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# Does agricultural mechanization reduce vulnerable employment? Evidence from cross-country panel data

Xiaoshi Zhou
*School of Economics & Management, Nanjing University of Science and Technology*

Wanglin Ma
*Department of Global Value Chains and Trade, Lincoln University*

## Abstract

Using cross-country panel data from the World Bank and an innovative unbalanced panel fractional response model, we show evidence that agricultural mechanization significantly reduces global vulnerable employment, and the vulnerable employment reduction effects of mechanization for women are larger than that for men. The findings underscore the importance of promoting agricultural mechanization to increase employment stability and mitigate gender gaps.

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**Contact:** Xiaoshi Zhou - Xiaoshi.Zhou@outlook.com, Wanglin Ma - Wanglin.Ma@lincoln.ac.nz.
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# 1. Introduction

Although the share of vulnerable employment in total employment has been decreasing since 1991, the world continues to experience a high vulnerable employment rate (e.g., 45% in 2019) (World Bank 2019).[1] Meanwhile, the gender gap remains. ILO (2020) estimated that, in 2018, the vulnerable employment rate among women is 10% higher than that of men in developing countries due primarily to the fact that women are more likely to have lower-quality jobs and lower salaries than men because of unequal care responsibilities and discrimination. The high share of workers in vulnerable employment is directly linked to the high share of people living in poverty (Bocquier et al. 2010; ILO 2020; Gammage et al. 2020), which challenges global economic growth and gender equality.

The global trend of agricultural mechanization has the potential to reduce vulnerable employment. Mechanization substitutes farm labours and saves household's farm management time that can be re-allocated to job-related training, which finally increases wage and salaried work opportunities, enhance employment stability and signify advanced economic development. Existing literature has demonstrated a positive impact of mechanization on off-farm employment, farm productivity, women empowerment, and economic development (e.g., Fischer et al., 2018; Ma et al., 2018; Sims et al., 2016; Zhou et al., 2020). However, to the best of our knowledge, no previous studies have investigated whether agricultural mechanization can help reduce vulnerable employment.

This short note adds to the literature in threefold, including (a) investigating the impact of agricultural mechanization on vulnerable employment; (b) accounting for gendered differences, and (c) addressing the endogeneity issue of mechanization variable and unbalanced panel data issue by applying an innovative unbalanced panel fractional response model.

# 2. Data

We use open data from the World Bank. Because the data for agricultural mechanization were recorded for the period 1961-2009 while the data for vulnerable employment were recorded for 1991-2018 in the World Bank database, in this short note we use an unbalanced dataset for the period 1991-2009 (i.e. 19 years). After data cleaning by dropping variables with missing information, the final dataset we use includes 130 countries and 1,529 observations (see Table A1 in Appendix), covering East Asia & Pacafic region, Europe & Central Asia region, Latin America & North Africa Region, North America region, South Asia region, and Sub-Saharan Africa Region.

Following the World Bank, we define the variables used for this short note and present them in Table 1. Especially, vulnerable employment is the dependent variable, which refers to the share of vulnerable employment in total employment. Agricultural mechanization is the key explanatory variable of our interests, which is measured by the number of agricultural machinery and tractors per 100 $km^2$ of arable land. We also include country-specific variables including GDP, rural population, population density and electricity access as control variables.

Table 1 shows that the mean of the total vulnerable employment is 0.376, with a standard deviation of 0.268. The share of vulnerable male employment in total male employment and the share of vulnerable female employment in total male employment are 0.355 and 0.375,

[1] Vulnerable employment is usually featured by inadequate earnings, low productivity and infovorable working conditions of work that undermine workers' dunamental rights, and the workers under vulnerable employment mainly include contributing fammily workers and own-account workers (World Bank 2019).

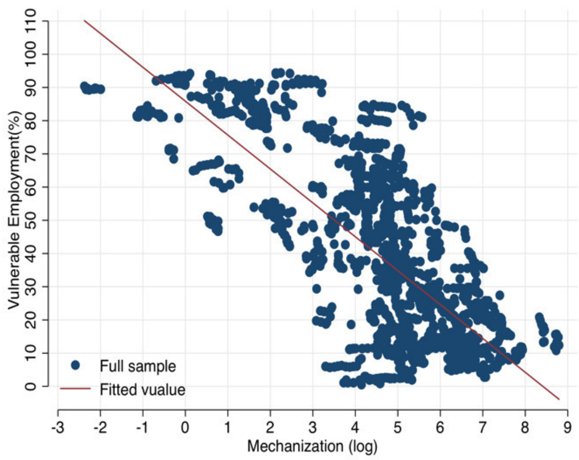
respectively. The GDP per capita is around 12,267 U.S. dollars. About 77% of the population in our sample have access to electricity.

Table 1 Definitions and descriptive statistics of the variables

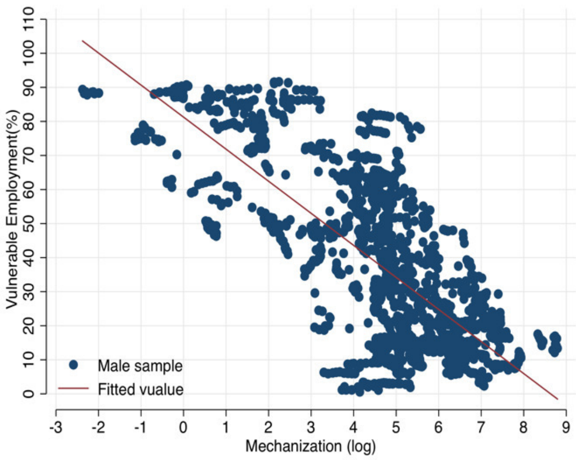
| Variables | Definition | Mean | S.D. [a] |
|---|---|---|---|
| Total vulnerable employment | The share of vulnerable employment in total employment | 0.376 | 0.268 |
| Vulnerable employment among men | The share of vulnerable male employment in total male employment | 0.355 | 0.250 |
| Vulnerable employment among women | The share of vulnerable female employment in total female employment | 0.375 | 0.299 |
| Mechanization | The number of agricultural machinery and tractors per 100 km$^2$ of arable land | 436.598 | 782.475 |
| GDP | GDP per capita ( in constant 2010 U.S. dollars) | 12,267.191 | 17,789.344 |
| Rural population | Rural population rate (% of total population) | 44.151 | 21.768 |
| Population density | Population density (people per km$^2$ of land area) | 107.143 | 150.574 |
| Electracity access | Access to electricity (% of population) | 77.459 | 32.616 |

Note: [a] S.D. refers to the standard deviation; The detailed definitions of variables are available at World Bank (World Bank 2019).

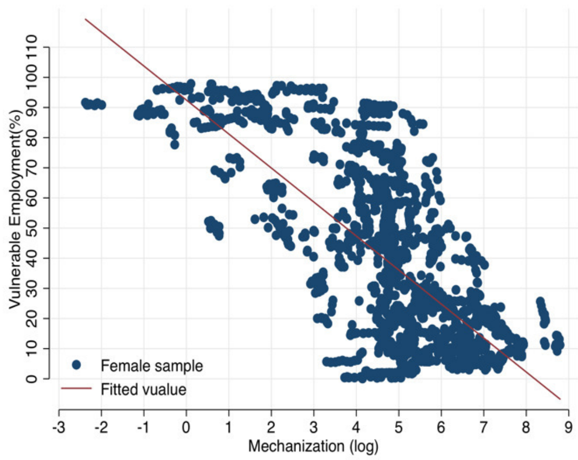
Figures 1A, 1B and 1C illustrate the relationship between agricultural mechanization and vulnerable employment for the full sample, sample for men and sample for women. Graphically, they show that mechanization is negatively associated with vulnerable employment. Hence, in the next section, we provide a better understanding of the effects of agricultural mechanization on vulnerable employment using an appropriate econometric model and controlling for other control variables.




Panel (A) Full sample




Panel (B) Sample for men




Panel (C) Sample for women

Figure 1 The relationship between agricultural mechanization and vulnerable employment

# 3. Model

We use a fractional response model to estimate the impact of agricultural mechanization on vulnerable employment. Let the vulnerable employment variable be $V_{it} \in [0,1]$, with 0 indicating that there is no vulnerable employment and 1 indicating that all employment is vulnerable employment, the regression model can be specified as:

$$V_{it} = a_i + \beta M_{it} + \gamma X_{it} + \varepsilon_{it} \tag{1}$$

where $M_i$ refers to the agricultural mechanization level of country $i$ in year $t$; $X_{it}$ is a vector of observed country-specific variables; $a_i$ is country $i$'s time-invariant unobserved effects; $\beta$ and $\gamma$ are the correspondence parameters to be estimated; $\varepsilon_{it}$ is the rondom error term.

Following Bluhm et al. (2018), we employ a revised correlated random effects (CRE) model to address the fractional response issue, and the endogeneity issue of the mechanization variable resulted from the unobserved heterogeneities in Equation (1). The CRE model for vulnerable employment can be expressed as:

$$E[V_{it}|M_{it}, X_{it}] = \Phi(\varphi_{at} + \beta_a M_{it} + \beta_a' \bar{M}_{it} + \gamma_a X_{it} + \gamma_a' \bar{X}_{it}) \tag{2}$$

where $\Phi(\cdot)$ represents the standard normal cumulative distribution function; $\varphi_{at}$ is the time-specific intercepts in year $t$; $\bar{M}_{it} = \frac{1}{T}\sum_{t=1}^{T} M_{it}$ refers to the time-averaged mechanization variable and $\bar{X}_{it} = \frac{1}{T}\sum_{t=1}^{T} X_{it}$ refers to the time-averaged other explanatory variables; $\beta_a$, $\beta_a'$, $\gamma_a$ and $\gamma_a'$ are the coefficients to be estimated, and the subscript $a$ indicates that the coefficients have been rescaled by the factor $(1+\sigma_a^2)^{-1/2}$. We use the Bernoulli quasi-maximum likelihood estimation (QMLE) approach to obtain robust and scaled coefficients of all time-varying explanatory variables in Equation (2) (Wooldridge 2019; Bluhm et al. 2018).

The estimates of the unbalanced panel data may be biased if the sample selection issue related to the country fixed effects occurs. To address the unbalancedness issue of panel data, we include the time-related dummies and their interaction terms with the time-averaged variables in Equation (2). Let $s_{it}$ be the selection indicators due to the unbalanced panel, and $\lambda_{T_i,\ell}$ be the time-related dummy variables ($\lambda_{T_i,\ell} = 1$ if $T_i = \ell$, and 0 otherwise), with $T_i = \sum_{t=1}^{T} s_{it}$ denoting the number of time periods observed for country $i$ and $\ell$ representing a given number of time periods ($\ell = 1, 2, \dots, 19$). The argument of $\Phi(\cdot)$ can then be scaled by the square root of $Var(a_i) = exp(2\sum_{\ell=2}^{T-1}\lambda_{T_i,\ell}\omega_\ell)$, where $T = max_i T_i$ and $\omega_\ell$ represents the unknown variance parameters. Finally, the heteroscedastic model can be expressed as:

$$E[V_{it}|s_{it}, s_{it}M_{it}, s_{it}X_{it}] = \Phi\left(\frac{\beta M_{it} + \gamma X_{it} + \sum_{\ell=2}^{T}\lambda_{T_i,\ell}(\varphi_{h\ell} + \beta'\bar{M}_{it} + \gamma'\bar{X}_{it})}{exp(\sum_{\ell=2}^{T-1}\lambda_{T_i,\ell}\omega_\ell)}\right) \tag{3}$$

where the subscript $h$ denotes the new scale factor. Because the interpretation of the coefficients estimates in Equation (3) is not straightforward, we also calculate the average partial effects (APEs) (Bluhm et al. 2018; Wooldridge 2019). For analytical convenience, we denote the linear predictors inside the cumulative density function in Equation (3) by $k'_{it1}\hat{\zeta}_1$ for the numerator and $k'_{it2}\hat{\zeta}_2$ for the denominator. Then, the APE of mechanization variable on vulnerable employment, for example, can be calculated as:

$$APE_t(M) = \hat{\zeta}_{1M} \times \frac{1}{N}\sum_{i=1}^{N} exp\left(-k'_{it2}\hat{\zeta}_2\right)\phi\left(\frac{k'_{it1}\hat{\zeta}_1}{exp(k'_{it2}\hat{\zeta}_2)}\right) \tag{4}$$

# 4. Empirical results

Table 1 presents the regression results. The estimated APE of mechanization variable in the full sample is negatively and statistically significant, suggesting that a 1% increase in agricultural mechanization reduces global vulnerable employment by 0.013%. The estimated APEs of mechanization variable in the samples for men and women are negative and significant, suggesting that a 1% increase in agricultural mechanization reduces vulnerable employment among men and women by 0.012% and 0.015%, respectively. Although global vulnerable employment appears to be more pervasive among women than men, we find evidence that agricultural mechanization enables to alleviate the gender gap by reducing more vulnerable employment among women than men.

Table 1 Average partial effects of agricultural mechanization on vulnerable employment

| Variables | Full sample (APEs) [a] | Sample for men (APEs) | Sample for women (APEs) |
|---|---|---|---|
| Mechanization (log) | -0.013** | -0.012** | -0.015** |
| | (0.005) | (0.006) | (0.007) |
| GDP (log) | -0.072*** | -0.080*** | -0.062*** |
| | (0.016) | (0.017) | (0.017) |
| Rural population | 0.285** | 0.373*** | 0.212 |
| | (0.125) | (0.133) | (0.151) |
| Population density (log) | -0.089** | -0.104** | -0.089 |
| | (0.044) | (0.043) | (0.056) |
| Electricity access | -0.036 | -0.064 | 0.013 |
| | (0.051) | (0.058) | (0.059) |
| CRE [b] | Yes | Yes | Yes |
| Time dummies | Yes | Yes | Yes |
| Panel size dummies | Yes | Yes | Yes |
| Panel size × CRE | Yes | Yes | Yes |
| Scale Factor | 0.282 | 0.292 | 0.263 |
| Observations | 1,529 | 1,529 | 1,529 |

| | | | |
|---|---|---|---|
| Pseudo $R^2$ | 0.965 | 0.963 | 0.962 |

Note: Cluster standard errors in the parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[a] APEs refers to the average partial effects; [b] CRE refers to correlated random effects.

Other control variables also affect vulnerable employment significantly. For example, the negative and significant APEs of GDP variable suggest that a 1% increase in GDP reduces global vulnerable employment, vulnerable employment among men and women by 0.072%, 0.080% and 0.062%, respectively. The estimated APEs of rural population variable are positive and significant in the full sample and the sample for men. The findings suggest that a 1% increase in rural population increases global vulnerable employment by 0.285% and vulnerable employment among men by 0.373%. The negative and significant APEs for population density variable in columns 2-3 of Table 1 suggest that a 1% increase in population density reduces global vulnerable employment by 0.089% and vulnerable employment among men by 0.104%.

To enrich our understanding, we also estimate the impact of agricultural mechanization on vulnerable employment, respectively, disaggregated by income levels (Table A2 in the Appendix) and by both gender and income levels (Table A3 in the Appendix). The results show that mechanization has a significant impact on vulnerable employment for people in medium-income countries in general and women in particular. We show that a 1% increase in agricultural mechanization reduces vulnerable employment for people in medium-income countries by 0.019% and for women in these countries by 0.022%.

# 5. Conclusion

This short note provided evidence that agricultural mechanization plays a significant role in reducing global vulnerable employment, and it enables to alleviate gender gap by reducing more vulnerable employment among women than men. The vulnerable employment reduction effects of mechanization are larger in medium-income countries, relative to high- and low-income countries. The promising evidence underscores the importance of developing policies and government programs that help speed up agricultural mechanization, reduce vulnerable employment globally, and mitigate the gender gap.

Due to data unavailability and the issue of insufficient-samples, we are unable to distinguish the types of farm machines that may heterogeneously affect vulnerable employment and to disaggregate the differences of mechanization impacts between poor and rich countries. However, we believe these are promising areas for future studies when required data are available.

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## Appendix

Table A1 The countries used in the analysis

| Country Name | Frequences | Country Name | Frequences |
|---|---|---|---|
| Albania | 18 | Lebanon | 9 |
| Algeria | 18 | Lesotho | 5 |
| Argentina | 12 | Libya | 2 |
| Armenia | 9 | Lithuania | 14 |
| Austria | 15 | Luxembourg | 9 |
| Azerbaijan | 9 | Madagascar | 14 |
| Bahamas | 6 | Malaysia | 5 |
| Bangladesh | 10 | Mali | 17 |
| Belarus | 18 | Malta | 12 |
| Belgium | 6 | Mauritania | 16 |
| Benin | 8 | Mexico | 17 |
| Bhutan | 10 | Moldova | 14 |
| Bolivia | 10 | Mongolia | 10 |
| Bosnia and Herzegovina | 3 | Morocco | 9 |
| Botswana | 18 | Myanmar | 10 |
| Brazil | 16 | Nepal | 10 |
| Bulgaria | 18 | Netherlands | 15 |
| Burkina Faso | 5 | Nicaragua | 7 |
| Burundi | 2 | Niger | 8 |
| Cabo Verde | 14 | Nigeria | 17 |
| Cambodia | 8 | North Macedonia | 16 |
| Canada | 16 | Norway | 15 |
| Chile | 17 | Pakistan | 10 |
| China | 10 | Panama | 10 |
| Colombia | 7 | Papua New Guinea | 7 |
| Cote d'Ivoire | 11 | Paraguay | 18 |
| Croatia | 8 | Peru | 5 |
| Cuba | 17 | Philippines | 10 |
| Cyprus | 10 | Poland | 19 |
| Czech Republic | 15 | Portugal | 15 |
| Denmark | 15 | Puerto Rico | 6 |
| Dominican Republic | 10 | Romania | 19 |
| Ecuador | 10 | Russian Federation | 18 |
| Egypt, Arab Rep. | 18 | Rwanda | 12 |
| Eritrea | 8 | Samoa | 11 |
| Estonia | 12 | Senegal | 14 |
| Eswatini | 17 | Serbia | 3 |
| Fiji | 17 | Sierra Leone | 7 |
| Finland | 15 | Slovak Republic | 16 |
| France | 15 | Slovenia | 11 |
| Georgia | 9 | South Africa | 14 |
| Germany | 9 | Spain | 19 |
| Ghana | 15 | St. Lucia | 17 |
| Greece | 16 | Vincent and the Grenadines | 13 |
| Guinea | 10 | Suriname | 18 |

| | | | |
|---|---|---|---|
| Guinea-Bissau | 6 | Sweden | 15 |
| Haiti | 8 | Switzerland | 17 |
| Honduras | 10 | Tajikistan | 9 |
| Hungary | 15 | Tanzania | 12 |
| Iceland | 14 | Thailand | 10 |
| India | 10 | Togo | 18 |
| Indonesia | 10 | Tonga | 13 |
| Iran, Islamic Rep. | 10 | Trinidad and Tobago | 14 |
| Iraq | 10 | Tunisia | 18 |
| Ireland | 15 | Turkey | 10 |
| Israel | 10 | Turkmenistan | 2 |
| Italy | 12 | Ukraine | 18 |
| Japan | 10 | United Arab Emirates | 10 |
| Jordan | 10 | United States | 17 |
| Kazakhstan | 9 | Uruguay | 18 |
| Kenya | 12 | Vietnam | 10 |
| Korea, Rep. | 6 | Virgin Islands (U.S.) | 6 |
| Kuwait | 6 | West Bank and Gaza | 7 |
| Kyrgyz Republic | 9 | Yemen, Rep. | 10 |
| Latvia | 13 | Zimbabwe | 7 |
| Total observations | 1,529 | | |

Table A2 Impact of agricultural mechanization on vulnerable employment by income levels

| | High-income countries | Medium-income countries | Low-income countries |
|---|---|---|---|
| Variables | APEs | APEs | APEs |
| Mechanization (log) | 0.001 | -0.019* | -0.007 |
| | (0.012) | (0.010) | (0.005) |
| GDP (log) | -0.044** | -0.065*** | -0.107*** |
| | (0.019) | (0.020) | (0.021) |
| Rural population | 0.034 | 0.424*** | 0.481** |
| | (0.201) | (0.135) | (0.201) |
| Population density (log) | 0.049 | -0.146** | -0.182* |
| | (0.064) | (0.064) | (0.108) |
| Electricity access | 0.315* | -0.163** | 0.025 |
| | (0.171) | (0.068) | (0.037) |
| CRE [b] | Yes | Yes | Yes |
| Time dummies | Yes | Yes | Yes |
| Panel size dummies | Yes | Yes | Yes |
| Panel size × CRE | Yes | Yes | Yes |
| Scale Factor | 0.212 | 0.325 | 0.254 |
| Observations | 546 | 798 | 185 |
| Pseudo $R^2$ | 0.975 | 0.970 | 0.996 |

Note: Cluster standard errors in the parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;
[a] APEs refers to the average partial effects; [b] CRE refers to correlated random effects.

Table A3 Impact of agricultural mechanization on vulnerable employment by gender and income levels

| | High-income | | Medium-income | | Low-income | |
|---|---|---|---|---|---|---|
| | Men | Women | Men | Women | Men | Women |
| Variables | APEs | APEs | APEs | APEs | APEs | APEs |
| Mechanization (log) | 0.002 | -0.002 | -0.015 | -0.022** | -0.009 | -0.008 |
| | (0.014) | (0.011) | (0.010) | (0.011) | (0.006) | (0.006) |
| GDP (log) | -0.048** | -0.030 | -0.075*** | -0.054** | -0.120*** | -0.089*** |
| | (0.021) | (0.022) | (0.021) | (0.022) | (0.028) | (0.014) |
| Rural population | 0.120 | -0.142 | 0.505*** | 0.390* | 0.594** | 0.388** |
| | (0.280) | (0.150) | (0.148) | (0.207) | (0.264) | (0.174) |
| Population density (log) | 0.061 | 0.044 | -0.175*** | -0.131 | -0.146* | -0.316 |
| | (0.065) | (0.079) | (0.061) | (0.082) | (0.085) | (0.195) |
| Electricity access | 0.315* | 0.384 | -0.198** | -0.104 | 0.019 | 0.053 |
| | (0.163) | (0.298) | (0.080) | (0.083) | (0.041) | (0.052) |
| CRE [b] | Yes | Yes | Yes | Yes | Yes | Yes |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Panel size dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Panel size × CRE | Yes | Yes | Yes | Yes | Yes | Yes |
| Scale Factor | 0.226 | 0.191 | 0.329 | 0.309 | 0.284 | 0.208 |
| Observations | 546 | 546 | 798 | 798 | 185 | 185 |
| Pseudo $R^2$ | 0.961 | 0.941 | 0.961 | 0.951 | 0.979 | 0.979 |

Note: Cluster standard errors in the parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;
[a] APEs refers to the average partial effects; [b] CRE refers to correlated random effects.