Asian Journal of Economic Modelling
ISSN(e): 2312-3656
ISSN(p): 2313-2884
DOI: 10.55493/5009.v14i1.5898
Vol. 14, No. 1, 135-148.

URL: www.aessweb.com

Exploring the determinants of income dynamics during crisis and recovery: A multinomial logit analysis of Vietnamese workers

Hau Huynh Thi Ai[1,2]
Dong Nguyen Thi[1,2]+

[1]*University of Economics and Law, Ho Chi Minh City, Vietnam.*
Email: hauhta21702@sdh.uel.edu.vn
[2]*Vietnam National University Ho Chi Minh City, Vietnam.*
Email: dongnt@uel.edu.vn

(+ Corresponding author)

Article History
Received: 13 November 2025
Revised: 16 January 2026
Accepted: 3 February 2026
Published: 11 February 2026

Keywords
Covid-19
Education
Income dynamics
Labor market
Multinomial logit
Vietnam
Workers.

JEL Classification:
C25; D31; E24; J21; J24.

ABSTRACT

This paper examines income dynamics among Vietnamese workers during the COVID-19 pandemic and the subsequent recovery period. Using the Labor Force Survey (LFS) conducted by the General Statistics Office of Vietnam from 2020 to 2023, the study analyzes more than 1.5 million individual observations. A multinomial logit model is employed to predict the probability of income gains and losses based on demographic characteristics, human capital, employment attributes, and institutional factors. The results show that income differentiation mirrors labor market segmentation. First, female workers are more likely to experience income increases, while male workers have a higher probability of income losses, with odds ratios ranging from 1.04 to 1.07 and 0.87 to 0.99, respectively. This suggests that women may have stronger long-term income resilience. Second, individuals with higher educational attainment are less likely to suffer income declines and are also less likely to recover income losses in the post-pandemic period, highlighting the protective role of education against economic shocks. By focusing on income movements rather than income levels, the study offers new evidence that women do not necessarily face higher income risk; instead, they demonstrate relatively strong income adjustment capacity. These findings contribute to understanding how Vietnamese workers adapt to income uncertainty in the digital era.

Contribution/ Originality: The research contributes to understanding dynamic income levels versus static income levels, offering new insights into gender vulnerability and income resilience to economic shocks. Using large-scale Vietnamese data, it shows that female and highly educated workers have a greater capacity to adjust incomes. This enhances understanding of income adjustment mechanisms in a developing economy undergoing digital transformation.

1. INTRODUCTION

Growth indicators are typically used in economic analysis to monitor changes in national income. In Vietnam, the economy has been growing positively over the decades, and up to 2020, when the world economy was in sharp decline, GDP increased by 2.91. However, aggregate stability does not always reflect individual workers' conditions. Recovery periods may coincide with increased economic activity and employment, but income stability at the worker level can remain uncertain.

Therefore, evaluating workers' economic security should rely on micro-level statistics rather than solely on macroeconomic indicators (Prause, Dooley, & Huh, 2009).

The Labor Force Survey (LFS) is one of the data sources that has attracted significant attention in researching income among workers in Vietnam in recent years. Most existing studies focus on the determinants of income levels, with comparatively little attention given to income volatility. Income volatility does not necessarily imply risk or uncertainty, as income declines can also occur among higher-income workers. However, continued or adverse income changes can be disastrous, posing challenges for consumption planning, saving, and investment, and negatively impacting mental health and financial stability (Prause et al., 2009). Consequently, there is little evidence regarding the susceptibility of workers to macroeconomic shocks and personal setbacks like pandemics, joblessness, or illnesses.

To bridge this gap, this study utilizes LFS data from 2020 to 2023 to analyze changes in incomes among Vietnamese workers. The study aims to answer three questions: (1) What factors correlate with income gains and losses during and after the COVID-19 shock? (2) Do men and women have different chances of increasing and losing income? (3) Does education decrease the probability of income loss and facilitate income restoration during the post-pandemic stage?

Although the LFS data usually serves the purpose of annual evaluation of the labor market and typically indicates higher unemployment among women and graduates due to structural differences, in the case of a crisis, our results present a different picture.

Female workers and those with higher education proved to be more resilient during the COVID-19 pandemic, as they were more likely to recover their incomes despite negative shocks. This suggests that, under normal circumstances, human capital may not necessarily guarantee employment benefits, but it is a crucial buffer during turbulent economic times. In this context, the research contributes to the field in two ways. First, it provides quantitative data on how human capital influences income stability during periods of stability and crisis in Vietnam. Second, it reveals that female employees respond more to income protection compared to males, offering new insights into gender inequality and highlighting women's flexibility in a changing work environment.

2. THEORETICAL REVIEW

2.1. International Studies on Labor Markets and Income Dynamics

The issue of income volatility has recently become a research question, with the vast majority of studies aimed at quantifying and breaking down the sources of risk that households can experience over time (Hardy & Ziliak, 2014; Moffitt & Gottschalk, 2012). Most studies highlight periods of economic recession or financial crises, as income shocks tend to be more intense and widespread during these times. Many focus on economic downturns or crises because income shocks are more pronounced and prevalent then. However, income volatility is also a significant issue during periods of high economic growth, when workers' incomes are more directly linked to firm performance and macroeconomic conditions.

This research area has primarily concentrated on the United States, not only because of its substantial economic changes but also due to the availability of high-quality, long-term panel data. One such source is the Panel Study of Income Dynamics (PSID), which is regarded as a credible dataset, allowing researchers to track the same individuals or families over many years (Johnson, McGonagle, Freedman, & Sastry, 2018; Moffitt & Zhang, 2018). Using PSID data, Jensen and Shore (2008) analyzed changes in income volatility distribution and argued that the overall increase in income volatility in the United States did not affect most workers. Instead, it is concentrated mainly among a few individuals whose incomes were already highly volatile. Among these, self-employment is the most significant factor increasing the risk of high income volatility.

Additionally, individuals with self-reported higher risk tolerance tend to experience greater income volatility compared to others. Conventional demographic variables such as educational level, income status, age, and family status remain significant in determining susceptibility to income risk. The findings suggest that income volatility is not universal but is closely linked to occupational attributes, risk attitudes, and demographic factors. Dynan, Elmendorf, and Sichel (2012), which also rely on PSID, also indicate that the shifts in working hours and government welfare policy played a role significant role in the volatility of incomes between 1970-2000.

A continued analysis of studies conducted during the COVID-19 era indicates that income variations were significantly uneven among different employee categories. Higher educational attainment, improved household economic status, working in the state sector, and having an urban hukou were social factors in China that reduced the risk of income loss. Conversely, income decreased more rapidly in regions with a higher pandemic impact (Qian & Fan, 2020).

In Ecuador, informal workers with a low level of human capital experienced an average hourly wage reduction of 29%, indicating their high susceptibility to supply and demand shocks (Botello & Rincón, 2022). In the United Kingdom, income shocks were concentrated among young and low-skilled workers, people working in service industries or on short-term contracts, and women, who faced additional family roles during lockdown times (Bell, Bloom, & Blundell, 2022). On the whole, these results suggest that Covid-19 failed to decrease existing social disparities; instead, it increased inequality, with education, human capital, employment arrangements, gender, and social position becoming primary factors influencing income changes during the crisis.

2.2. Vietnamese Studies on Labor Markets and Income Dynamics

Research in Vietnam on how the Covid-19 pandemic and subsequent recovery affect the labor market highlights increasing instability and uneven adaptation among different worker groups. Gender-wise, most existing literature emphasizes the disadvantaged status of female employees. Empirical data by Lan (2021) and Trinh (2022) confirms that women were disproportionately relegated to service industries and the informal sector, both of which are extremely sensitive to mobility restrictions, and a significant amount of unpaid care work was also being pushed on them during lockdowns. There are also statistical reports and empirical studies that record increased unemployment rates among women compared to men during the pandemic, resulting in significant and long-term income losses (Nasati, 2021; Trinh, 2022). In even the formal sector, such as industrial zones, income inequalities based on gender persist. Cu and Nguyen (2025) discover that female employees still face more limitations than their male counterparts in earning additional income through overtime work.

Besides gender, human capital has been a popular topic in analyzing Vietnam's labor market. The idea of higher education is often seen as a benefit that enables employees to adapt more easily to online or remote work during crisis situations (Nasati, 2021). Nonetheless, there is empirical evidence showing that education may not necessarily ensure income protection. Chien (2023) demonstrates that university-educated or better-educated workers can sometimes experience higher unemployment rates, which are symptoms of labor supply-demand mismatches and firms' tendency to reduce high-skill jobs during economic downturns. Moreover, another phenomenon described in the research by Bích, Khúc, and Quang (2024) is overeducation, where university graduates face a wage penalty when employed in jobs that do not match their training or qualifications.

The more flexible view of workers' adaptability has also been suggested in recent studies. For example, Son and Hiep (2025) demonstrate that female employees and those with higher adaptability to the market utilized social capital networks and other livelihoods to sustain income during the crisis. However, Vietnamese literature continues to focus on inert indicators like unemployment rates or incomes at specific moments. Consequently, there is a lack of systematic evidence on income dynamics.

In general, the dynamics of income received by workers have been analyzed in various ways, but the aspects of income formation and income instability seem to be quite constant over the years. As early as seminal research, personal traits and human capital were considered fundamental bases for explaining income levels and income instability (Card, 1993; Jones & Peck, 1989; Mincer, 1958; Mincer, 1974). Later studies have added to this model by including job characteristics, institutional contexts, and exposure to risks as other defining factors (Alsulami, 2018; Lim & Han, 2018; Meghir, Narita, & Robin, 2015).

The context of the United States, China, Vietnam, and other countries has always indicated that income and income dynamics are not universal but are strongly determined by demographic factors, human capital, occupational roles, and the institutional context. Based on these strategies, the present research aims to illuminate income dynamics in Vietnam based on four broad clusters of variables: demographic factors, human capital, job factors, and institutional and risk factors.

3. DATA AND EMPIRICAL MODEL

3.1. Data

The current research utilizes data from the Vietnam Labor Force Survey (LFS) conducted annually from 2020 to 2023 by the General Statistics Office of Vietnam, with technical support from the International Labour Organization (ILO). It is a national household survey collecting data on over 800,000 people each year. The final sample for analysis includes between 218,385 and 489,165 individuals, after filtering for working-age people aged 19 to 60 and excluding those with missing data.

The years 2020-2023 recorded high volatility in income among Vietnamese workers due to the Covid-19 pandemic. The situation was relatively stable in 2020, when the outbreak initially appeared, with about 20 percent of employees indicating increased income and nearly 19 percent reporting decreased income. In 2021, the pandemic's adverse impact intensified: over a third of workers experienced income reduction, and the proportion reporting income increases was insignificant. The situation improved in 2022, when the percentage of workers with declining income fell to 12%, and further to just 5% in 2023. At the same time, 2023 also saw a strong recovery, with over 32% of workers reporting income gains. These results illustrate the trajectory of income decline and recovery among Vietnamese workers during and after the pandemic (see Table 1).

Table 1. Income change of labor in Vietnam between 2020-2023.

Income change	Category	2020		2021		2022		2023	
		Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
Unchanged	0	133,860	61.30	241,662	64.31	366,238	87.68	306,674	62.69
Increase	1	43,707	20.01	1,216	0.32	1,170	0.28	157,790	32.26
Decrease	2	40,818	18.69	132,922	35.37	50,306	12.04	24,701	5.05
Total		218,385	100	375,800	100	417,714	100	489,165	100

Source: Obtained from the research findings.

Based on the LFS data, the study employs four main groups of explanatory variables. The first is labor characteristics (age, gender), representing basic demographic factors. The second is human capital (educational attainment, engagement in jobs that require information technology), reflecting workers' capacity and skills. The third is job attributes (type of employment, sector of employment, and whether workers have income from more than one job), which capture the nature of work and the labor environment. Finally, institutional and risk-related factors (formal employment, jobs affected by the Covid-19 pandemic) are included to account for institutional protection and exposure to external shocks (see Table 2).

In the LFS questionnaire, most items are designed as binary choices with "yes" or "no" responses. Examples include whether a worker holds more than one job, whether the job involves the use of information technology, or whether the job was affected by Covid-19. Among the variables selected for this study, only the question on age was collected as a continuous measure. According to the nature of the data, the research coded the data into dummy variables. This method simplifies the estimation model and allows for comparison of worker groups, highlighting the correlation between income change and other aspects, including demographics, human capital, job factors, institutional, and risk-related states.

Table 2. Description of variables used in the estimated model.

Components	Variable	Description and coding	Reference category
	Income_change (Dependent variable)	0 = Unchanged 1 = Increase 2= Decrease	Unchanged
Demographic characteristics	Age	Age31_40: 1 = Yes; 0 = No Age41_50: 1 = Yes; 0 = No Age51_60: 1 = Yes; 0 = No	Age19_30
	Gender	1 = Men; 0 = Women	Women
Human capital	Education	Vocational: 1 = Yes; 0 = No College: 1 = Yes; 0 = no University: 1 = Yes; 0 = No	High school diploma and lower:
	IT use at work	Individuals use information technology in work: 1 = Yes; 0 = No	No
	Working experience	Experience_3years: 1 = Yes; 0 = No Experience_over3years: 1 = Yes; 0 = No (Just for lfs 2020) Experience_9years: 1 = Yes; 0 = No Experience_over9years: 1 = Yes; 0 = No	Experience under 1 year
Job attributes	Government_job	Individuals work in Government sector: 1 = Yes; 0 = No	Non-government job
	Area	1 = Urban ; 0 =Rural	Rural
	Multi_job	Individuals have income from at least two jobs: 1 = Yes; 0 = No	One job only
Institutional and risk factors	Formal_labor	Individuals have social insurance and labor contract: 1 = Yes; 0 = No	Informal_labor
	COVID	Work is affected by covid: 1 = Yes; 0 = No	Not affected

Source: Obtained from the research findings.

3.2. Empirical Model

The multinomial logit regression model is a generalization of the binary logit model, designed to examine discrete dependent variables with more than two choices. McFadden (1974) proposed the model during his research on the mode choice of transportation among people. One of the main assumptions of the multinomial logit model is that there is independence of irrelevant alternatives, meaning the probability of a given outcome does not depend on the existence or nonexistence of other alternative outcomes (Hartzel, Agresti, & Caffo, 2001).

For a binary dependent variable (Y=0,1), the probability of the event Y=1 is given by the S-shaped logit function.

$$p(Y = 1|X) = \frac{e^{Xb}}{1+e^{Xb}} = \frac{1}{1+e^{-Xb}}$$

with p(Y = 0|X) = 1 - p(Y = 1|X)

For a multinomial dependent variable (Y = 0, 1, …, k), the probability of an observation falling into category j (j = 1, 2, …, k) is:

$$p(Y = j|X) = \frac{e^{Xb_j}}{1+\sum_{k=1}^{k-1} e^{Xb_j}}$$

X is defined to be the set of independent variables, b_j is the coefficient vector of category j, and k is the number of categories of the dependent variable.

The dependent variable in this study is workers' income change, which has three potential outcomes: no change in income (Y = 0), increased income (Y = 1), and reduced income (Y = 2). These are discrete and unordered outcomes, making the multinomial logit model the most appropriate choice to examine the factors related to each income change state. Taking unchanged income (Y = 0) as the reference category, the probability of observation i falling into category j (j = 1, 2) is specified as:

$$p(Y_i = j|X_i) = \frac{e^{X_{j}b_j}}{1+e^{Xb_1+e^{Xb_2}}}$$

$p(Y = 0 | X_i) = 1 - p(Y = 1 | X_i) - p(Y = 2 | X_i)$

The full empirical specification to be estimated is:

$$\ln\left(\frac{P(Y_i = j)}{P(Y_i = 0)}\right) = b_{0j} + b_{1j}Demographic_i + b_{2j}HumanCapital_i + b_{3j}JobAttributes_i + b_{4j}InstitutionalRisk_i$$

Where $Demographic_i$ includes age and gender; $HumanCapital_i$ captures educational attainment, work experience, and IT use at work; $JobAttributes_i$ refers to job sector, urban location, and multiple-job holding; and $InstitutionalRisk_i$ includes formal labor status and Covid-related work disruption.

4. RESULTS AND DISCUSSION

Using the multinomial logit framework, we estimate the probabilities of different states of income change among workers, with unchanged income selected as the reference group. The observed data vary somewhat across years. In 2021 and 2022, the questionnaire structure was relatively similar, as both waves included additional questions related to the impact of COVID-19 and the use of information technology at work. In addition, the measure of working experience in 2020 differs from that of subsequent years: in 2020, only workers with at least three years of experience were recorded, whereas from 2021 onward, the data distinguish between two groups, those with less than nine years and those with nine years or more. The detailed results are presented in Tables 3 and 4.

Table 3. Results of multinomial logit estimation for income increase.

Components	Variables	2020		2021		2022		2023	
		Coefficient	Odd ratio	Coefficient	Odd ratio	Coefficient	Odd ratio	Coefficient	Odd ratio
Y = 1, base = 0									
	_cons	-1.05***	0.35	-6.21***	0.00	-6.39***	0.00	-0.70***	0.50
Demographic characteristics	age31_40	0.21***	1.24	0.12	1.13	0.17*	1.18	-0.14***	0.87
	age41_50	0.22***	1.25	0.15	1.16	0.16	1.17	-0.16***	0.85
	age51_60	0.03	1.03	-0.04	0.96	0.33**	1.39	-0.18***	0.83
	gender	-0.14***	0.87	-0.12	0.89	-0.07	0.93	-0.02*	0.99
Human capital	vocational	0.42***	1.52	-0.05	0.95	-0.15	0.86	0.14***	1.15
	college	-0.02	0.98	-0.05	0.95	0.10	1.11	0.06***	1.06
	university	-0.18***	0.83	-0.52***	0.60	-0.21	0.81	0.13***	1.14
	IT			0.48***	1.61	0.28**	1.32		
	experience_3years	-0.12***	0.88	0.50***	1.65	-0.06	0.94	0.19***	1.21
	experience_over3years	-0.43***	0.65						
	experience_9years			0.32**	1.37	0.37**	1.45	0.25***	1.28
	experience_over9years			0.36***	1.44	-0.18	0.83	0.24***	1.27
Job attributes	sector_state	-1.07***	0.34	-0.53***	0.59	-1.17***	0.31	0.03*	1.03
	area	0.65***	1.92	0.17***	1.18	-0.02	0.98	-0.20***	0.82
	multi_job	-0.20***	0.82	-0.12	0.89	0.10	1.11	0.40***	1.50
Institutional and risk factors	Covid			1.87***	6.50	2.62***	13.74		
	formal_labor	0.54***	1.71	0.45***	1.56	0.72***	2.04	0.02**	1.02
Number of observations		218,385		375,800		417,714		489,165	

Note: *, **, and *** indicate statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

Table 4. Results of multinomial logit estimation for income decrease.

Components	Variables	2020		2021		2022		2023	
		Coefficient	Odd ratio	Coefficient	Odd ratio	Coefficient	Odd ratio	Coefficient	Odd ratio
Y = 1, base = 0									
	_cons	-1.14***	0.32	-1.85***	0.16	-2.77***	0.06	-2.44***	0.09
Demographic characteristics	age31_40	0.03*	1.04	0.17***	1.18	0.14***	1.15	0.21***	1.23
	age41_50	0.07***	1.07	0.17***	1.18	0.13***	1.14	0.22***	1.25
	age51_60	0.01	1.01	0.07***	1.07	0.11***	1.12	0.12***	1.12
	Gender	-0.11***	0.90	0.04***	1.04	0.03***	1.04	0.07***	1.07
Human capital	Vocational	0.09***	1.09	0.28***	1.32	0.16***	1.17	0.12***	1.13
	College	-0.01	0.99	-0.05**	0.95	0.08**	1.08	-0.07*	0.94
	University	-0.08***	0.92	-0.51***	0.60	-0.27***	0.76	-0.25***	0.78
	IT			0.09***	1.10	0.18***	1.20		
	experience_3years	-0.02	0.98	0.22***	1.24	0.27***	1.31	0.02	1.02
	experience_over3years	-0.04	0.96						
	experience_9years			0.33***	1.39	0.29***	1.34	-0.30***	0.74
	experience_over9years			0.30***	1.35	0.05*	1.05	-0.47***	0.63
Job attributes	sector_state	-0.26***	0.77	-2.10***	0.12	-1.74***	0.18	-0.67***	0.51
	Area	0.11***	1.12	0.57***	1.77	0.26***	1.30	0.14***	1.15
	multi_job	0.05**	1.06	-0.07***	0.93	-0.12***	0.88	0.39***	1.48
Institutional and risk factors	Covid			2.60***	13.41	3.31***	27.48		
	formal_labor	-0.08**	0.92	-0.45***	1.57	-0.29***	0.75	-0.23***	0.8
Number of observations		218,385		375,800		417,714		489,165	

Note: *, **, and *** indicate statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

Tables 3 and 4 present the estimation results of factors influencing income dynamics among Vietnamese workers during 2020–2023, based on a multinomial logit model. The focus is on odds ratios, which indicate the likelihood of income growth or reduction for each group compared to the reference group. The results are organized into four categories: demographic variables, human capital, job variables, and institutional and risk variables.

4.1. Effects of Demographic Characteristics on Income Dynamics

The findings show that there is a distinct age and gender division in income dynamics during times of economic turbulence and recovery.

With respect to age, in 2020, when the economy was not yet seriously impacted by the pandemic, middle-aged workers (31-50 years old) were more likely to increase their income by 24% than younger workers (OR = 1.24). This trend, however, changed by 2023, as the odds ratios of these age groups were below one, indicating a lower chance of income increase compared to younger employees. This change suggests that technological flexibility and job flexibility have become increasingly important for maintaining and enhancing income, serving as alternatives to the traditional protective role of work experience (The ASEAN Post, 2020; Tuoitre Online, 2025).

In addition to age, gender has a unique and non-traditional trend. Although a significant portion of the current literature defines female employees as being more exposed to economic crises (ILO, 2023; Robinson et al., 2021; Santos et al., 2020), the estimates in the current study are moving in the contrary direction. In most years, female workers exhibit a greater likelihood of increasing income and a lower likelihood of decreasing income than male workers. In particular, the odds ratios show that women are approximately 1-13% more likely to gain income, and men are at a risk of losing income 4-7% more frequently, depending on the year. This indicates that women's incomes are more responsive to economic shocks. The result offers an alternative perspective on the impacts of crises on gender gaps, with women demonstrating relatively high adaptive capacity and less hazardous distribution in Vietnam. It is also one of the primary contributions of the study, showing that in conditions of increased uncertainty, women not only retain their income levels but can also improve their relative income position.

4.2. Effects of Human Capital on Income Dynamics

The aspects of human capital, such as information technology skills, education level, and work experience, show multidimensional impacts on income dynamics.

Speaking of information technology skills, despite this variable being observed only in 2021-2022, the outcomes suggest a distinctly polarized tendency. Employees who used information technology in their occupations were much more likely to increase their incomes, with odds ratios between 1.32 and 1.61, indicating an increase of 32-61%. Simultaneously, this group was also at a high risk of losing income, with the probability approximately 10-20 times higher than non-IT workers. Economically, this implies that digital skills can act as an engine of income growth and a force that increases the risk of income loss during crises.

On the same note as digital skills, work experience also exhibits a two-fold pattern of income dynamics. Experienced employees are more likely to continue enjoying an income advantage during normal times but are more prone to negative effects when a crisis occurs. This result reflects the precise impact of the Covid-19 pandemic, where numerous sectors, including manufacturing and traditional services, were severely impacted. Flexible or short-term jobs were better positioned to support income during this period. The findings indicate that traditional experience as a form of protection is being eroded amid rapid transformations in the economic order and workforce demand.

Concerning the education level, the most significant result is the evident protective nature of education during a crisis. The probability of higher education increasing income in the first two years of the pandemic was not significant, but it was considerably lower than that of workers with lower educational levels, with an OR of up to 0.6. This advantage was even greater in 2023, as the economy recovered, with higher income recovery among more educated workers. These findings indicate that education is productive as well as a self-insuring process, creating real welfare benefits by increasing income stability and recovery potential amid increased uncertainty.

4.3. Effects of Job-Related Attributes on Income Dynamics

The type of jobs, the place of work, and multi-jobholding significantly influence income dynamics. Regarding job type, there is a high level of stability in both sides of the income distribution within government employment. The likelihood of income loss is very low, approximately one in twelve (OR = 0.12), while the chance of a substantial income increase is also considerably lower (OR = 0.59). This supports the perception that the state sector in Vietnam functions as a default income-protection system, enabling employees to maintain stable income even during economic turbulence. Although wages in the public sector are typically adjusted according to fixed pay scales and coefficients, which limit income growth, the institutional structure provides an income buffer. This buffer can help mitigate the risk of significant income decline during crises, offering a form of financial security for public sector employees.

Unlike job type, urban workers were far more likely to increase income than their rural counterparts by about 92 and 18 in 2020 and 2021, respectively. This, however, changed in 2023 as there were increasing challenges in finding jobs and gaining income in cities.

The pandemic caused numerous people to leave their cities to go back to their towns because of massive layoffs. During the post-pandemic period, the improvement of employment was slow, but the cost of living and housing in urban centers became even more significant, and therefore, the growth of income was not as beneficial as in rural locations (Vietnam News, 2024). It is interesting to note that the income-decline model also shows that urban workers were at greater risk of losing income during crisis years. These results indicate that cities are places where more opportunities and risks are concentrated during economic instability, while countries offer more stability but less flexibility for income breakthroughs.

Moreover, multiple jobholding also seems to be a form of income insurance that is natural. The rate of income loss among workers whose income sources were more than one job during 2020-2022 was lower compared to those with a single income source, which shows that diversification reduced risk. Nevertheless, with the economy's revival, multiple jobholding increasingly became a "high-risk, high-return" approach, capturing the dynamism of this income type and its associated uncertainty.

4.4. Effects of Institutions and Risk on Income Dynamics

The institutional dimension is formal employment, which includes workers subjected to labor contracts and social insurance. This population is typically employed in organizations or companies with stable operations, legal protections, and formal welfare benefits. These features collectively define a two-fold benefit: earning prospects and earning security.

In 2022, formally employed workers were 2.04 times more likely to experience income increases than informal workers. The key finding is that institutional structures and social protection mechanisms are crucial in reducing income instability. This discovery is particularly relevant in Vietnam, where informal employment remains widespread. Extending institutional coverage can help narrow the gap in income stability between formal and informal workers.

In industries directly exposed to the pandemic, such as tourism and food services, the outcomes reveal a significant risk-opportunity distinction. There was a sharp decline in many traditional industries, while revenues increased in areas like e-commerce, online services, and critical sectors. This suggests that risky jobs are not necessarily linked to income loss but are often high-volatility roles where change and risk coexist. This trend exemplifies a typical aspect of digital transformation in emerging economies.

Table 5. Measures of fit for Multinomial Logit of income status.

Pseudo R-Square	2020	2021	2022	2023
Prob > LR	0.000	0.000	0.000	0.000
Maximum Likelihood R^2	0.03	0.290	0.156	0.014
Cragg & Uhler's R^2	0.036	0.393	0.290	0.017
McFadden's R^2	0.016	0.255	0.220	0.008
Count R^2	0.612	0.643	0.877	0.627
Number of observations	218,385	375,800	417,714	489,165

Source: Obtained from the research findings.

The goodness-of-fit test results for the multinomial logit model, presented in Table 5, show that the likelihood ratio test yields a probability of 0.000 across all four years. This confirms that the model is statistically significant, indicating that at least one independent variable affects income volatility. However, the explanatory power of the model varies markedly across different years.

In 2021 and 2022, the indicators suggest that the model achieved a relatively good fit. Specifically, the McFadden R^2 values were 0.255 and 0.220, indicating a strong level of explanatory power for a discrete choice model. Additionally, the Count R^2 values were 0.643 and 0.877, meaning the model accurately predicted income status for approximately 64 to 88 percent of observations. These encouraging results may be attributed to the inclusion of two variables: jobs affected by Covid-19 and jobs involving information technology. These variables provided significant differentiation, enabling the model to better explain variations in income volatility across worker categories.

Conversely, the explanatory power of the model in 2020 and 2023 was quite weak (McFadden R^2 of 0.016 and 0.008), although this is normal because the model is expected to be almost perfect in this scenario. However, the Count R^2 was 61.2% and 62.7%, which means that the model still had some predictive power. Such findings also indicate that, in addition to the usual variables, more needs to be done to introduce and include other factors that can better capture the post-Covid-19 and digital transformation environment to account for the income volatility of workers.

5. CONCLUSION AND RECOMMENDATIONS

This paper provides an analysis of the factors affecting income dynamics of Vietnamese workers based on the Labor Force Survey (LFS) from 2020 to 2023, focusing on the crisis and recovery during the post-pandemic period. The findings indicate that income fluctuations are influenced by demographic attributes, human capital, job attributes, institutional factors, and risk factors simultaneously, highlighting the multidimensionality of the Vietnamese labor market. Notably, two main findings offer new insights compared to previous research. First, women have been found to be better at sustaining and regaining their income than men, suggesting that the employment system for female workers in Vietnam is more adaptable and resilient to economic shocks. Second, the protective effect of human capital remains confirmed by educational achievement, aligning with global experiences, contrary to national attitudes that often believe unemployment among highly educated employees is worse than among those with basic education. These findings demonstrate that crises have revealed unique adaptive strategies within the Vietnamese labor market, enhancing understanding of the roles gender and human capital play in determining income resilience. Based on these insights, several policy and institutional implications can be proposed to improve workers' income resilience during periods of economic instability.

To begin with, adaptive capacity and lifelong learning should be discussed as one of the priority pillars of the labor policy in the long term. The findings show that educational achievement is not only a means to increase productivity but also a way to minimize income risk. Thus, reskilling and upskilling initiatives need to be developed to enhance the portability of skills between occupations, especially those more prone to the impact of digital transformation.

Second, the result on the resilience of female workers implies that gender equality policy must not be based on protective measures but rather on empowering strategies. Instead of focusing only on vulnerable groups, policies should leverage the advantages of female workers in stable sectors and facilitate their movement into fields with high income growth potential in the digital economy.

Third, the findings on the stability of the public sector and the benefits of formal employment indicate the importance of institutional structures and social security programs in stabilizing income. A possible way to reduce income inequalities and strengthen social stability is by expanding social insurance coverage, enhancing labor contract enforcement, and formalizing the informal sector over time.

Fourth, the focus should be on cultivating workers' flexible skills and their ability to transfer competencies across various jobs, enabling them to actively increase their income sources when needed. The multiple-job model has also proven to be a positive self-insurance mechanism during crisis periods. Therefore, instead of concentrating solely on training, policies must promote the active practice of flexible skills, allowing workers to effectively utilize new economic opportunities and maintain a steady income during economic turmoil.

Even though this research is a significant contribution to the empirical data on the mechanisms of income dynamics among Vietnamese workers in 2022–2023, it is important to mention several shortcomings. First, the data primarily rely on annual cross-sectional surveys, which do not capture changes at the individual level over time. Second, many variables in the LFS dataset are coded in binary form, limiting analysis in reflecting the intensity or degree of these characteristics. Third, certain potential factors, such as specific industry characteristics and job positions, have not been fully quantified. Therefore, future research could expand by using micro-level data with more detailed measurement scales or panel data over time, as well as conducting cross-country comparisons to better clarify income adaptation mechanisms and the protective role of human capital in the context of digital transformation and global economic volatility.

Funding: This research is supported by Vietnam National University Ho Chi Minh City (VNU-HCM) under (Grant number B2023-34-03).
Institutional Review Board Statement: This study uses secondary data from the Vietnam Labor Force Survey (LFS) conducted by the General Statistics Office of Vietnam. The dataset provided to the authors contains no personally identifiable information and is fully anonymized. The study involves no direct interaction or intervention with human participants. Therefore, ethical approval from an Institutional Review Board was not required
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: Upon a reasonable request, the supporting data of this study can be provided by the corresponding author.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Both authors contributed equally to the conception and design of the study. Both authors have read and agreed to the published version of the manuscript.
Disclosure of AI Use: The authors confirm that we used ChatGPT to correct language and grammar to enhance the clarity of the manuscript. The authors fully commit that all data, analyses, and writing were independently carried out by us.

REFERENCES

Alsulami, H. (2018). The effect of education and experience on wages: The case study of Saudi Arabia. *American Journal of Industrial and Business Management*, *8*(1), 129-142. https://doi.org/10.4236/ajibm.2018.81008

Bell, B., Bloom, N., & Blundell, J. (2022). Income dynamics in the United Kingdom and the impact of the Covid-19 recession. *Quantitative Economics*, *13*(4), 1849-1878. https://doi.org/10.3982/QE1872

Bích, N. V. T., Khúc, T., Anh, & Quang, T. T. (2024). Wage disparity arises from jobs not matching the qualifications of university graduates in Vietnam. *Journal of Economics and Development*, *321*, 31-40. https://doi.org/10.33301/JED.VI.1595

Botello, P. H. A., & Rincón, G. I. (2022). Informal economy and income distribution in Ecuador during the COVID-19 pandemic. *Revista Facultad de Ciencias Económicas*, *30*(1), 11-28. https://doi.org/10.18359/rfce.5206

Card, D. (1993). *Using geographic variation in college proximity to estimate the return to schooling*. Working Paper No. 4483. National Bureau of Economic Research Cambridge, Mass., USA.

Chien, N. Đ. (2023). Labor structure transformation in the context of the Covid-19 pandemic in Vietnam. *Vietnam Journal of Social Sciences, 182*(2), 29-37.

Cu, T. T., & Nguyen, T. A. (2025). Income of workers in industrial parks post-COVID-19 pandemic: The raised issues in Vietnam. *Problems and Perspectives in Management, 23*(1), 90-100. https://doi.org/10.21511/ppm.23(1).2025.07

Dynan, K. E., Elmendorf, D. W., & Sichel, D. E. (2012). The evolution of household income volatility. *The BE Journal of Economic Analysis & Policy, 12*(2), 1–42. https://doi.org/10.1515/1935-1682.3347

Hardy, B., & Ziliak, J. P. (2014). Decomposing trends in income volatility: The "wild ride" at the top and bottom. *Economic Inquiry, 52*(1), 459-476. https://doi.org/10.1111/ecin.12044

Hartzel, J., Agresti, A., & Caffo, B. (2001). Multinomial logit random effects models. *Statistical Modelling, 1*(2), 81-102. https://doi.org/10.1177/1471082X0100100201

ILO. (2023). *Women and men in the informal economy: A statistical update. International Labour Office*. Retrieved from https://www.ilo.org/sites/default/files/wcmsp5/groups/public/%40ed_protect/%40protrav/%40travail/documents/publication/wcms_869188.pdf

Jensen, S. T., & Shore, S. H. (2008). Changes in the distribution of income volatility. *arXiv preprint arXiv:0808.1090*. https://doi.org/10.48550/arXiv.0808.1090

Johnson, D. S., McGonagle, K. A., Freedman, V. A., & Sastry, N. (2018). Fifty years of the panel study of income dynamics: Past, present, and future. *The ANNALS of the American Academy of Political and Social Science, 680*(1), 9-28. https://doi.org/10.1177/0002716218809363

Jones, J. E., & Peck, C. J. (1989). The effect of human capital, socioeconomic, and labor market factors on wages. *Home Economics Research Journal, 18*(2), 110-125. https://doi.org/10.1177/1077727X8901800201

Lan, T. T. H. (2021). Impact of Covid-19 pandemic on migrant workers in the informal sector of Vietnam. *Journal of Social Sciences, 11*, 35-44.

Lim, J., & Han, M. (2018). *Impact of technology on wages and productivity in Singapore (No. 18-04)*. Manila, Philippines: ASEAN+3 Macroeconomic Research Office (AMRO).

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics, 3*(4), 303-328. https://doi.org/10.1016/0047-2727(74)90003-6

Meghir, C., Narita, R., & Robin, J.-M. (2015). Wages and informality in developing countries. *American Economic Review, 105*(4), 1509-1546.

Mincer, J. (1958). Investment in human capital and personal income distribution. *Journal of Political Economy, 66*(4), 281-302. https://doi.org/10.1086/258055

Mincer, J. A. (1974). Schooling and earnings. In Schooling, experience, and earnings. In (pp. 41–63). Cambridge, MA: National Bureau of Economic Research

Moffitt, R., & Zhang, S. (2018). *Income volatility and the PSID: Past research and new results*. Paper presented at the AEA Papers and Proceedings, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Moffitt, R. A., & Gottschalk, P. (2012). Trends in the transitory variance of male earnings: Methods and evidence. *The Journal of Human Resources, 47*(1), 204-236. https://doi.org/10.3368/jhr.47.1.204

Nasati. (2021). *Covid-19 and employment: Impacts and responses*. Retrieved from https://vista.gov.vn/vn-uploads/chuyen-de-thong-tin/2023_10/24.2021.pdf

Prause, J., Dooley, D., & Huh, J. (2009). Income volatility and psychological depression. *American Journal of Community Psychology, 43*(1), 57-70. https://doi.org/10.1007/s10464-008-9219-3

Qian, Y., & Fan, W. (2020). Who loses income during the COVID-19 outbreak? Evidence from China. *Research in Social Stratification and Mobility, 68*, 100522. https://doi.org/10.1016/j.rssm.2020.100522

Robinson, L., Schulz, J., Ragnedda, M., Pait, H., Kwon, K. H., & Khilnani, A. (2021). An unequal pandemic: Vulnerability and COVID-19. *American Behavioral Scientist*, *65*(12), 1603-1607. https://doi.org/10.1177/00027642211003141

Santos, K. O. B., Fernandes, R. D. C. P., Almeida, M. M. C. D., Miranda, S. S., Mise, Y. F., & Lima, M. A. G. D. (2020). Work, health and vulnerability in the COVID-19 pandemic. *Cadernos de Saude Publica*, *36*, e00178320. https://doi.org/10.1590/0102-311X00178320

Son, N. N., & Hiep, V. H. (2025). Vulnerability and resilience: Informal labor income dynamics during economic disruption in Vietnam's post-COVID recovery phase. *Global Business & Finance Review*, *30*(11), 210-226. https://doi.org/10.17549/gbfr.2025.30.11.210

The ASEAN Post. (2020). *Pandemic hitting older workers harder*. Retrieved from https://theaseanpost.com/article/pandemic-hitting-older-workers-harder

Trinh, N. T. T. (2022). Impact of the COVID-19 on the labor market in Vietnam. *International Journal of Health Sciences*, *6*,(S1) 8355-8367. https://doi.org/10.53730/ijhs.v6nS1.6973

Tuoitre Online. (2025). *Haunted by unemployment after COVID-19, struggling to find a job in middle age*. Retrieved from https://www.vietnam.vn/en/am-anh-that-nghiep-tu-sau-dich-covid-19-lao-dao-tim-viec-o-tuoi-trung-nien

Vietnam News. (2024). *HCM City faces labour exodus as workers move out*. Retrieved from https://vietnamnews.vn/sunday/1687521/hcm-city-faces-labour-exodus-as-workers-move-out.html