS models for all workers as well as the type of workers (elementary and non-elementary workers) to capture heterogeneity in the effects of calorie intake on wages by workers' occupation types.

Before estimating the wage model, we assess whether it is appropriate to pool workers across different sectors and occupation types. Figures A1 and A2 in the Appendix present a non-parametric distribution (Kernel density) of the natural log of wages. The kernel density graph in Figure A1 shows that the wage distribution of the workers employed across various elementary occupations is similar in shape, suggesting that these groups can be combined for analysis. While elementary workers in agriculture earn marginally higher wages than those in manufacturing and services, the differences are not statistically significant. Similarly, Figure A2 shows that although average wage levels vary across broader occupational or sectoral groups, the shape of the wage distributions is comparable. These patterns support the use of a pooled estimation strategy in the analysis that follows.

4.2 Instruments Validity

Several studies in the literature have used instruments such as food prices, household characteristics (e.g., household size), and religious affiliation to address the potential endogeneity of calorie intake (Strauss, 1986; Weinberger, 2004; Jha et al., 2009). Following this approach, we instrument per capita calorie intake using multiple variables that are plausibly correlated with calorie consumption but not directly with wage outcomes. Specifically, our instruments include per capita monthly consumption expenditure, the price per unit of calorie consumed, and the education level of the household head. Since the number of instruments exceeds the number of endogenous variables, our IV model is overidentified (number of instruments > number of endogenous variables), allowing us to test the validity of the instruments.

We consider these instruments valid under the assumption that they satisfy the relevance condition— exhibiting a strong correlation with calorie intake — and the exclusion restriction, whereby they affect wages solely through their effect on calorie intake, conditional on the covariates included in the IV specification. As mentioned before, previous studies guided our choice of instruments in our analysis. For example, Strauss (1986) instrumented calorie intake by food price and farm assets and reported a significant positive effect of calorie intake on farm labor productivity in Sierra Leone. Calorie intake may also depend on the household socio-economic conditions, such as the household head or father's education & job, and household assets such as land (Strauss, 1986; Jha et al., 2009). Calorie consumption of workers belonging to the better socio-economic strata is usually higher, which is not much correlated with the wage and productivity of the workers.

The rationale for using per capita consumer expenditure as an instrument comes from the fact that at the low level of economic equilibrium, monthly per capita consumption expenditure is highly correlated with food expenditure. However, as per Engel's law, the share of food expenditure to the total expenditure either remains constant or declines with an increase in MPCE. Hence, per capita consumption expenditure will be highly correlated with calorie intake, demonstrating strong first-stage correlations. Regarding exclusion restriction, one may argue that wages represent the income of the household, and consumption expenditure is a proxy for income; thus, daily wages and consumption expenditure are likely to be correlated.

We argue that consumption expenditure is plausibly exogenous, as in developing countries like India, consumption expenditure captures the household's overall economic status rather than individual wages, incorporating income from diverse sources such as remittances, agricultural activities, and rentals, rather than being solely tied to individual wages. This broader scope reduces its direct correlation with the respondent's wages, particularly in households with multiple income streams. Its exogeneity is supported by the assumption that household consumption patterns, especially nutrition, are primarily driven by long-term income and wealth, rather than short-term wage fluctuations, are often predetermined independently of labor market participation decisions, and are relatively stable and predate wage changes (Ravallion, 1990). This temporal separation between consumption decisions and labor market outcomes further supports instrument exogeneity. Additionally, the weaker relationship between per capita consumption expenditure and individual wages, due to intra-household resource allocation and non-wage income influences, is likely to strengthen the validity of the instrument.

While acknowledging that the correlation between consumption expenditure and wages may not be exactly zero, potentially causing upward bias, we implement multiple strategies to minimize this concern. Following Strauss (1986), we strengthen identification by combining consumption measures with additional instruments, allowing for formal over-identification tests. Finally, the third instrument, the education level of the household head, is plausibly related to calorie intake because it may determine household food choices and nutritional knowledge. This choice of the household head's education as an instrument is grounded in the literature (Strauss, 1986; Thomas and Strauss, 1997) that demonstrates how parental or household head education shapes household food choices, dietary knowledge, and nutritional investments, making it a strong predictor of calorie intake. Importantly, our empirical strategy controls for the worker's own education, occupation, household socio-economic characteristics, and regional fixed effects, thereby limiting the potential for direct effects of the household head's education on wages, apart from its influence through calorie intake. While we recognize that shared genetic traits or personality characteristics could pose some risk of violating the exclusion restriction, we mitigate this concern by employing multiple instruments (including per capita consumption expenditure and calorie price), which allows us to conduct formal over-identification tests. These tests do not reject the validity of our instruments. Overall, we believe that combining multiple instruments and a rich set of household socio-economic control variables in the IV model 2SLS reduces reliance on any single instrument and helps minimize the risk of violation of the exclusion restriction from a single instrument.

4.3 Instrumental Variable Quantile Regression

The effect of calories on wages is unlikely to be constant throughout the distribution of wages. The association between calories and wages depends not only on the wealth status of the farmers but also on the stages of production and agricultural season (Behrman et al., 1997b; Swamy, 1997). Therefore, the wage elasticity of calorie intake depends on the wage distribution, and such heterogeneity is informative while estimating the calorie-wage association. This is particularly useful in contexts where the impact of an endogenous variable, such as calorie intake, may vary at different points of the wage distribution—for example, the effect of improved nutrition might be more pronounced for low-wage workers compared to high-wage workers. To analyze the causal relationship between calorie intake and wages when both endogeneity and heterogeneity in treatment effects are present, we estimate the IVQR model developed by (Chernozhukov and Hansen, 2008). By combining QR with the IV approach, the IVQR model accounts for unobserved heterogeneity and enables the identification of causal effects that vary across quantiles, offering richer insights into the underlying economic relationships. Finally, all models, OLS, 2SLS, QR, and IVQR, account for sample selection bias through the Heckman two-step correction model.

5 Empirical results

5.1 Descriptive statistics

Table 1 displays summary statistics for the main dependent and independent variables as well as the control variables. The data shows significant disparities in wages and calorie consumption between elementary and non-elementary workers. The average daily wage of currently employed workers is Rs 232.6 (about $4 at the 2020 exchange rate). Elementary workers earn lower wages than the wages earned by non-elementary workers. On average, elementary workers earn Rs 124, while the mean wage for non-elementary workers is Rs 336. The per consumer unit calorie consumption of all workers is 2653 kcal/day, while the average calorie consumption per capita is 2167 kcal/day. Elementary workers consume fewer calories than non-elementary workers (2067 kcal/day vs. 2262 kcal/day). The average age of the workers is 36 years, and the majority of the workers are male. The female labor force participation rate in the sample is 22%. Approximately one-third of the sampled workers are illiterate, and 14% of them have completed primary schooling. Since the sample includes non-elementary workers, who require a slightly higher level of education, the higher secondary schooling completion rate is 21%.

The majority of the workers are rural (66%), Hindu (84%), and only 5% of the sample has acquired some technical education. The caste structure is quite diverse. One-third of the sample belongs to the socially disadvantaged community, the scheduled caste, and the scheduled tribe. More than two-fifths of the sample (41%) belong to other backward castes, and 25% of the workers are from other non-backward castes. The landholding size is quite fragmented and small. A very high percentage of the sample owns less than one acre of land (85%), and another 10% own 1-3 acres of land. So, a combined total of 95% of the workers own less than 3 acres of land. The average size of the land is 2.8 acres. In terms of occupational structure, the sample is quite heterogeneous. Close to 4% of the sample work in skilled agricultural and fishery work, while another 49% work in elementary occupations that are mainly less skilled work.

5.2 OLS results

Table 2 presents the OLS and Heckman sample selection model estimates for the relationship between calorie intake and wages. The OLS results indicate a statistically significant calorie-wage elasticity of 0.17, meaning that a 10% increase in calorie intake per consumer unit is associated with a 1.7% increase in wages. This relationship remains consistent across all specifications with and without NSS region fixed effects (columns 1 and 2), reinforcing the positive impact of calorie consumption on earnings. The results also reveal that age has a non-linear effect on wages, with earnings increasing at a decreasing rate over time. Additionally, gender disparities in wages are stark, as female workers earn approximately 41% less than male workers (column 2). Education plays a crucial role in determining wages, with higher levels of schooling significantly boosting earnings. For instance, workers with secondary education earn approximately 28% more than those with only primary education, while technical education is associated with an additional 27-28% increase in wages. Furthermore, urban workers earn 24-25% more than their rural counterparts, underscoring the wage disparity between rural and urban labor markets.

To account for potential selection bias, the Heckman sample selection model is applied, which corrects for the possibility that observed wages are reported only for employed workers, potentially biasing the OLS estimates in columns (1) and (2). Results from the Heckman sample selection model are reported in columns (3) and (4). The IMR in the Heckman model is statistically significant, indicating the presence of selection bias. After correcting for this bias, the calorie-wage elasticity remains similar to the estimates in models without the Heckman correction in columns (1) and (2). Since these OLS estimates are likely to be biased due to endogeneity, we use the 2SLS estimator to correct for biases in the OLS estimates and discuss the 2SLS results in the next section.

5.3 Two-stage Instrumental Variable Results

5.3.1 First-stage estimates

Table 3 presents the first-stage results from the IV model, which examines the causal effects of calorie consumption on wages. Panel A shows the first-stage estimates, while Panels B-D report the diagnostic statistics for the instrument validity. The first-stage regression results in Panel A are presented for the full sample in columns (1-2) and for elementary and non-elementary workers in columns (3) and (4), respectively. Column (1) shows results without region fixed effects, while columns (2-4) show results with region fixed effects. Columns

(2-4) use the Heckman sample selection model.

The relevance condition is satisfied as the three instruments are strongly correlated with the endogenous variable (calorie intake), are statistically significant, and the signs of the first-stage coefficients are consistent with theoretical predictions. Monthly per capita expenditure is positively correlated with calorie intake, while the price of calories is negatively correlated with calorie intake. The results indicate that MPCE has a strong positive effect on calorie intake, with an elasticity of 0.66–0.76 across different worker categories. Conversely, the price of calories negatively affects calorie intake, with elasticities ranging from -0.85 to -0.87, highlighting that rising food costs reduce calorie consumption. The education of the household head also plays a role; while primary and middle education levels positively impact calorie intake, higher secondary education and above exhibit a negative effect, possibly reflecting shifts toward higher-quality, lower-calorie food preferences. The statistical significance of education coefficients is mixed and does not follow a consistent pattern.

To assess instrument strength, the first-stage F-statistics exceed 10 in all specifications, suggesting that the instrumental variables (MPCE, calorie price, and household head's education) are sufficiently strong. Additionally, the Anderson-Rubin Wald test and Stock-Wright LM S test confirm the robustness of the instruments. The overidentification test results (Hansen J-statistics) indicate that the instruments are valid and not correlated with the error term. These results provide strong justification for using the IV approach in estimating the causal impact of calorie intake on wages, ensuring that the second-stage wage estimates are not biased by endogeneity concerns.

5.3.2 2SLS results

Table 4 presents the results of the 2SLS regression estimates, examining the causal impact of calorie intake per consumer unit on wages. Columns (1) and (2) show results for all workers with and without region fixed effects, respectively. Column 3 shows estimates for elementary workers, while column 4 shows the results for non-elementary workers. The regression estimates in Table 4 are positive and statistically significant, indicating that higher calorie consumption has positive impacts on wages, supporting the efficiency wage hypothesis. Specifically, a 10% increase in daily calorie intake per consumer unit leads to a 2.5% increase in wages for all workers. When disaggregated by occupation, the wage elasticity of calorie intake is 0.10 for elementary workers and 0.33 for non-elementary workers, highlighting that non-elementary workers benefit more from increased calorie intake. These results remain statistically significant at the 1% level of significance, indicating robust evidence of a positive calorie-wage relationship. All regression models in Table 4 always control for various demographic and socio-economic factors, such as age, gender, education, urban residence, caste, religion, landholding size, agricultural seasons, and occupation types. Furthermore, all models in Table 4 are corrected for sample selection bias through the Heckman sample selection model.

These findings further suggest that the return to calorie consumption varies across worker categories. Non-elementary workers, who are more likely to engage in skilled or knowledge-based work, experience a greater wage increase compared to elementary workers, who perform more physically demanding labor. This suggests that while physical laborers benefit from increased calorie intake, those in non-elementary jobs may experience greater productivity gains due to improved cognitive function and overall well-being.

At the sample mean wage of Rs 232.6/day, this effect would lead to an increase of Rs 5.52/day. If we assume that these workers are employed for six months in a year, the wage income of these workers would increase by Rs 1007.4. The increased income is equivalent to meeting the poverty line expenditure for 31 days.[10] The calorie-wage elasticity estimate of 0.25 in this study is non-negligible and is comparable with those reported in other studies in India and elsewhere (Strauss, 1986; Sahn and Alderman, 1988; Jha et al., 2009). Jha et al. (2009) estimated calorie-wage elasticity of 0.013-0.017 for female workers in India, but no significant effects of calories on wages were detected for male workers in this study. The calorie-farm output elasticity estimated by Strauss (1986) ranged from 0.16-0.34 in Sierra Leone, while Sahn and Alderman (1988) estimated the effects of per capita calorie intake on wage labor to be 0.2 for men in rural areas of Sri Lanka.

Our estimates are slightly larger than the estimates in Jha et al. (2009). This difference

[10]The poverty line is Rs 32 per day in villages, and Rs 47 in cities.

could be due to variations in study design, data sources, choice of instruments, and methodologies. For example, Jha et al. (2009) use data from 1994 on a small sample of 6500 households spread across only 16 states in India. In contrast, we use nationally representative data on a sample of 70,000 individuals. Our sample includes both elementary and non-elementary workers across different occupation sectors, while Jha et al. (2009) focused only on agricultural workers. Jha et al. (2009) data lacked food price information, so they used "religion" as an instrument for calorie intake, while our study is methodologically different, as we use multiple instruments and account for selection bias through the Heckman selection model.

Weinberger (2004) estimated the effects of iron intake on wages, finding an iron-wage elasticity ranging from 0.102 to 0.34 among agricultural workers in India. The calorie-wage elasticity estimated in our study should be interpreted differently from iron-wage elasticity, as micronutrients and calories impact labor productivity and, subsequently, wages through distinct biological mechanisms. While calorie elasticity measures the responsiveness of total energy intake, iron elasticity reflects a micronutrient-specific demand shift, often motivated by dietary diversification. This distinction aids our understanding of whether income growth or policy interventions should prioritize improving overall caloric sufficiency or addressing specific micronutrient deficiencies, such as iron, which are critical for health outcomes like anemia reduction. This comparison is particularly relevant given India's double burden of malnutrition, where both caloric adequacy and micronutrient deficiencies remain problematic.

5.3.3 Heterogeneous effects

Table 5 presents the heterogeneous effects of calorie intake on wages using the 2SLS estimates. The results indicate that the impact of calorie intake on wages differs significantly based on occupational type and calorie consumption levels in India. The results reveal significant heterogeneity in the relationship between nutrition and wages. For workers with below mean calorie intake, the impact is substantially larger (elasticity of 0.33 for all workers and 0.52 for non-elementary workers) compared to those with above mean calorie intake (elasticity of 0.17 for all workers and 0.20 for non-elementary workers). The average daily calorie intake per capita varies across worker categories, with all workers consuming an average of 2,228 kcal/day. However, elementary workers have a lower calorie intake of 2,036 kcal/day, while non-elementary workers consume a higher average of 2,329 kcal/day. We used these cutoffs to conduct the heterogeneity analyses in Table 5.

It should be noted that these cutoffs are based on calorie intake per capita and not on calorie consumption per unit. All estimates are statistically significant at a 1% level of significance. This pattern suggests diminishing returns to nutrition as calorie consumption increases. The results further show that non-elementary workers experience much stronger wage benefits from improved nutrition compared to elementary workers. For elementary workers, the calorie-wage elasticity ranges from 0.07-0.11, while for non-elementary workers it ranges from 0.20-0.52, depending on their initial nutritional status. These findings emphasize that non-elementary workers experience a larger return on increased calorie consumption, likely due to the role of cognitive functions and skill-based productivity in these occupations. The results remain robust after including NSS region fixed effects and the analysis accounts for potential selection bias using Heckman's correction method. The statistical diagnostics (F-statistics and Hansen J-statistics) confirm the relevance and validity of the instruments. Overall, results from the heterogeneity analyses provide strong evidence for targeted nutritional interventions focused on workers with low calorie intake, particularly those in elementary occupations.

5.3.4 Robustness checks

Table 6 presents robustness checks for the relationship between calorie intake per capita and wages across different worker categories. In this table, we use calorie intake per capita instead of calorie intake per consumer unit. The regression results are qualitatively similar to our main findings in Table 4. The results indicate that an increase in daily calorie intake per capita has a significant positive effect on wages for all workers, with a coefficient of 0.27. However, when disaggregated by occupation type, the effect varies: the coefficient for elementary workers is 0.09, whereas for non-elementary workers, it is substantially higher at 0.37. These findings suggest that non-elementary workers, who likely engage in more skill-intensive or physically demanding tasks, benefit more from increased calorie consumption in terms of wage gains.

5.3.5 Estimated return to investment in calorie

So far, we interpreted our results as the estimated impacts on wages due to a 10% increase in calorie intake per consumer unit. The calorie-wage elasticity of 0.25 in Table 4 reflects the causal effects of calorie intake on wages, but it should be interpreted in the broader context of overall dietary quality and cost-effectiveness. It is important to note that while increasing calorie intake may improve productivity for undernourished workers, the associated costs may outweigh the wage benefits if calories are sourced from expensive foods or if workers are already consuming near-adequate levels of calories.

To assess whether the observed wage gains would outweigh the cost of additional calories, we conduct a back-of-the-envelope calculation. We estimate the cost of consuming an additional 250 kilocalories, the threshold used in the interpretations of our main findings. Our calculations suggest that the wage benefits of increased calorie intake outweigh the costs. Using rice as an example (widely consumed staple diet), 250 additional calories would require about 76 grams of rice, costing approximately Rs. 1.52 per day in 2011.[11] Given the estimated calorie-wage elasticity of 0.25 in Table 4, a 250-calorie increase would lead to a wage rise of Rs. 5.8 per day, significantly exceeding the cost of calorie intake (Rs. 1.52 per day). While rice is used as a reference food due to its status as a dietary staple across most Indian states, we acknowledge that individuals consume a range of food items, and it is difficult to identify the exact sources of calorie intake, particularly the more expensive ones. However, we also compute the average cost per kilocalorie using detailed food consumption data from our sample, which provides a more representative estimate of dietary behavior. The average price per kilocalorie is approximately Rs. 0.011, implying that 250 additional kilocalories would cost about Rs. 2.75. This is substantially lower than the estimated wage gain of Rs. 5.80, suggesting that even modest improvements in income are sufficient to cover the cost of increased caloric intake.

[11] The average cost of a kilo of rice in 2011 was about Rs 20, and one kilo of rice contains approximately 3300 calories (**?**).

However, the economic returns to improved nutrition may not be uniformly positive across all worker groups, particularly for elementary workers, who tend to have lower baseline wages and lower calorie-wage elasticities. For instance, the estimated cost of consuming an additional 250 kilocalories per day—approximately Rs. 1.52—exceeds the corresponding wage gain of Rs. 1.10 among elementary workers. This cost is likely even higher for those at the lower end of the calorie distribution, where food prices may be less efficient or dietary needs more acute. In contrast, the same nutritional improvement yields a much larger estimated wage gain of Rs. 11.02 for non-elementary workers, reflecting both higher returns and better baseline nutritional status. These calculations underscore the broader economic rationale for investing in nutritional improvements, especially for undernourished workers. At the same time, they highlight that for elementary workers—who often experience more severe calorie deficits, lower dietary diversity, and limited earnings potential—nutritional interventions may need to be more intensive and targeted in order to generate meaningful wage gains.

5.4 IVQR Results

The OLS and 2SLS results in Tables 2 and 4 provide the average effect of calories on wages when the effect of calories is constant at each point of the wage distribution. However, these results mask the distributional impact of nutrition on earnings when the effect of higher calorie consumption is not constant at different levels of wages. To further examine the distributional impact of calorie intake at different points of the distribution of wages, we estimate the relationship between calories and wages in a QR and an IVQR framework. Both the QR and IVQR models are estimated for wage quantiles 0.1, 0.25, 0.5, 0.75, and 0.9.[12]

Table 7 presents the results of the QR and IVQR models, highlighting how the impact of calorie intake on wages varies across different points of the wage distribution. Panel A shows the results for all workers, Panel B shows the results for elementary workers, and Panel C shows the results for non-elementary workers. Column (1) shows the results of the QR model, while column (2) shows the results from the IVQR model. The results indicate that

[12]We conducted diagnostic checks, including assessments of data variability within each quantile, to ensure that there is sufficient variability in both the dependent and independent variables to support the QR and IVQR analysis.

the impact of calorie consumption on wages is most pronounced at the lower end of the wage distribution and diminishes at higher wage levels. For all workers, the calorie–wage elasticity ranges from 0.21 to 0.25 at the 10th and 25th quantiles, while the IVQR estimate falls to 0.20 at the 90th quantile. This pattern suggests that lower-wage workers derive greater wage gains from increased calorie intake compared to their higher-wage workers at the 90th quantiles. This implies that a 10% increase in calorie consumption will increase wages by 2.5% at the 25th quantile.

The pattern differs by worker type: for elementary workers, the elasticity is 0.11 at the 10th quantile and declines to 0.09 at the 90th quantile, while for non-elementary workers, it is significantly larger, peaking at 0.35 at the 25th quantile and decreasing to 0.25 at the 90th quantile. In general, the calorie effect is larger among non-elementary workers than among elementary workers, findings consistent with the IV estimates. These results indicate that calorie intake has a greater effect on wages for lower-income workers, particularly those in non-elementary occupations. The IVQR results for non-elementary workers in column (2) show that the calorie-wage elasticity increases from 0.25 to 0.35 from the 10th to 25th quantile of the wage distribution. Calorie-wage elasticity at the highest (90th) quantile of the wage distribution is 0.25, which means that a 10% increase in calorie intake per consumer unit will lead to a 2.5% (Rs 9.5) increase in the daily wage of non-elementary workers. We used the Wald test to check the joint significance of coefficients across quantiles, and we rejected the null at a 99% level of significance.[13]

Figure 1 graphically presents the results from QR, 2SLS, and IVQR models. The x-axis represents the wage distribution of workers, and the y-axis represents wage elasticities. The QR estimates are considerably lower than the IVQR estimates at each level of the wage distribution. This again reinforces the need to correct the endogeneity bias. If we ignore the endogeneity bias, the estimates obtained from the QR model severely underestimate the true effect of calories on wages. Both the QR and IVQR models show that the effects of calorie intake on wages decrease by the quantile order, with substantially larger effects at the lower tail of the wage distribution. Among the three models, the wage elasticity is highest in the

[13] The p-value for all workers sample is tau (0.1, 0.25, 0.5, 0.75, 0.90) = 0.03; the p-value for elementary workers sample is tau (0.1, 0.25, 0.5, 0.75, 0.90) $<$ 0.000; the p-value for non-elementary workers sample is tau (0.1, 0.25, 0.5, 0.75, 0.90) $<$ 0.000.

IVQR model.

A comparison of the quantile and linear regression estimates is presented in Figure 2. Results show that the linear regression coefficient does not converge with the QR coefficient, except at one or two points. Calorie-wage elasticity for the elementary workers at the mean of the wage distribution is equal to the calorie-wage elasticity between the 80th to 90th quantiles of the wage distribution (Figure 2a). Similarly, Figure (2b) shows that the linear regression coefficient converges with the QR coefficient at the 10th and 20th, and about the 60th quantile of wage distribution for non-elementary workers. These figures justify the need for a QR model rather than a simple mean-based regression.

Comparing the QR and IVQR results, we find that QR results consistently underestimate the true effect of nutrition on wages. Our results also support that the self-selection bias is more pronounced among workers at the upper tail of the wage distribution. For instance, the IVQR effect of nutrition on wages for all workers at the extreme right of the wage distribution is 50% larger than the QR estimate (0.9 quantiles) but only 26% larger at the extreme left of the wage distribution (0.1 quantiles). For non-elementary workers, the percent difference in QR and IVQR estimates is larger at 0.9 quantiles (47%) than at 0.1 quantiles (21%). This implies that if we ignore the self-selection bias and endogeneity in calorie consumption, the calorie-wage elasticity is more underestimated for workers at the upper tail of the wage distribution than the workers at the lower tail of the wage distribution. These findings suggest that variation in the magnitude of selection bias in the nutrition-wage link depends on the initial distribution of wages.

6 Conclusions

How does calorie intake affect wages in India? Is there evidence of the efficiency-wage hypothesis in India? These questions have intrigued policymakers for a long time. Previous studies have modeled the efficiency wage hypothesis as the reason why people are trapped in poverty in developing countries. According to EWH, poor people are stuck in a vicious cycle of poverty due to inadequate nutrition intake and have identified undernutrition as a source of an S-shaped poverty trap. Undernourished people are less productive at the workplace and therefore receive lower wages compared to adequately nourished people. Furthermore, lower wage and earning exacerbates their ability to consume more calories, and thus they are stuck in a self-perpetuating poverty trap. Banerjee and Duflo (2011) argue that inadequate nutrition can be a source of the poverty trap in developing countries.

We explore this question in India using NSS data collected in 2011-12. We examine the causal relationship between calorie intake and wages in India, applying 2SLS and IVQR methods to account for endogeneity and heterogeneity. Our results support the efficiency wage hypothesis, showing that higher calorie consumption significantly raises wages. However, the wage benefits of calorie intake vary across occupational groups and along the wage distribution, with lower-wage (10th quantiles) and non-elementary workers gaining the most from increased calorie intake. The IVQR model shows a declining calorie-wage elasticity at higher wage levels, suggesting that elementary workers, who generally consume fewer calories, would gain the most from nutritional interventions. This aligns with prior research indicating that in low-income settings, such as elementary occupation-based households, improved nutrition enhances earnings but at a diminishing rate (Strauss, 1986; Deolalikar, 1988; Strauss and Thomas, 1998). Among the non-elementary workers, the regression coefficient at the 10th quantile is 0.34 compared to 0.28 at the 90th quantile of the wage distribution. This implies that the same amount of food supplementation among the non-elementary workers at the 10th wage quantile will result in more wage gain compared to the wage gain at the 90th quantile.

These findings have significant policy implications, particularly in the context of India's contemporary food security initiatives. Our study suggests that targeted nutritional support for the poorest populations could maximize both income gains and social welfare, given the constraints of limited economic resources. However, the steady decline in per capita calorie intake over the past three decades underscores the need for universal food security measures (Srivastava and Chand, 2017). Additionally, our findings highlight the vulnerability of workers in elementary occupations, who face lower wage gains from increased calorie intake. Since a majority of the poor are employed in the elementary sectors, inadequate nutrition can have devastating consequences for their productivity and well-being. Policymakers should consider designing specialized nutritional interventions to break the cycle of low wages and undernutrition for these workers.

Our results should be interpreted with caution. The average calorie consumption per consumer unit in our sample is 2,657 kcal/day, exceeding the recommended daily intake. However, when interpreting these findings for policy recommendations, it is essential to distinguish between calorie intake per consumer unit versus per capita intake. Simply increasing calorie intake may not always lead to proportional health or productivity gains; in some cases, excessive calorie consumption could result in diminishing returns or even adverse health effects. This underscores the importance of targeted nutritional policies that go beyond calorie quantity and emphasize dietary quality and micronutrient sufficiency.

Furthermore, for workers already meeting their caloric needs, improving the nutritional composition of their diet—through greater intake of proteins, iron, and essential vitamins—may be more beneficial than increasing calorie consumption alone. Our findings highlight the marginal effect of calorie intake on wages, demonstrating a positive but not limitless impact on productivity. Beyond a certain threshold, additional calorie intake is unlikely to yield proportional wage or efficiency gains. Therefore, policy efforts should focus not only on ensuring adequate caloric intake for undernourished workers but also on enhancing diet quality to promote better health, sustained productivity, and long-term economic well-being.

Finally, it is important to note that household calorie requirements vary based on physical activity, age, and sex. While our study accounts for age and sex-based adjustments in calorie consumption, future research should incorporate more detailed measures of individual energy needs. Additionally, while our study establishes a strong link between calorie intake and wages among elementary workers, calorie intake alone does not fully capture nutritional adequacy. A well-balanced diet that includes proteins, vitamins, and essential micronutrients is crucial for overall productivity and economic mobility. If future datasets capture broader dietary intake, future research could be expanded to explore the combined effects of calorie, protein, and micronutrient consumption on wages. Ultimately, our findings reinforce the critical role of nutrition in enhancing labor productivity and earnings, emphasizing the need for comprehensive policies that improve dietary intake to drive economic growth and poverty reduction.

7 Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Table 1: Descriptive statistics

Variable	All workers (N: 70,202)			Elementary workers (N: 23,907)			Non-elementary workers (N: 46,295)		
	Mean	SD	Obs	Mean	SD	Obs	Mean	SD	Obs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Daily wages (INR)	232.6	337	70,202	123.9	144	23,907	336.1	424.1	46,295
Calorie intake per consumer unit	2653.4	1230.1	70,202	2539.8	1071.3	23,907	2761.4	1355.4	46,295
Calorie intake per capita	2167.2	990.7	70,202	2067.3	850	23,907	2262.3	1100	46,295
Age in years	36	11.8	70,202	37	12	23,907	35	11	46,295
Gender (Male)	0.78	0.41	55,939	0.73	0.44	17,615	0.83	0.37	38,324
Education level (%)									
Illiterate	0.28	0.45	13,458	0.43	0.50	8,957	0.14	0.35	4,501
Below primary	0.11	0.31	6,124	0.15	0.36	3,409	0.07	0.26	2,715
Primary completed	0.14	0.34	8,400	0.16	0.37	4,025	0.11	0.32	4,375
Middle education	0.16	0.36	11,545	0.15	0.36	4,257	0.17	0.37	7,288
Secondary education	0.11	0.31	8,975	0.08	0.26	2,168	0.14	0.34	6,807
Higher sec. and above	0.21	0.41	21,700	0.04	0.19	1,091	0.37	0.48	20,609
Technical education (Yes)	0.05	0.21	4,156	0.00	0.04	63	0.09	0.29	4,093
Rural (%)	0.66	0.47	38,365	0.85	0.36	16,905	0.48	0.50	21,460
Hindu (%)	0.84	0.37	54,028	0.86	0.35	19,204	0.82	0.38	34,824
Muslim (%)	0.11	0.31	8,338	0.10	0.30	2,927	0.12	0.32	5,411
SC/ST	0.34	0.48	23,912	0.45	0.50	10,461	0.25	0.43	13,451
OBC	0.41	0.49	26,120	0.40	0.49	9,030	0.41	0.49	17,090
Other caste	0.25	0.43	20,170	0.15	0.36	4,416	0.34	0.47	15,754
Landholding (%)									
Less than one acre	0.85	0.35	58,255	0.87	0.34	20,615	0.84	0.36	37,640
1-3 acre	0.10	0.29	7,578	0.10	0.30	2,433	0.09	0.29	5,145
More than three acres	0.05	0.22	4,369	0.03	0.18	859	0.07	0.25	3,510
Occupation of the worker (%)									
Legislators, officials, manager	0.02	0.14	1,693	–	–	–	0.04	0.19	1,693
Professionals	0.05	0.21	5,419	–	–	–	0.09	0.29	5,419
Associate professionals	0.06	0.23	7,820	–	–	–	0.11	0.31	7,820
Clerks	0.04	0.20	4,257	–	–	–	0.08	0.27	4,257
Service workers, shops, marketing	0.07	0.26	7,271	–	–	–	0.14	0.35	7,271
Skilled agricultural and fishery	0.04	0.21	2,398	–	–	–	0.09	0.28	2,398
Craft and related trades	0.16	0.36	11,672	–	–	–	0.30	0.46	11,672
Plant, machine operators, assembler	0.08	0.26	5,765	–	–	–	0.15	0.35	5,765
Elementary occupations	0.49	0.50	23,907	–	–	–	–	–	–
Types of elementary occupation (%)									
Sales, service, and elem occup	–	–	–	0.08	0.27	3,373	–	–	–
Agr., fishery, and related labour	–	–	–	0.65	0.48	10,516	–	–	–
Labourer in elem. occup.	–	–	–	0.27	0.44	10,018	–	–	–

Notes: SD denotes the standard deviation. SC refers to scheduled caste, ST refers to scheduled tribe, and OBC refers to other backward caste. INR refers to Indian rupees.

Table 2: OLS and Heckman sample selection results for all workers

	Log(Daily wage)			
	Currently employed workers		All workers	
	OLS		Heckman sample selection model	
	(1)	(2)	(3)	(4)
Log of calorie intake	0.17***	0.17***	0.17***	0.17***
	(0.02)	(0.02)	(0.02)	(0.02)
Age	0.04***	0.04***	0.05***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	-0.04***	-0.04***	-0.05***	-0.04***
	(0.00)	(0.00)	(0.00)	(0.00)
Female	-0.42***	-0.41***	-0.51***	-0.44***
	(0.01)	(0.03)	(0.03)	(0.01)
Below primary	0.06***	0.06***	0.06***	0.06***
	(0.02)	(0.02)	(0.01)	(0.01)
Primary completed	0.10***	0.09***	0.07***	0.08***
	(0.02)	(0.02)	(0.01)	(0.01)
Middle education	0.15***	0.15***	0.10***	0.11***
	(0.02)	(0.02)	(0.02)	(0.02)
Secondary education	0.28***	0.28***	0.19***	0.22***
	(0.02)	(0.02)	(0.02)	(0.02)
Higher sec. and above	0.55***	0.54***	0.49***	0.50***
	(0.03)	(0.03)	(0.02)	(0.02)
Technical education	0.28***	0.27***	0.28***	0.25***
	(0.03)	(0.03)	(0.03)	(0.03)
Urban dummy	0.24***	0.25***	0.21***	0.23***
	(0.02)	(0.02)	(0.02)	(0.02)
Inverse Mills ratio			-0.02	0.10**
			(0.03)	(0.03)
R-squared	0.50	0.54	0.50	0.54
NSS Region fixed effects	No	Yes	No	Yes
Observations	70,195	70,195	70,182	70,182

Notes: Standard errors, clustered at the district level, are reported in parentheses. Calorie intake is expressed as per consumer unit consumption per day. Significance levels: * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 3: First-stage results from the IV model

	Log(Calorie intake)			
	All workers		Elementary workers	Non-elementary workers
	(1)	(2)	(3)	(4)
Panel A: First-stage estimates				
Log of monthly per capita cons exp	0.66***	0.67***	0.76***	0.61***
	(0.01)	(0.011)	(0.02)	(0.01)
Log of calorie price	-0.85***	-0.86***	-0.87***	-0.85***
	(0.02)	(0.02)	(0.02)	(0.03)
Education of the household head				
Below primary	-0.004	0.02***	0.02**	0.003
	(0.008)	(0.008)	(0.01)	(0.01)
Primary completed	0.002	0.03***	0.03***	0.009
	(0.008)	(0.008)	(0.01)	(0.009)
Middle education	0.004	0.03***	0.03**	0.02**
	(0.008)	(0.009)	(0.01)	(0.01)
Secondary education	-0.014	0.006	0.02	-0.01
	(0.009)	(0.009)	(0.02)	(0.01)
Higher sec. and above	-0.05***	-0.04***	-0.04	-0.04***
	(0.001)	(0.01)	(0.03)	(0.01)
Panel B: First-stage statistics				
F-stat	577.12	612.25	467.78	453.68
Weak identification test				
K-P Wald rk F stat	577.25	612.25	467.78	453.68
Cragg-Donald Wald F statistic	21462.2	21777.20	7255.79	14460.17
Panel C: Weak-instrument robust inference				
Anderson-Rubin Wald test F-stat	135.88	132.80	8.24	130.78
Stock-Wright LM S stat (p-value)	< 0.000	< 0.000	< 0.000	< 0.000
Panel D: Overidentification test				
Hansen J-stat	124.03	131.49	33.65	113.69
P-value	< 0.000	< 0.000	< 0.000	< 0.000
Heckman sample selection	No	Yes	Yes	Yes
Observations	70,186	70,182	23,899	46,283

Notes: Calorie intake is expressed as per consumer unit consumption per day. Standard errors, clustered at the district level, are reported in parentheses. Regression results are adjusted for age, age squared, gender, general education, technical education, urban dummy, caste, religion, land holding size, agriculture seasons, occupation types, and NSS region fixed effects. Significance levels: * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 4: Calorie intake and wages (2SLS estimates)

	DV: Log(Daily wage)			
	All workers		Elementary workers	Non-elementary workers
	(1)	(2)	(3)	(4)
Log of calorie intake	0.27***	0.25***	0.10***	0.33***
	(0.03)	(0.03)	(0.03)	(0.04)
R-squared	0.47	0.47	0.19	0.49
NSS Region fixed effects	Yes	Yes	Yes	Yes
Heckman sample selection	No	Yes	Yes	Yes
Observations	70,186	70,182	23,899	46,283

Notes: Standard errors, clustered at the district level, are reported in parentheses. Calorie intake is expressed as per consumer unit consumption per day. Regression results are adjusted for age, age squared, gender, general education, technical education, urban dummy, caste, religion, land holding size, agriculture seasons, and occupation types. Significance levels: * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 5: Heterogeneity in the effects (2SLS estimates)

	DV: Log(daily wage)					
	All workers		Elementary workers		Non-elementary workers	
	Calorie intake $\leq$ mean	Calorie intake $>$ mean	Calorie intake $\leq$ mean	Calorie intake $>$ mean	Calorie intake $\leq$ mean	Calorie intake $>$ mean
	(1)	(2)	(3)	(4)	(5)	(6)
Log of calorie intake	0.33***	0.17***	0.06	0.11***	0.52***	0.20***
	(0.05)	(0.04)	(0.07)	(0.04)	(0.06)	(0.06)
F-stat	385.26	197.49	141.35	140.9	385.96	122.53
Hansen J-stat	106.79	123.62	24.22	36.22	101.82	105.62
R-squared	0.38	0.54	0.21	0.16	0.42	0.53
NSS Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Heckman sample selection	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,502	30,680	13,223	10,676	26,080	20,203

Notes: Standard errors, clustered at the district level, are reported in parentheses. Calorie intake is expressed as per consumer unit consumption per day. Regression results are adjusted for age, age squared, gender, general education, technical education, urban dummy, caste, religion, land holding size, agriculture seasons, and occupation types. Significance levels: * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 6: Robustness checks: Calorie intake per capita

	DV: Log(Daily wage)		
	All workers	Elementary workers	Non-elementary workers
	(1)	(2)	(3)
Log of calorie intake per capita	0.27***	0.09***	0.37***
	(0.03)	(0.03)	(0.04)
F-stat	573.35	454.98	425.79
Hansen J-stat	129.73	33.27	109.58
R-squared	0.47	0.19	0.49
Mean calorie consumption	2269.68	2065.32	2375.20
NSS Region fixed effects	Yes	Yes	Yes
Heckman sample selection	Yes	Yes	Yes
Observations	70,182	23,899	46,283

Notes: Standard errors, clustered at the district level, are reported in parentheses. The regression models in this table used daily calorie intake per capita instead of daily calorie intake per consumer unit. Mean calorie consumption is in per capita terms. Regression results are adjusted for age, age squared, gender, general education, technical education, urban dummy, caste, religion, land holding size, agriculture seasons, and occupation types. Significance levels: * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 7: QR and IVQR coefficients of calorie intake on wage

	DV: Log(Daily wage)	
	QR model	2SLS-IVQR model
	(1)	(2)
Panel A: Total workers		
Quantile 10	0.18*** (0.01)	0.21*** (0.02)
Quantile 25	0.18*** (0.01)	0.25*** (0.01)
Median	0.13*** (0.01)	0.20*** (0.01)
Quantile 75	0.13*** (0.01)	0.20*** (0.01)
Quantile 90	0.13*** (0.01)	0.20*** (0.01)
Panel B: Elementary workers		
Quantile 10	0.11*** (0.01)	0.11*** (0.02)
Quantile 25	0.11*** (0.01)	0.11*** (0.02)
Median	0.07*** (0.01)	0.06*** (0.01)
Quantile 75	0.04*** (0.01)	0.05*** (0.01)
Quantile 90	0.07*** (0.01)	0.09*** (0.01)
Panel C: Non-elementary workers		
Quantile 10	0.21*** (0.02)	0.25*** (0.02)
Quantile 25	0.25*** (0.01)	0.35*** (0.02)
Median	0.20*** (0.01)	0.31*** (0.02)
Quantile 75	0.20*** (0.01)	0.31*** (0.02)
Quantile 90	0.16*** (0.01)	0.25*** (0.02)

Note: Standard errors, clustered at the district level, are in parentheses. Calorie intake is expressed as per consumer unit consumption per day. Quantiles are for wages. Regression results are adjusted for age, age squared, sex, education, technical training, place of residence, caste, religion, land holding, agriculture seasons, type of occupation, and district agro-climatic region fixed effects. The model is not converging at 0.25 quantiles for elementary workers; therefore, quantile 0.26 has been used. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

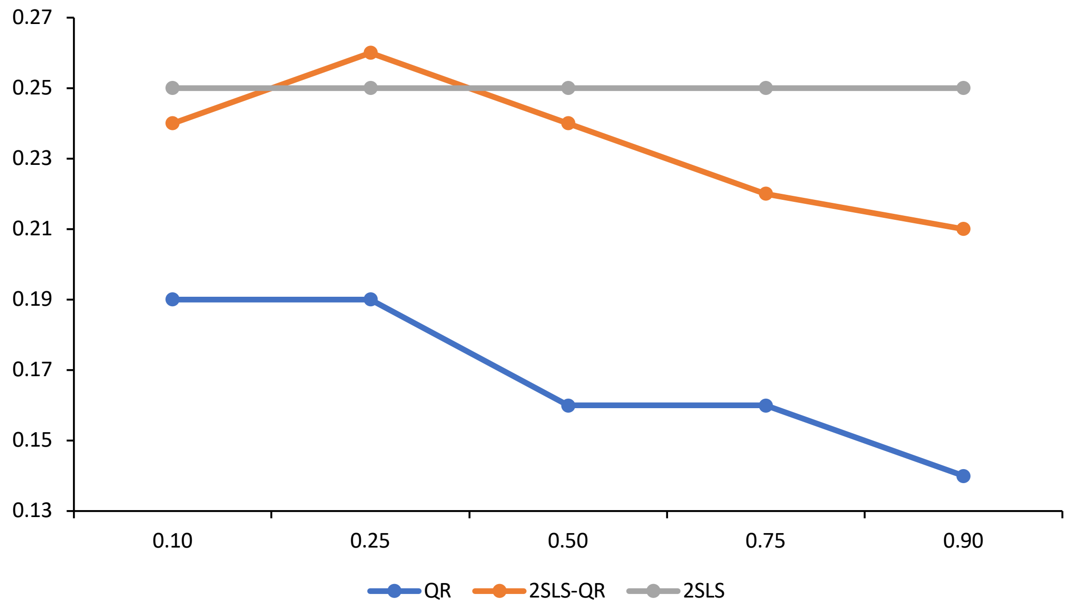

Figure 1: Effect of calories on wage: QR, 2SLS, and IVQR estimates

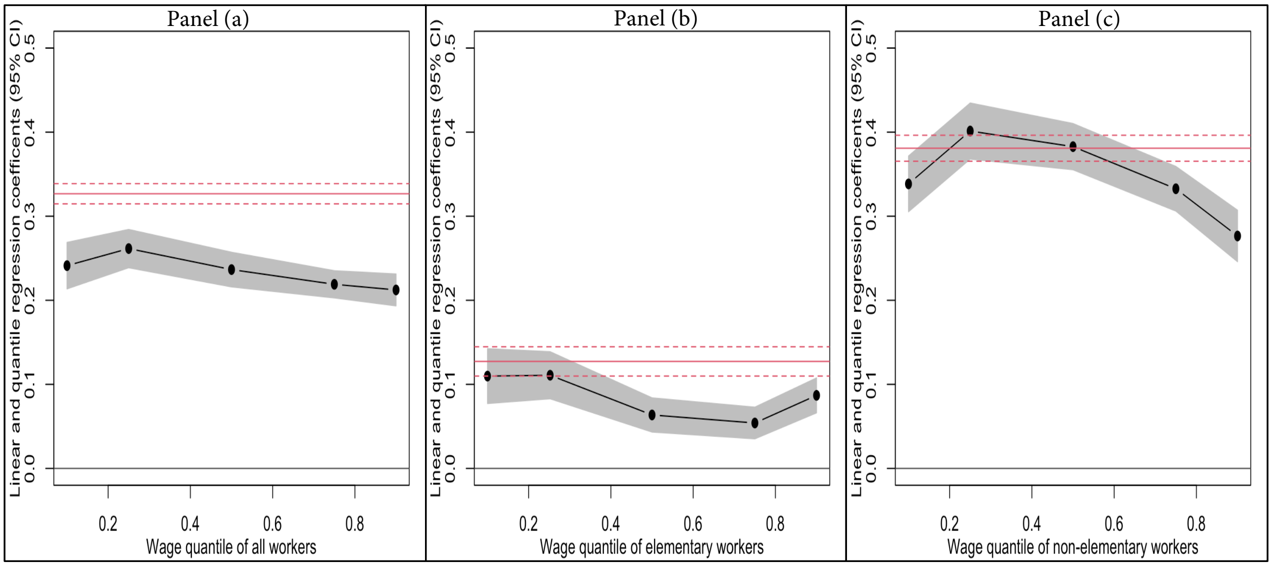

Figure 2: 2SLS and IVQR coefficients at different quantiles of wage distribution.

Notes: Heckman sample selection model used. Inverse Mills ratios were estimated separately for each group.

Appendix

Table A1: Summary statistics

	All workers		Elementary workers		Non-elementary workers	
	Daily wage	Calorie intake	Daily wage	Calorie intake	Daily wage	Calorie intake
	(1)	(2)	(3)	(4)	(5)	(6)
Inter-quartile range	120	1169	71	1087	286	1213
10th percentile	57	1533	51	1492	71	1587
25th percentile	94	1951	79	1886	114	2020
Median	140	2452	107	2357	200	2545
75th percentile	214	3120	150	2973	400	3234
90th percentile	529	3920	200	3759	800	4090
Observations	70,202	70,202	24,907	23,907	46,295	46,295

Notes: Calorie intake is expressed in per consumer unit per day.

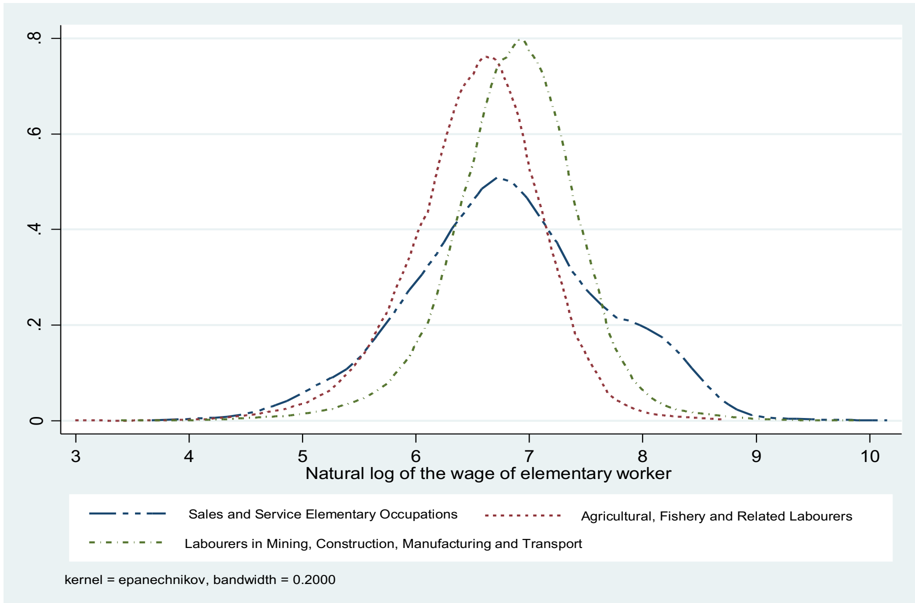

Figure A1: Kernel density of the natural log of wage earnings of the elementary workers engaged in different occupations, India, 2011-12

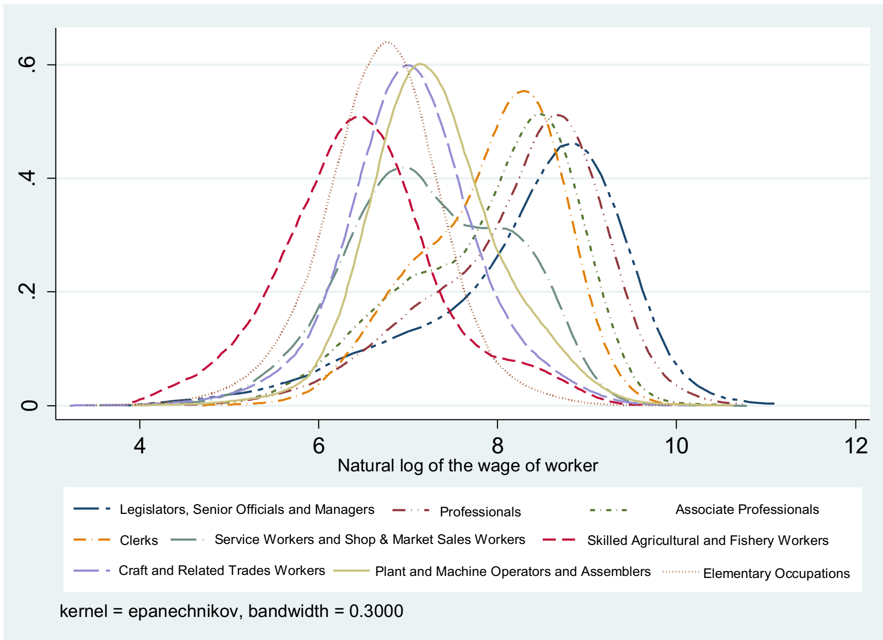

Figure A2: Kernel density of the natural log of wages of all workers engaged in different occupations, India, 2011-12