Spillover Impacts of Informal Employment on Indonesia's Food Security

Rizki Tri Anggara[1,*], Elsya Gumayanti Alfahma[1]

[1] BPS-Statistics of Prabumulih Municipality, Indonesia

*Corresponding author's email: rizki.anggara@bps.go.id

Abstract. This study analyzes the impact of informal employment on household food security in Indonesia, focusing on regional disparities in provinces with high concentrations of informal workers. Using national socioeconomic survey data, logistic regression models initially assessed the associations between informal employment and food security outcomes. To strengthen causal inferences and mitigate selection bias, a comprehensive Propensity Score Matching (PSM) analysis was subsequently conducted. The findings from both approaches consistently link informal employment to adverse food security outcomes, including food availability concerns, limited access to nutritious food, and lower dietary diversity. Provinces with a high prevalence of informal workers consistently demonstrate poorer food security metrics, with the PSM analysis revealing more pronounced negative impacts in these regions, indicating significant spillover effects. Factors such as tertiary education, internet access, and health insurance are positively associated with improved food security, highlighting the critical role of human capital and resource access. These results underscore the importance of employment stability and regional labor market structures in shaping food security. Policies promoting formal employment and stronger social safety nets are critical for equitable food security across Indonesia.
Keyword: Food security, Indonesia, informal employment, socioeconomic disparities.

1. Introduction

Global food security, defined by consistent access to sufficient and nutritious food for all individuals to meet their dietary needs and food preferences for an active and healthy life, persists as a critical humanitarian and developmental challenge. The Food and Agriculture Organization (FAO), in its 2021 report, underscored the alarming statistic that over 811 million individuals globally experienced hunger in 2020, with the most severe impacts disproportionately borne by developing regions in Asia and Africa [1]. This pervasive crisis extends beyond mere caloric deficiency, encompassing the complex interplay of socioeconomic determinants that profoundly influence household food security. Among these, employment status emerges as a pivotal factor in shaping a household's capacity to secure adequate nourishment [2, 3].

The global labor landscape is significantly characterized by the widespread prevalence of informal employment, which constitutes over 60% of all jobs worldwide and nearly 90% in developing nations [4]. While informal jobs often serve as critical income sources, their inherent instability and lack of social safety nets expose workers and their households to increased risks of poverty and food insecurity [5, 6]. This economic precariousness amplifies exposure to financial shocks, making it difficult for households to sustain consistent access to sufficient and nutritious food [7].

The relationship between informal employment and food security is particularly relevant in Indonesia, a country characterized by a high prevalence of informal labor and diverse socioeconomic landscapes. Prior research has shown that informal employment negatively impacts food security, often resulting in income instability and dependence on low-cost calorie-dense diets [8-11]. Sectoral and geographical variations complicate these dynamics, highlighting the need for tailored policy interventions to address the unique challenges faced by different groups of informal workers [12-16]. The COVID-19 pandemic further exacerbated these vulnerabilities, with lockdowns causing significant declines in income and food security [17-19].

Despite significant advancements in understanding the link between informal employment and food security, several gaps remain in the literature. Many studies aggregate formal and informal employment into broader categories, failing to disaggregate the specific vulnerabilities associated with informal work. Furthermore, existing research often focuses on singular dimensions of food security, such as food expenditure or caloric intake, neglecting broader considerations like psychological concerns about food sufficiency, nutritious food consumption, or dietary diversity. The broader contextual effects stemming from a high concentration of informal employment within a region also remain underexplored, raising questions about how high concentrations of informal workers in specific regions influence collective food security.

This study aims to explore the spillover effects of informal employment on household food security in Indonesia, focusing on three dimensions: psychological concerns over food availability, access to nutritious food, and dietary diversity. We refer to these as 'spillover effects,' defining them as the aggregate impact a dominant informal labor market has on the overall economic environment within a province. By examining these outcomes, the research addresses critical gaps in the existing literature, such as the limited exploration of geographic and sectoral variations and the lack of comprehensive analysis of food security's multidimensional aspects. Additionally, the study investigates community-level spillover effects, as regions with high concentrations of informal workers may face collective vulnerabilities that influence household food security.

Using nationally representative data from the March 2021 Indonesia National Socioeconomic Survey (SUSENAS), this research employs rigorous logistic regression methods to provide insights into these relationships. Building upon these findings, a comprehensive Propensity Score Matching (PSM) analysis was conducted as a further, more robust step to investigate the causal impact of informal employment on household food security outcomes. While logistic regression effectively identified associations, PSM was employed to mitigate potential selection bias inherent in observational studies, thereby strengthening the causal inferences. By creating a quasi-experimental setting, PSM allowed for a more direct comparison between households headed by informal workers and observationally similar households headed by formal workers. The PSM analysis specifically aimed to assess the differences in food security outcomes across all observations, as well as within provinces categorized by high and low concentrations of informal employment.

The findings reveal that informal employment is strongly associated with adverse food security outcomes, including heightened concerns about food availability, reduced access to nutritious food, and diminished dietary diversity. Moreover, provinces with a high prevalence of informal workers consistently demonstrate poorer food security indicators. These results highlight the critical role of employment stability and regional labor market structures in shaping food security.

The contributions of this study are both theoretical and practical. Academically, it advances understanding of the impact of informal employment on food security by offering a multidimensional perspective that incorporates geographic, sectoral, and community-level analyses, further strengthened by the causal inferences drawn from the PSM approach. Practically, the findings provide evidence-based recommendations for targeted policy interventions, such as expanding social protections for informal workers, improving access to education and health insurance, and enhancing food security infrastructure in high-risk regions. Ultimately, the research seeks to inform strategies for building resilient and equitable food systems, aligning with broader sustainable development goals.

2. Research Method

This study utilizes cross-sectional data from the March 2021 Indonesia National Socioeconomic Survey, conducted by Statistics Indonesia (BPS). The survey is nationally representative and provides extensive information on household socioeconomic characteristics, employment status, and food security outcomes. The analysis focuses on employed household heads, as their employment type significantly impacts household well-being. Households where the head was unemployed or not actively engaged in the labor force were excluded to ensure the analysis centers on the relationship between employment and food security.

The dependent variables in this study represent three dimensions of food security and are measured as binary outcomes. These include psychological concerns over food availability, access to nutritious food, and dietary diversity. These variables are aligned with global food security frameworks, providing a comprehensive perspective on psychological, qualitative, and behavioral dimensions of food security.

The primary independent variable is the employment status of the household head, categorized as informal and formal. Informal employment includes workers without formal contracts or access to employment benefits, such as casual laborers, self-employed individuals without permanent staff, and workers in non-regulated or non-standard arrangements. Formal employment includes workers with permanent contracts and access to legal protections and social security. This classification follows internationally recognized definitions from BPS and the 13th International Conference of Labour Statisticians [20].

Table 1. Research Variables.

Variable	Definition	Measurement
Dependent variables		
Concern about insufficient food	The household's psychological concern about food sufficiency	1 = Not worried 0 = Worried
Nutritious food	The household's consumption of nutritious food	1 = Consumed 0 = Not consumed
Dietary diversity	The diversity of the household's diet based on food groups consumed	1 = Diverse 0 = Not diverse
Independent variables		
Employment status	The household head's type of employment	1 = Informal 0 = Formal
Employment sector	The household head's employment sector	1 = Non-agricultural 0 = Agriculture
High informal province	Proportion of informal workers in the province	1 = High (>59.45%) 0 = Low (≤59.45%)
Area	The household's area of residence	1 = Urban 0 = Rural
Sex	Gender of household head	1 = Male 0 = Female
Education level	Highest education level of household head	1 = Tertiary 0 = Lower education
Household size	Total number of individuals living in the household.	Continuous variable
Internet access	Availability of internet access	1 = Has access 0 = Has no access

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Health insurance	Coverage of household head by national health insurance	1 = Has coverage 0 = Has no coverage

One key contextual variable is the proportion of informal workers in each province, categorized as high informal employment and low informal employment. Provinces with a proportion of informal workers exceeding the national average of 59.45% in 2021, as reported by BPS [20], are classified as high informal provinces. While there is no specific economic theory identifying a precise 'tipping point' at which contextual effects emerge, the national average was selected as a meaningful and objective benchmark. It provides an empirically grounded criterion to distinguish between provinces with a typical versus an unusually high concentration of informal labor. By using this threshold, we can effectively categorize regions where the structural challenges associated with informality—such as depressed local economies, limited formal job opportunities, and weaker social safety nets—are most acute. Therefore, this classification serves as a robust proxy for identifying provinces where the aggregate negative effects on community-wide food security are most likely to be pronounced.

Control variables include demographic and socioeconomic factors: area of residence, gender of the household head, education level, household size, internet access, health insurance coverage, and employment sector. These variables account for potential confounders influencing food security outcomes. For instance, higher education levels and internet access are often associated with better access to income-generating opportunities, while larger household sizes may increase vulnerability to food insecurity due to resource constraints.

The analytical framework employs logistic regression to estimate the likelihood of achieving favorable food security outcomes as a function of employment status and other predictors. Logistic regression is an appropriate method for analyzing binary dependent variables, as it estimates the probability of achieving specific food security outcomes based on the influence of predictor variables [21, 22]. The models are adjusted for the complex survey design by incorporating strata, primary sampling units, and sample weights, ensuring robust standard errors and generalizability. The strata are defined by a combination of province and urban/rural classification to account for geographic and developmental variations, while the PSUs correspond to the specific census blocks selected in the first stage of the multi-stage sampling frame. Crucially, the final household sample weights are applied to correct for unequal probabilities of selection, non-response, and other demographic imbalances.

Given the binary nature of the dependent variables, logistic regression is employed to model the probability of achieving a favorable food security outcome. For each food security dimension $Y_{\mathrm{j}} \in \{Y_1, Y_2, Y_3\}$, we assume that Y_{j} follows a Bernoulli distribution, where $P\ (Y_{\mathrm{j}} = 1)$ is the probability of a favorable outcome. The logistic regression model relates the probability $P\ (Y_{\mathrm{j}} = 1)$ to a linear combination of predictor variables through the logit link function:

$$\mathrm{logit}\big(\mathrm{P}(Y_{\mathrm{j}} = 1)\big) = \ln\left(\frac{P\ (Y_{\mathrm{j}} = 1)}{1 - P\ (Y_{\mathrm{j}} = 1)}\right) = \beta_{0\mathrm{j}} + \sum_{i=1}^{k} \beta_{ij}\, X_i + \varepsilon_i$$

Where $P\ (Y_{\mathrm{j}} = 1)$ is the probability of the j-th food security outcome being 1 (favorable outcome), β coefficients capture the effects of predictors, X_i represents the independent and control variables, and ε is the error term. This equation allows the analysis to disentangle the direct and contextual impacts of informal employment on food security. The odds ratio for informal employment is given by $e^{\beta 1}$, indicating how the odds of a favorable food security outcome change for informal employment relative to formal employment, holding other variables constant.

Rearranging the equation, the probability $P\ (Y_{\mathrm{j}} = 1)$ can be expressed as:

$$P\left(Y_{\mathrm{j}} = 1\right) = \frac{\exp(\beta_{0\mathrm{j}} + \sum_{i=1}^{k} \beta_{ij}\, X_i)}{1 + \exp(\beta_{0\mathrm{j}} + \sum_{i=1}^{k} \beta_{ij}\, X_i)}$$

This is the logistic function, which constrains the predicted probabilities to lie between 0 and 1.

The coefficients β_{ij} are estimated using the method of Maximum Likelihood Estimation (MLE). For a dataset of N independent observations, the likelihood function $L(\beta)$ is the product of the probabilities of observing the actual outcomes:

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$$L(\beta) = \prod_{n=1}^{N} P(Y_{\text{jn}} = 1)^{Y_{\text{jn}}} \left(1 - P(Y_{\text{jn}} = 1)\right)^{1-Y_{\text{jn}}}$$

Where Y_{jn} is the observed outcome for the n-th household for the j-th food security dimension. Substituting the logistic function for $P(Y_{\text{jn}} = 1)$:

$$L(\beta) = \prod_{n=1}^{N} \left(\frac{\exp(X_n\beta)}{1 + \exp(X_n\beta)}\right)^{Y_{\text{jn}}} \left(\frac{1}{1 + \exp(X_n\beta)}\right)^{1-Y_{\text{jn}}}$$

For computational convenience, it is common to maximize the natural logarithm of the likelihood function, known as the log-likelihood function, $l(\beta)$=$ln(L(\beta))$:

$$l(\beta) = \sum_{n=1}^{N} [Y_{\text{jn}}\,(X_n\beta) - \ln\,(1 + \exp(X_n\beta))]$$

Where $X_n\beta = \beta_{0j} + \sum_{i=1}^{N} \beta_{ij} X_{1n}$. The MLE estimates $\hat{\beta}$ are the values of β that maximize this log-likelihood function. This maximization is typically achieved using iterative numerical methods, such as Newton-Raphson.

The coefficients β_{ij} in logistic regression represent the change in the log-odds of the outcome for a one-unit increase in the corresponding predictor variable, holding all other variables constant. While log-odds are not intuitively interpretable, exponentiating the coefficients yields the odds ratio (OR):

$$OR_{ij} = \exp\,(\beta_{ij})$$

The odds ratio OR_{ij} indicates how the odds of a favorable food security outcome change for a one-unit increase in X_i. An OR_{ij} greater than 1 indicates that the odds of the favorable outcome increase, whereas an OR_{ij} less than 1 indicates a decrease in the odds. A value of exactly 1 implies that there is no change in the odds. For a binary predictor (e.g., informal employment vs. formal employment), exp (β_{ij}) represents the ratio of the odds of the outcome for the group coded 1 (informal employment) compared to the group coded 0 (formal employment).

Building upon the initial logistic regression findings, PSM analysis was conducted to investigate the causal impact of informal employment on household food security outcomes. The process began with the estimation of a propensity score for each household using a probit model, which calculated the conditional probability of the household head being in informal employment based on observed covariates. The propensity score, $e(X)$is the conditional probability of receiving the exposure (being informally employed) given a set of observed covariates X. It is estimated using a probit regression model:

$$e(x) = P(D = 1\,|X) = \emptyset\,(\gamma_0 \sum_{i=1}^{k} \gamma_i X_i)$$

Where $D = 1$ denotes informal employment (exposed group), $\emptyset(.)$ represents the cumulative distribution function (CDF) of the standard normal distribution, and X is the vector of covariates used for matching: area, sex, education level, household size, internet access, and health insurance. Furthermore, γ_0 is the intercept and γ_i are the coefficients for the covariates X_i. This step generates a single score for each household, representing its likelihood of being in informal employment based on its observable characteristics.

To ensure valid comparisons, a region of common support was then established, restricting the analysis to observations where there was a sufficient overlap in characteristics between the informal (exposed) and formal (control) groups. The region of common support ensures that for every exposed individual, there is at least one control individual with a similar propensity score, and vice versa. This condition is crucial for valid causal inference, as it ensures that comparisons are made only among individuals who have a realistic chance of being in either the exposed or control group. Observations falling outside this region are excluded from the matching process. The analysis confirmed a robust overlap, with most observations falling within this common support region across all observation groups (all observations, high informal provinces, and low informal provinces).

After estimating propensity scores and defining the common support region, exposed observations were matched to control observations using the Nearest Neighbor (NN=5 ties) matching algorithm. The selection of five neighbors is a common and well-regarded choice in applied econometrics that represents a pragmatic balance between reducing bias and minimizing variance in the estimation of treatment effects [23]. This method selects the 5 control observations with the closest propensity scores to each exposed observation, allowing for ties. The matching was performed with replacement to maximize the number of matched units and improve balance. The covariates used for matching were area, sex, education level, household size, internet access, and health insurance.

The quality of the matching procedure was rigorously assessed through a balancing check, employing independent samples t-tests to compare the means of key covariates between the exposed and control groups both before and after matching. The objective was to achieve a significant reduction in bias and ensure that any remaining differences in covariate means were statistically insignificant ($p > 0.05$) after the matching process. The percentage bias reduction was also calculated to quantify the improvement in covariate balance. The percentage bias for a covariate X_i is calculated as:

$$Bias = \frac{(\bar{X}_{i,exposed} - \bar{X}_{i,control})}{\sqrt{\frac{S^2{}_{i,exposed} + S^2{}_{i,control}}{2}}} X\ 100\%$$

Where $\bar{X}$ and S^2 are the mean and variance of covariate X_i for the exposed and control groups, respectively.

Finally, The Average Treatment Effect on the Exposed (ATE) quantifies the causal impact of informal employment on the food security outcomes. The ATE is estimated as the average difference in outcomes between the exposed individuals and their matched control counterparts:

$$ATT = E[Y_1|D = 1] - E[Y_0|D = 1] = E[Y_1|D = 1] - E[Y_0|D = 1], e(X)]$$

Where $E[Y_0|D = 1]$ is the expected outcome for the exposed group and $E[Y_0|D = 1], e(X)]$ is the expected outcome for the control group, conditional on their propensity scores being similar to the exposed group. The ATE was estimated for all observations, as well as separately for observations in high informal provinces and low informal provinces, for each of the three food security outcomes.

To assess the robustness of the estimated exposure effects against potential unobserved confounding, a Rosenbaum sensitivity analysis was conducted. This analysis explores how strong an unobserved covariate would need to be to alter the conclusions regarding the exposure effect. It calculates the upper and lower bounds of the significance level (p-values) for the estimated ATE under different assumptions about the magnitude of unobserved bias, represented by Gamma (Γ).

The core idea of Rosenbaum's sensitivity analysis is to quantify how much an unobserved covariate, U, would have to influence both the assignment to the exposed group and the outcome, to explain away the observed effect. Consider two individuals, k and l, who are matched on their observed covariates X, meaning their propensity scores $e(X_k)$=$e(X_l)$. If there is an unobserved covariate U, then their true probability of exposure might differ.

Rosenbaum and Silber [24] defines Γ as the ratio of the odds of exposure for two individuals who are identical on observed covariates but may differ on an unobserved covariate U:

$$\Gamma = \frac{P(D = 1|X, U = 1/P(D = 0|X, U = 1)}{(D = 1|X, U = 0/P(D = 0|X, U = 0)}$$

This implies that for two individuals k and l with the same observed covariates X, the ratio of their odds of exposure is bounded by Γ:

$$\frac{1}{\Gamma} \leq \frac{P(D = 1|X_k)}{P(D = 0|X_k)} . \frac{P(D = 0|X_l)}{P(D = 1|X_l)} \leq \Gamma$$

For a given Γ, the analysis calculates a range of possible p-values for the hypothesis of no exposure effect. If the entire range of p-values (from sig− to sig+) includes values greater than the chosen significance level (e.g., 0.05), then the estimated effect is sensitive to an unobserved confounder of that magnitude. Conversely, if the entire range remains below the significance level, the results are robust.

The analysis provides sig+ and sig− values, which represent the upper and lower bound significance levels, respectively. If the conclusions about the ATE remain consistent across a reasonable range of Γ values (e.g., $\Gamma = 1$ to $\Gamma = 3$), it suggests that the findings are robust to moderate levels of unobserved confounding.

3. Result and Discussion

The findings highlight significant disparities in food security outcomes based on employment status and provincial informal employment proportions. These disparities are evident across all three dimensions of food security. The results from t-tests and logistic regression analyses demonstrate the impact of informal employment on household food security and the contextual spillover effects of high informal employment provinces.

The t-tests reveal that households with formal employment exhibit significantly better food security outcomes compared to households with informal employment. For concern about insufficient food, the mean value is 0.842 for formal employment households and 0.775 for informal employment households, resulting in a statistically significant mean difference of 0.067 ($t = 45.39$, $p < 0.001$). This indicates that formal employment households are 6.7 percentage points more likely to report not worrying about food sufficiency.

Similarly, for nutritious food, the mean value is 0.927 for formal employment households and 0.879 for informal employment households, with a mean difference of 0.048 ($t = 42.37$, $p < 0.001$). For dietary diversity, the mean value is 0.934 for formal employment households and 0.898 for informal employment households, with a mean difference of 0.036 ($t = 34.53$, $p < 0.001$). These results indicate that formal employment households consistently experience better food security outcomes compared to their informal employment counterparts.

The analysis of provinces with high and low informal employment proportions shows a consistent pattern of disparities. Provinces with high informal employment consistently exhibit lower levels of food security across all three dimensions. These disparities, revealed through t-test analyses, highlight the systemic vulnerabilities in regions with a high concentration of informal workers.

For concern about insufficient food, the mean value is 0.831 in low informal provinces, compared to 0.777 in high informal provinces. The mean difference of 0.053 ($t = 38.19$, $p < 0.001$) indicates that households in low informal provinces are significantly more likely not to worry about food sufficiency compared to those in high informal provinces. This finding suggests that lower informal employment concentrations are associated with improved psychological stability regarding food security.

For nutritious food, the mean value in low informal provinces is 0.925, while in high informal provinces it is 0.876. The mean difference of 0.049 ($t = 46.18$, $p < 0.001$) demonstrates that households in provinces with lower informal employment proportions have significantly better access to nutritious food. This reflects the economic advantages and stability often found in provinces with a higher proportion of formal employment opportunities.

Table 2. T-Test Results for Formal vs. Informal Employment.

Variable	Status	Obs	Mean	Std. Err.	95% CI	Difference
Concern about insufficient food	Formal employment	117,088	0.842	0.001	0.840, 0.844	0.067***
	Informal employment	185,151	0.775	0.001	0.773, 0.777	
Nutritious food	Formal employment	117,014	0.927	0.001	0.926, 0.928	0.048***
	Informal employment	184,851	0.879	0.001	0.877, 0.880	

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Dietary diversity	Formal employment	117,141	0.934	0.001	0.933, 0.935	0.036***
	Informal employment	185,194	0.898	0.001	0.896; 0.899	

Note: * p < 0.10, ** p < 0.05, *** p < 0.01
Source: Authors' calculations

Table 3. T-Test Results for High vs. Low Informal Provinces.

Variable	Type	Obs	Mean	Std. Err.	95% CI	Difference
Concern about insufficient food	Low informal province	140,198	0.831	0.001	0.829, 0.833	0.053***
	High Informal province	198,817	0.777	0.001	0.776, 0.779	
Nutritious food	Low informal province	140,096	0.925	0.001	0.923, 0.926	0.049***
	High informal province	198,519	0.876	0.001	0.874, 0.877	
Dietary diversity	Low informal province	140,282	0.933	0.001	0.932, 0.934	0.041***
	High informal province	198,857	0.893	0.001	0.892, 0.894	

Note: * p < 0.10, ** p < 0.05, *** p < 0.01
Source: Authors' calculations

Dietary diversity follows a similar trend, with a mean value of 0.933 in low informal provinces compared to 0.893 in high informal provinces. The mean difference of 0.041 (t = 40.65, p < 0.001) underscores the positive association between lower informal employment proportions and dietary diversity. These results collectively illustrate that those provinces with high informal employment face notable challenges in ensuring food security for their populations.

The logistic regression analysis examines the impact of employment status and provincial informal employment proportions on food security outcomes, controlling for demographic and socioeconomic factors. The results confirm that informal employment is negatively associated with food security across all three dimensions. The analysis underscores the economic vulnerabilities linked to informal work and highlights key factors that mediate food security outcomes.

For concern about insufficient food, informal employment is associated with a negative and statistically significant coefficient (-0.146, p < 0.01). This finding suggests that households headed by informal workers are less likely to report not worrying about food sufficiency. The trend is consistent across other food security dimensions. For nutritious food, informal employment reduces the likelihood of consuming nutritious food, with a coefficient of -0.148 (p < 0.01). Similarly, dietary diversity is negatively affected, with a coefficient of -0.111 (p < 0.01). These results align with the premise that informal workers often experience irregular income and lack access to social safety nets, which constrain their ability to secure sufficient and nutritious food [11, 25, 26].

Regional variations are notable. Provinces with higher proportions of informal employment face significantly greater food security challenges. The coefficient for high informal provinces is -0.068 (p < 0.01) for concern about insufficient food, -0.222 (p < 0.01) for nutritious food, and -0.193 (p < 0.01) for dietary diversity. These findings demonstrate the spillover effects of regional labor market structures, revealing how systemic vulnerabilities extend beyond individual households. Households in rural areas also exhibit heightened vulnerabilities. Rural residence is associated with negative coefficients across all dimensions: -0.077 (p < 0.01) for concern about insufficient food, -0.056 (p < 0.10) for nutritious food, and -0.205 ($p < 0.01$) for dietary diversity. This aligns with prior findings, which emphasize the disproportionate food security challenges in such areas [27, 28]. Rural residence is associated with food insecurity possibly due to limited access to diverse food options, infrastructure, and services, compounded by reliance on subsistence agriculture and seasonal income variability [29, 30].

The sectoral coefficient adds further nuance to these findings by highlighting how employment in agriculture versus non-agriculture affects food security outcomes. For dietary diversity, the negative and statistically significant coefficient for the non-agriculture sector (-0.079, $p < 0.01$) indicates a disadvantage for workers outside agriculture, likely due to greater reliance on market-based food systems, which may limit access to diverse and fresh food. In contrast, the coefficients for concern about insufficient food (-0.021) and nutritious food (0.003) are statistically insignificant, suggesting that sectoral differences do not substantially influence these dimensions of food security. These findings suggest that while agricultural employment offers some dietary advantages through access to self-produced food, it does not necessarily mitigate concerns about food sufficiency or ensure greater consumption of nutritious food [31, 32].

Table 4. Logistic Regression Results.

Variable	Concern about insufficient food	Nutritious Food	Dietary Diversity
Employment status	-0.146*** (0.020)	-0.148*** (0.028)	-0.111*** (0.029)
Employment sector	-0.021 (0.021)	0.003 (0.027)	-0.079*** (0.029)
High informal province	-0.068*** (0.025)	-0.222*** (0.032)	-0.193*** (0.032)
Area	-0.077*** (0.027)	-0.056* (0.033)	-0.205*** (0.033)
Sex	0.226*** (0.024)	0.254*** (0.031)	0.280*** (0.034)
Education level	0.876*** (0.037)	0.810*** (0.054)	0.901*** (0.058)
Household size	-0.069*** (0.005)	-0.061*** (0.007)	-0.055*** (0.007)
Internet access	0.413*** (0.019)	0.600*** (0.027)	0.592*** (0.029)
Health insurance	0.016 (0.019)	0.056** (0.025)	0.058** (0.026)
Constant	1.476*** (0.041)	2.281*** (0.053)	2.463*** (0.055)
Number of observations	290,167	289,842	290,284

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations

The positive association of tertiary education, internet access, and health insurance with improved food security outcomes highlights critical protective factors. Tertiary education shows strong positive effects across all models: 0.876 ($p < 0.01$) for concern about insufficient food, 0.810 ($p < 0.01$) for nutritious food, and 0.901 ($p < 0.01$) for dietary diversity. These results highlight the critical role of higher education in improving food security, likely through increased income-earning potential, better access to resources, and enhanced knowledge about nutrition and food management [33]. Internet access similarly enhances food security, with coefficients of 0.413 ($p < 0.01$), 0.600 ($p < 0.01$), and 0.592 ($p < 0.01$), likely due to better access to information, markets, and services [34, 35]. Health insurance shows smaller but significant effects for nutritious food (0.056, $p < 0.05$) and dietary diversity (0.058, $p < 0.05$), suggesting it supports food quality by reducing financial strain [36, 37]. These results underscore the importance of education, digital inclusion, and health coverage in promoting food security.

Building upon the initial logistic regression findings, PSM analysis was conducted as a further, more robust step to investigate the causal impact of informal employment on household food security outcomes. While logistic regression effectively identified associations, PSM was employed to mitigate potential selection bias inherent in observational studies, thereby strengthening the causal inferences. The PSM methodology systematically applied through six key steps: estimating propensity scores, defining the region of common support, matching observations, assessing matching quality via balancing checks, estimating the ATE, and finally, performing a Rosenbaum sensitivity analysis.

The initial phase of the PSM analysis involved estimating the propensity score, which quantifies the probability of a household head being in informal employment given their observed characteristics. Following this, the crucial step of defining the region of common support was undertaken to ensure a substantial overlap in the propensity score distributions between the exposed and control groups, thereby enabling valid comparisons. As illustrated in Figure 1, the analysis confirmed a robust overlap in these distributions, with most observations falling within this common support region. Specifically, for the aggregated dataset, 115,174 control households and 173,896 treated households were found to be on support. Similarly, in provinces characterized by a high prevalence of informal employment, 59,476 control households and 109,422 exposed households were on support. For provinces with low informal employment, 55,698 control households and 64,474 exposed households were on support. This high degree of common support indicates that the informal and formal employment groups possessed sufficiently similar observable characteristics to allow for effective matching, a critical prerequisite for drawing reliable causal inferences.

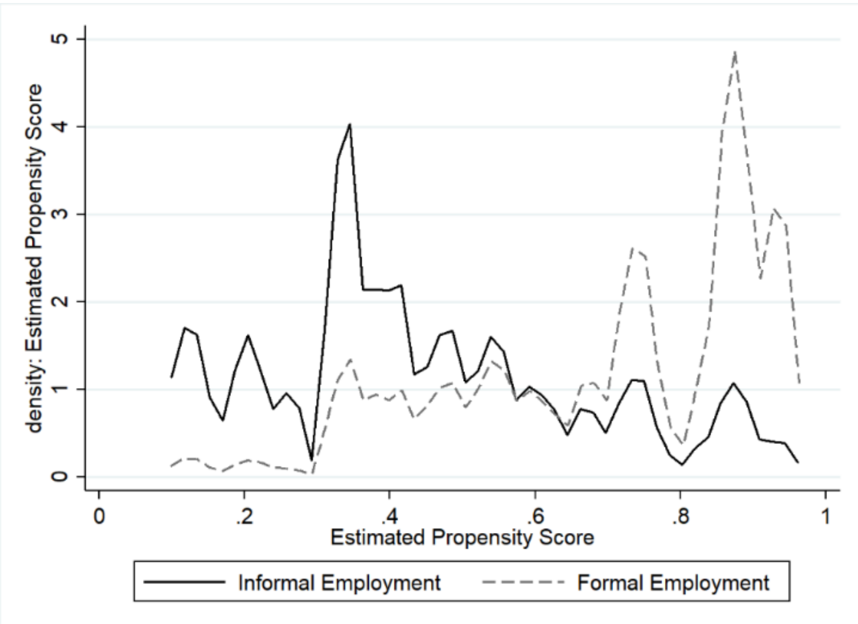

Figure 1. Common Support

Table 5. t-test Results for Balancing Check.

Variable	Sample	Mean			p > |t|
		Treated	Control	%bias	
All observations					
Area	Unmatched	.31531	.55818	-50.5	0.000***
	Matched	.31531	.31538	-0.0	0.966
Sex	Unmatched	.88085	.9213	-13.6	0.000***
	Matched	.88086	.88021	0.2	0.554
Education level	Unmatched	.03977	.19149	-48.8	0.000***
	Matched	.03977	.0391	0.2	0.306
Household size	Unmatched	3.8484	3.8787	-1.9	0.000***
	Matched	3.8484	3.8426	0.4	0.315
Internet access	Unmatched	.34963	.70288	-75.6	0.000***
	Matched	.34963	.34952	0.0	0.946
Health insurance	Unmatched	.69844	.74071	-9.4	0.000***
	Matched	.69844	.69823	0.0	0.893
Sector	Unmatched	.38898	.79382	-90.4	0.000***
	Matched	.38898	.38983	-0.2	0.606
High informal province					
Area	Unmatched	.24959	.49432	-52.3	0.000***
	Matched	.24959	.25008	-0.1	0.792
Sex	Unmatched	.87825	.9198	-13.8	0.000***
	Matched	.87826	.87807	0.1	0.893
Education level	Unmatched	.03886	.21121	-54.0	0.000***
	Matched	.03886	.03807	0.2	0.335
Household size	Unmatched	3.9509	3.9874	-2.1	0.000***
	Matched	3.9508	3.9481	0.2	0.721
Internet access	Unmatched	.30648	.67182	-78.5	0.000***
	Matched	.30648	.30671	-0.0	0.908
Health insurance	Unmatched	.69948	.73867	-8.7	0.000***
	Matched	.69948	.69907	0.1	0.831
Sector	Unmatched	.32668	.78003	-102.5	0.000***
	Matched	.32668	.32715	-0.1	0.813
Low informal province					
Area	Unmatched	.42684	.62638	-40.8	0.000***
	Matched	.42684	.42691	-0.0	0.979
Sex	Unmatched	.88527	.92291	-12.8	0.000***
	Matched	.88527	.88564	-0.1	0.837
Education level	Unmatched	.04132	.17044	-42.9	0.000***
	Matched	.04132	.04017	0.4	0.297
Household size	Unmatched	3.6744	3.7626	-5.9	0.000***

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Variable	Sample	Mean			p > |t|
		Treated	Control	%bias	
	Matched	3.6744	3.663	0.8	0.186
Internet access	Unmatched	.42285	.73606	-66.9	0.000***
	Matched	.42285	.42325	-0.1	0.884
Health insurance	Unmatched	.69667	.7429	-10.3	0.000***
	Matched	.69667	.69603	0.1	0.803
Sector	Unmatched	.49471	.80856	-69.8	0.000***
	Matched	.49471	.49547	-0.2	0.786

Note: * p < 0.10, ** p < 0.05, *** p < 0.01
Source: Authors' calculations

The quality of the matching procedure was rigorously assessed through a balancing check, employing t-tests to compare the means of key covariates between the treated and control groups both before and after matching. The primary objective was to achieve a significant reduction in bias and ensure that any remaining differences in covariate means were statistically insignificant after the matching process. As detailed in the t-test results for the balancing check, substantial biases were initially observed across most covariates (e.g., Area, Sex, Education level, Internet access, Sector) for all observation groups, with corresponding p-values consistently below 0.001. This initial imbalance underscored the necessity of PSM to address confounding. However, the application of PSM proved highly effective. Post-matching, the percentage bias for all covariates was drastically reduced, often approaching zero, and the p-values for the t-tests became statistically insignificant. This successful balancing of observable characteristics between the informal and formal employment groups significantly strengthens the internal validity of the subsequent impact estimates, providing a more reliable basis for understanding the direct effects of informal employment beyond mere correlation.

The ATE was then estimated to quantify the specific impact of informal employment on the three critical food security outcomes. The results, presented in table 5, consistently demonstrated a negative and statistically significant impact of informal employment across all food security outcomes and all three observation groups. These findings largely reinforce and provide a more causally interpreted dimension to the negative associations identified in the preceding logistic regression analysis. For the aggregate of all observations, the ATE of -0.02887 indicates that, on average, households with informal employment are approximately 2.89 percentage points less likely to report not worrying about food sufficiency compared to observationally similar households with formal employment. This statistically significant effect provides a causal estimate for the higher level of food insecurity concern among informal workers, consistent with the negative coefficient observed in the logistic regression. The ATE of -0.01901 signifies that informal employment is associated with an approximate 1.90 percentage point lower likelihood of consuming nutritious food compared to formal employment households. This causally interpreted reduction in access or ability to afford diverse and healthy diets aligns with the negative relationship found in the logistic regression. Furthermore, the ATE of -0.01267 means that, on average, informal employment leads to about a 1.27 percentage point reduction in the likelihood of having a diverse diet compared to formal employment, highlighting causally linked challenges in accessing a variety of food groups essential for balanced nutrition, mirroring the logistic regression's findings.

Within provinces characterized by high informal employment, the negative impacts were generally more pronounced, reinforcing the "spillover effects" discussed in the logistic regression. Informal employment is associated with an approximate 3.04 percentage point greater likelihood of worrying about food sufficiency compared to formal employment. This indicates a heightened and causally estimated anxiety regarding food availability in regions with a high concentration of informal workers, a stronger effect than seen in the overall sample. For nutritious food, the ATE of -0.02394 signifies an approximate 2.39 percentage point lower likelihood of consuming nutritious food for informal workers in high informal provinces. This causally estimated reduction further supports the notion that the regional labor market structure exacerbates the challenge of accessing quality food. Lastly, an

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approximate 1.54 percentage point reduction in dietary diversity for informal workers in these provinces, further emphasizing the compounded food security challenges that are more severe in these regions.

Table 6. PSM Analysis Results: The Impact of informal employment on Food Security Outcomes.

Outcome	Mean of Matched Exposed	Mean of Matched Controls	ATE
All observations			
Concern about insufficient food	0.77652	0.80539	-0.02887***
Nutritious food	0.88216	0.90117	-0.01901***
Dietary diversity	0.90097	0.91364	-0.01267***
High informal province			
Concern about insufficient food	0.75399	0.78442	-0.03043***
Nutritious food	0.86160	0.88554	-0.02394***
Dietary diversity	0.88480	0.90019	-0.01538***
Low informal province			
Concern about insufficient food	0.81476	0.83011	-0.01535***
Nutritious food	0.91705	0.92130	-0.00425**
Dietary diversity	0.92841	0.93034	-0.00194

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors’ calculations

Conversely, in provinces with low informal employment, while still negative, the effects were generally of a smaller magnitude, suggesting a less severe causal impact. The informal employment in these provinces is associated with an approximate 1.53 percentage point greater likelihood of worrying about food sufficiency. While still statistically significant, the causally estimated impact is less severe than in high informal provinces, indicating a mitigating regional context. For nutritious food, the ATE of -0.00425 signifies a marginal, but still statistically significant, approximate 0.43 percentage point lower likelihood of consuming nutritious food for informal workers. This small causal effect suggests that access to nutritious food is less severely impacted by informal employment in these regions. Notably, for dietary diversity, the ATE of -0.00194 indicates a very small approximate 0.19 percentage point reduction. This impact was not statistically significant at the 5% level, suggesting that in provinces with lower informal employment concentrations, the causal effect on dietary diversity is minimal or negligible, a significant contrast to the findings in high informal provinces and the overall sample. These ATE results consistently reinforce and provide a more causally robust interpretation of the findings from the logistic regression, confirming that informal employment negatively impacts food security outcomes. Furthermore, the generally greater magnitude of the negative impact in provinces with a high concentration of informal workers, as revealed by both analytical approaches, strongly suggests a significant spillover effect where regional labor market structures exacerbate individual household vulnerabilities.

To further assess the robustness of the estimated treatment effects against potential unobserved confounding, a Rosenbaum sensitivity analysis was conducted. This analysis explores how strong an unobserved covariate would need to be to alter the conclusions regarding the treatment effect. The results, as presented in the Rosenbaum bounds sensitivity analysis table, indicate the sensitivity of the findings to hidden bias, with the Gamma value representing the log odds of differential assignment due to unobserved factors. For all food security outcomes across all observation groups, the analysis reveals that for a Gamma value of 1, both the lower bound significance level (sig-) and the upper bound significance level (sig+) remain at 0. This crucial finding implies that even if there were an unobserved covariate that doubled the odds of a household being in the informal employment group (Gamma = 1), the statistical significance of the estimated treatment effects would remain robust at the 5% level. Even for a higher Gamma value of 3, the results largely hold, with sig+ and sig- remaining 0 for most outcomes, except for 'concern about insufficient food’ in both the overall and low informal observations, where sig+ is 0.5. This suggests that the findings are relatively robust to the presence of unobserved confounders, particularly for smaller unobserved biases. The consistent stability of the results across various Gamma values significantly enhances confidence in the estimated causal effects of informal employment on food security, reinforcing the conclusions drawn from both the logistic regression and the PSM analysis.

Table 7. Rosenbaum Bounds Sensitivity Analysis.

Variable	Gamma	sig+	Sig-	t-hat+	t-hat-	CI+	CI-
All observations							
Concern about insufficient food	1	0	0	1	1	1	1
	3	0	0	.5	1	.5	1
Nutritious food	1	0	0	1	1	1	1
	3	0	0	1	1	1	1
Dietary diversity	1	0	0	1	1	1	1
	3	0	0	1	1	1	1
High informal province							
Concern about insufficient food	1	0	0	1	1	1	1
	3	0	0	.5	1	.5	1
Nutritious food	1	0	0	1	1	1	1
	3	0	0	1	1	1	1
Dietary diversity	1	0	0	1	1	1	1
	3	0	0	1	1	1	1
Low informal province							
Concern about insufficient food	1	0	0	1	1	1	1
	3	0	0	.5	1	.5	1
Nutritious food	1	0	0	1	1	1	1
	3	0	0	1	1	1	1
Dietary diversity	1	0	0	1	1	1	1
	3	0	0	1	1	1	1

*	Gamma	: Log odds of differential assignment due to unobserved factors
	ig+	: Upper bound significance level
	sig-	: Lower bound significance level
	t-hat+	: Upper bound Hodges-Lehmann point estimate
	t-hat-	: Lower bound Hodges-Lehmann point estimate
	CI+	: Upper bound confidence interval (α= .95)
	CI-	: Lower bound confidence interval (α= .95)

Source: Authors' calculations

Thus, the comprehensive PSM analysis provides robust and compelling evidence supporting the adverse impact of informal employment on household food security in Indonesia. By effectively balancing observable covariates and demonstrating resilience to unobserved confounding, these findings strengthen the argument for the implementation of targeted policy interventions aimed at formalizing employment, particularly in regions with high concentrations of informal workers where vulnerabilities are exacerbated. The convergence of evidence from both the logistic regression and PSM analyses provides a strong empirical basis for these policy recommendations.

The adverse effects of informal employment on food security can be attributed to the economic instability inherent in such jobs. The absence of formal contracts and benefits, coupled with irregular earnings, restricts households' ability to plan for and access sufficient and nutritious food [11, 13]. The heightened vulnerability in high informal provinces underscores the need for targeted regional interventions. These could include expanding social safety nets, subsidized food programs, and initiatives aimed at formalizing informal employment [38-43].

Urban-rural disparities, as evidenced by the stronger negative effects in rural areas, point to the importance of enhancing rural infrastructure and economic diversification. Programs that support agricultural productivity and market access could buffer against the risks associated with rural informal employment [44, 45]. Moreover, the protective role of education, internet access, and health insurance underscores the importance of long-term investments in human capital and digital inclusion to enhance household resilience [33, 34, 36].

4. Conclusion

This study investigates the relationship between informal employment and household food security in Indonesia, focusing on the dimensions of psychological concerns over food availability, nutritious food, and dietary diversity. The findings reveal that informal employment is significantly associated with adverse food security outcomes, highlighting the economic vulnerabilities faced by informal worker households. Additionally, provinces with high informal employment proportions demonstrate spillover challenges, with households in these regions consistently exhibiting poorer food security outcomes. These results underscore the importance of employment status and regional labor market structures in shaping household food security.

The study provides several key conclusions. First, informal employment poses substantial risks to food security, driven by income instability and limited access to social safety nets. Comprehensive PSM analysis further strengthens this conclusion by providing robust causal evidence that informal employment negatively impacts food security outcomes, even after controlling for observable confounders. The consistently negative ATE across all food security dimensions and observation groups confirm that informal workers face a statistically significant disadvantage in achieving food security compared to observationally similar formal workers. Second, regional disparities in food security outcomes call for targeted interventions, particularly in provinces with high informal employment concentrations, as the PSM results indicated generally more pronounced negative impacts in these areas, reinforcing the concept of spillover effects from regional labor market structures. Third, protective factors such as higher education, internet access, and health insurance significantly improve food security outcomes, suggesting the value of long-term investments in human capital and digital inclusion. These conclusions align with the broader goals of fostering sustainable and equitable development.

Based on the findings, several recommendations are proposed. Policymakers should prioritize formalizing informal employment through regulatory frameworks and incentives, ensuring that workers gain access to stable incomes and social protections. Additionally, food security programs, such as subsidized food schemes and nutritional education, should be tailored to address the unique needs of informal worker households. Investments in rural infrastructure, education, and internet access can further enhance resilience against food insecurity, particularly in underserved regions. Efforts to strengthen the social safety net for informal workers, such as health insurance subsidies and access to credit, are critical for mitigating vulnerabilities.

This research has some shortcomings that need to be acknowledged. Firstly, because it only looks at a single point in time, it can't definitively prove cause-and-effect relationships between different factors. To improve this, future studies should incorporate longitudinal data to capture the dynamics of employment and food security over time. Secondly, the study could benefit from including qualitative data to understand the personal experiences of informal workers and their households. Finally, expanding the analysis to include other dimensions of food security, such as caloric intake and food utilization, would also provide a more comprehensive understanding of the issue.

In brief, this study contributes to the understanding of how informal employment influences food security in Indonesia. By addressing the systemic challenges identified, policymakers can develop targeted interventions to improve the well-being of informal worker households and promote equitable development. Future research should build on these findings to deepen insights and enhance the effectiveness of policy responses.

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