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LABOR STRUCTURAL TRANSFORMATION AND UNEMPLOYMENT RATE IN VIETNAM: TESTING IN THE FREQUENCY DOMAIN

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ABSTRACT

This study investigates the causal relationship between labor structural transformation and the unemployment rate in Vietnam over the period 2003-2023. Utilizing time-series data and frequency-domain causality testing, the research employs the Modified Lilien Index (MLI) to quantify the extent of labor reallocation across economic sectors. The empirical findings reveal that structural labor shifts exert a significant causal impact on unemployment in the medium and long term, while no clear effect is observed in the short term. Moreover, unemployment does not appear to influence labor reallocation in reverse. These results suggest that long-term policy interventions such as workforce reskilling, labor market information systems, rural-to-urban labor mobility incentives, and enhanced social protection are essential to sustainably mitigate structural unemployment. By applying frequency-domain analysis, the study offers a novel perspective on the temporal dynamics of labor market adjustments, contributing valuable empirical evidence for labor policy formulation in transitioning economies.

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1. Introduction

Labor structural transformation is a central theme in development economics, closely associated with modernization and productivity growth across economies. A substantial body of literature has emphasized that the shift of labor from agriculture to industry and services serves as a key driver of economic expansion and poverty reduction (Dieppe & Matsuoka, 2021; McMillan & Rodrik, 2011). This process not only enhances resource allocation efficiency but also contributes to the creation of stable employment, increased income, and improved living standards for workers (Autor, 2015; World Bank, 2017).

However, labor structural transformation also entails considerable challenges, particularly the risk of structural unemployment when workers fail to adapt to evolving market demands (Lilien, 1982; Valletta & Cleary, 2008). Empirical studies conducted in the United States and Europe indicate that sectoral disparities in employment growth may exacerbate unemployment, especially during periods of economic volatility (Caroleo et al., 2010; Figura & Wascher, 2010). In transitional economies, labor reallocation across sectors and regions can lead to mismatches in labor supply and demand, thereby increasing regional unemployment in the absence of adequate policy support (Ansari et al., 2014; Byun & Hwang, 2015).

In Vietnam, labor structural transformation has progressed significantly over the past three decades, marked by a sharp decline in agricultural employment and a notable rise in industrial and service sector participation (General Statistics Office, 2023; World Bank, 2017). While several domestic studies have examined the impact of this transformation on economic growth and unemployment, most remain descriptive or rely on conventional econometric models, lacking in-depth analysis of cyclical effects and the mechanisms operating across short-term, medium-term, and long-term horizons. Furthermore, context-specific factors such as regional disparities, variations in workforce skill levels, and the influence of digital transformation on labor market dynamics have yet to be thoroughly explored (Nguyen Minh Hai, 2023; Pham Thi Du et al., 2023; Vo Thanh Dung et al., 2010).

Methodologically, most existing studies rely on conventional time-domain econometric approaches, which tend to capture aggregate trends without adequately disentangling the cyclical and frequency-specific nature of the causal relationship between sectoral labor shifts and unemployment dynamics. This limitation makes it difficult to distinguish short-term shocks from long-term structural effects, thereby hindering a deeper understanding of how labor reallocation influences unemployment across different stages of economic development. In the context of Vietnam, empirical research has largely remained descriptive or employed aggregate time-series models, with limited attention to sectoral, regional or demographic heterogeneity in the labor market. The country's rapid industrialization, urbanization, and global integration present both challenges and opportunities for labor market adjustment, yet these contextual factors have not been thoroughly examined. Data constraints, particularly, the lack of high-frequency and sector-disaggregated labor statistics pose significant barriers to the application of advanced analytical techniques such as frequency-domain causality testing. Another critical gap lies in the translation of empirical findings into actionable policy recommendations. Although prior studies have affirmed the role of structural transformation in job creation and poverty reduction, few have systematically evaluated the effectiveness of labor transition policies in mitigating structural unemployment in Vietnam. This leaves policymakers without

robust empirical foundations to design context-sensitive interventions.

Given the aforementioned limitations, employing frequency-domain analysis to examine the temporal dimensions of the relationship between labor structural transformation and unemployment emerges as a necessary research direction. This approach not only enhances the precision of empirical findings but also enables a clearer identification of the timing and magnitude of labor market adjustments. Addressing these gaps holds significant relevance for the formulation of inclusive and sustainable employment policies, particularly in the context of Vietnam's rapidly evolving economic landscape.

2. Literature review

According to Lilien (1982), structural changes resulting from labor reallocation across sectors may generate "reallocation shocks," which contribute to rising unemployment at the regional level. When labor shifts occur, declining sectors often require time before displaced workers can be absorbed by emerging industries. McCallum (1975) empirically examined the role of sectoral shifts in explaining short-term fluctuations in unemployment and concluded that much of the variation in short-run unemployment stems from substantial intersectoral labor flows. Similar findings have been reported in subsequent studies by Bakas et al. (2017), Garonna and Sica (2000), reinforcing the notion that structural transformation can have significant implications for labor market stability.

The standard Lilien index has been widely employed in studies such as Barbier (2013), Wu et al. (2024), Demidova et al. (2020). However, Abraham and Katz (1986) emphasized the need to distinguish between sectoral structural changes and aggregate market shocks. They argued that the Lilien index only accurately reflects sectoral shifts if aggregate demand fluctuations are excluded from the measurement. To address this, Abraham and Katz (1986), Kazamaki Ottersten (1993) and Neelin (1987) regressed sectoral employment changes on variables representing aggregate demand, using the residuals to construct a refined dispersion index. Nevertheless, Samson (1985) and Charette and Kaufmann (1987) found that such adjustments had minimal impact on their results. Similarly, Bakas et al. (2017) demonstrated that both the standard and the "purged" Lilien index yielded comparable effects on unemployment.

To examine the impact of job reallocation on labor market outcomes, numerous studies have employed micro-level data on employment flows to assess its effects on unemployment, wages, and overall economic activity. For instance, Belzil (2000) utilized Danish microdata at both individual and firm levels over a 12-year period to estimate the influence of job creation and destruction on wages and net employment. Using a wage equation framework, the study found that job creation closely linked to labor reallocation had a significantly positive effect on wages throughout the business cycle. However, indicators directly measuring reallocation effects were less stable and less clearly associated with wage dynamics. Similarly, Rutkowski (2003) analyzed firm-level data to investigate the coexistence of high labor reallocation and elevated unemployment in Lithuania. The study attributed this paradox to wage rigidity, which hindered labor market adjustments and prevented low-productivity workers from transitioning into new employment. Consequently, reallocation from low- to high-productivity sectors led to skill mismatches and rising unemployment. Kerr et al. (2014), using microdata from South Africa's Quarterly Employment Survey, estimated job creation and destruction rates and found that labor reallocation exerted a negative effect on

employment. Their findings also highlighted that net job creation was contingent on firm size, with larger enterprises demonstrating greater capacity to absorb labor following sectoral shocks.

Finally, Tyrowicz et al. (2017) conducted a meta-analysis of labor flow studies in transitional economies across Central and Eastern Europe (CEE) to examine the effects of job reallocation on productivity growth and income inequality. Their findings revealed a weak association between labor flows and short-term productivity during periods of intense reallocation, but a strong link between labor mobility and short-term income inequality. Using a similar analytical framework, Hyatt and McElroy (2019) explored the relationship between labor reallocation, employment, and earnings in the United States from 1993 to 2013. Applying a vector autoregression (VAR) model, they found that a 1% increase in labor reallocation could generate between 100,000 and 560,000 new jobs, reducing the unemployment rate by 0.05 to 0.25 percentage points. Conversely, a 1 percentage point rise in job destruction was associated with an increase in unemployment ranging from 0.14 to 0.42 percentage points. It is important to note that the type of micro-level longitudinal data used in these studies is often difficult to obtain in developing countries, where such datasets are either scarce or not publicly available.

3. Methodology

3.1. Measurement of labor structural transformation

One of the most commonly used indicators for measuring labor structural transformation is the Lilien Index, originally proposed by Lilien (1982). This index captures the degree of dispersion in employment growth across sectors, thereby reflecting the intensity of structural shifts within the economy. The primary rationale for employing the Lilien Index lies in its ability to quantify not only absolute changes in labor shares across sectors but also the asymmetry in employment growth rates. During periods of economic transition such as shifts from agriculture to industry or services sectoral employment growth tends to diverge, resulting in an increase in the Lilien Index. Consequently, this index serves as a sensitive tool for identifying and quantifying episodes of pronounced structural transformation in the labor market (Ansari et al., 2014).

Another notable strength of the Lilien Index lies in its ability to integrate both dynamic and structural dimensions of labor market changes. Specifically, the index is calculated as the weighted standard deviation of employment growth rates across sectors, where the weights correspond to each sector's share in total employment. This formulation allows the Lilien Index to capture not only quantitative fluctuations but also structural shifts in labor allocation (Autor, 2015). In the context of Vietnam's ongoing industrialization and modernization, the application of the Lilien Index enables researchers and policymakers to identify sectors that are either attracting or losing labor, thereby informing more targeted training programs and resource allocation strategies. Furthermore, numerous empirical studies have employed the Lilien Index to examine the relationship between structural transformation and unemployment, demonstrating its effectiveness when integrated into econometric models such as VAR and Bayesian VAR to assess the spillover effects of labor reallocation on broader labor market dynamics (Fraser, 1990). Additionally, the index has been widely used in international research to compare the flexibility and adaptability of economies in response to supply and demand shocks, underscoring its broad applicability and analytical value (Valletta & Cleary, 2008).

Subsequent studies have expanded the application of the Lilien Index across various contexts. For example, Figura and Wascher (2010) employed the index to analyze labor reallocation following economic shocks in the United States, demonstrating that sectoral dispersion in employment growth can lead to prolonged unemployment. Caroleo et al. (2010) applied the Lilien Index to assess labor market imbalances across regions in Eastern Europe after EU accession, highlighting the role of structural transformation in regional unemployment. Additionally, Dieppe and Matsuoka (2021) utilized data from 91 countries to show that intersectoral labor reallocation is a key driver of labor productivity convergence, particularly in developing economies. Byun and Hwang (2015) proposed an extension of the Lilien framework by incorporating skewness in the distribution of sectoral growth rates, aiming to more accurately capture the cyclical effects of structural transformation on unemployment.

3.2. Lilien Index (1982)

Lilien (1982) is designed the index to measure the extent of labor reallocation across sectors within an economy. It reflects structural labor market volatility by capturing differences in sectoral employment growth rates relative to the overall economy. The formula for calculating the Lilien Index is as follows:

$$LI_t = \sqrt{\sum_{i=1}^{n} (S_{irt}) \left\{ \ln\left(x_{irt} / x_{irt-1}\right) - \ln\left(X_{rt} / x_{rt-1}\right) \right\}^2} \quad (3.1)$$

where:

- LI_t: Labor structural transformation Index in year t (Lilien, 1982)
- i: Sector or economic region
- r: Region or geographical area
- t: Time period or observation point
- S_{irt}: The share of employment in sector i within the total labor force of region r at time t.
- $S_{irt} = x_{irt} / X_{rt}$
- x_{irt}: Employment level in sector i of region r at time t
- $\ln(x_{irt}/ x_{irt-1})$: Labor growth rate in sector i from period t-1 to t
- $\ln(X_{rt}/ X_{rt-1})$: The growth rate of employment across the whole region.

3.3. Lilien Index (1982)

The Modified Lilien Index (MLI) was developed to address the limitations of the original Lilien Index (LI), which is highly sensitive to short-term fluctuations and instantaneous changes in labor share. Unlike LI, MLI employs the average labor share over the entire study period rather than the share at a single point in time, thereby offering a more robust reflection of long-term structural trends (Ansari et al., 2014).

$$MLI_t = \sqrt{\sum_{i=1}^{n} \left(S_{irt}^{avg}\right) \left\{ \ln\left(x_{irt} / x_{irt-1}\right) - \ln\left(X_{rt} / x_{rt-1}\right) \right\}^2} \quad (3.2)$$

Where:

- MLI_t: The index measuring labor structural transformation in year t
- $S_{irt}^{avg} = avg\_x_{irt} / X_{rt}$: labor share of sector i in region r at time t.

Table 1. Comparison between the Lilien Index

Criteria	**LI (1982)**	**MLI (2014)**
Weighting	Labor share at time t	Average labor share over the entire period
Sensitivity	Sensitive to short-term fluctuations	More stable, reflects long-term trends
Application	Short-term analysis	Long-term analysis

As shown in Table 1, the Modified Lilien Index (MLI, 2014) demonstrates greater stability and better captures long-term structural shifts compared to the original Lilien Index (LI, 1982). Therefore, this study adopts MLI (2014) as the primary indicator for measuring labor structural transformation. The MLI ranges between 0 and 1. A high MLI value (close to 1) indicates strong labor reallocation, implying that structural changes in employment are occurring rapidly and significantly. Conversely, a low MLI value (close to 0) suggests weak labor reallocation, implying that structural transformation is slow or minimal.

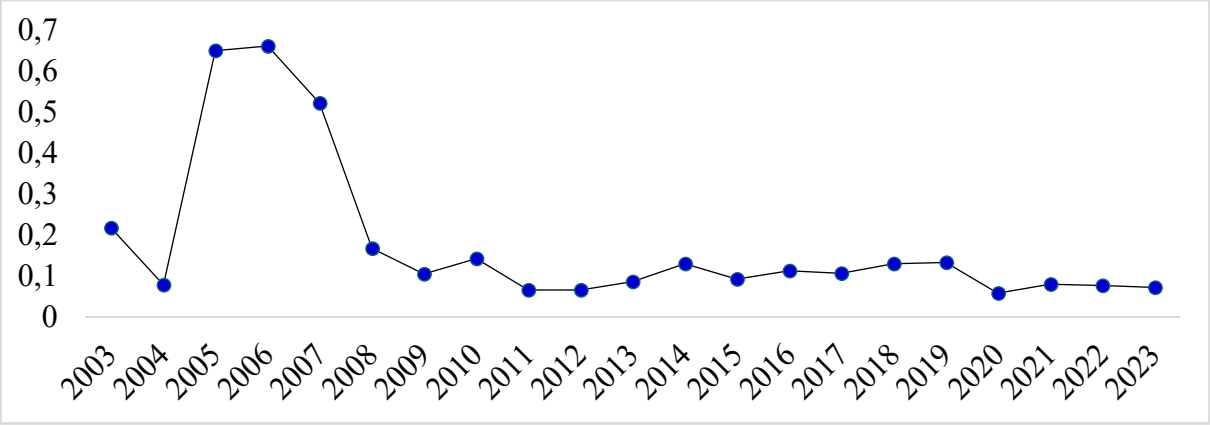

Figure 1. Lilien Index of Vietnam during the period 2003-2023

3.4. Causal analysis using frequency domain approach

Bates and Granger (1969) pioneered a method for testing causal relationships in time series data, grounded in two fundamental assumptions: (1) the causal variable must precede the affected variable in time, and (2) the causal variable must contain information useful for predicting the affected variable. In other words, a time series Y_t is said to Granger-cause another series X_t if the historical values of Y_t improve the forecast accuracy of future values of X_t. This approach is typically implemented through regression models that examine the significance of lagged coefficients. However, Ciner (2011) argues that the Granger causality test may not provide robust evidence of causal relationships across different time horizons namely short-term, medium-term, and long-term because it relies on a single test statistic that overlooks the possibility of frequency-dependent causality. In response to this limitation, (Chen et al., 2006) propose a more nuanced approach using frequency domain analysis, which allows for the identification of causal linkages at distinct temporal frequencies, thereby offering a more comprehensive understanding of dynamic interactions between variables.

The primary objective of frequency domain analysis (also known as spectral analysis) is to decompose the variability of a time series into its constituent periodic signals, thereby identifying the key frequencies that contribute to fluctuations in the observed variables (Geweke, 1984). According to Geweke (1984) and Hosoya (1991), causality between time series can be assessed by examining the distribution of predictive power across different frequencies. This approach enables researchers to determine whether causal relationships exist at specific temporal scales short-term, medium-term, or long-term rather than relying solely on aggregate measures of predictability.

$$M_{Y\to X}(\omega) = \log\left[\frac{2\pi f_X(\omega)}{\left|\psi_{12}(e^{-i\omega})\right|^2}\right] \quad (3.3)$$

$$= \log\left[1 + \frac{\left|\psi_{12}(e^{-i\omega})\right|^2}{\left|\psi_{11}(e^{-i\omega})\right|^2}\right]$$

where:

- $f_X(\omega) = \frac{1}{2\pi}\left\{\left|\psi_{11}(e^{-i\omega})\right|^2 + \left|\psi_{12}(e^{-i\omega})\right|^2\right\}$ denotes the spectral density function of the variable X_t ($f_x(\omega)$ is constructed through the Fourier transformation),
- $\psi_{11}(e^{-i\omega})$ represents the intrinsic part of the process, formed by the historical shocks of the variable X_t, $\psi_{12}(e^{-i\omega})$ reflects the causal part of the spectral function, which encapsulates the predictive power of the variable Y_t.

If $|\psi_{12}(e^{-i\omega})| = 0$ induces $M_{Y\to X}(\omega) = 0$ it implies that there is no causal relationship from Y to X at frequency ω. According to Breitung and Candelon (2006) examining the influence of variable Y on variable X, it is essential to formulate a hypothesis that specifies the nature and direction of the expected relationship between the two variables $H_0 : M_{Y\to X}(\omega) = 0$ "This implies that variable Y does not exert any causal influence on variable X at the specified frequency ω". In this case, a linear restricted model is formulated under the corresponding null hypothesis H_0

$$H_0 : R(\omega)\beta = 0 \quad (3.4)$$

where $\beta = [\beta_1, \ldots \beta_p]'$ and

$$R(\omega) = \begin{bmatrix} \cos(\omega) & \cos(2\omega) & \ldots & \cos(p\omega) \\ \sin(\omega) & \sin(2\omega) & \ldots & \sin(p\omega) \end{bmatrix}$$

The null hypothesis H_0 is tested using an F-statistic with degrees of freedom F(2,T−2p), where 2 corresponds to the number of linear restrictions imposed by the frequency-domain causality test, T denotes the number of observations used to estimate the VAR(p) model, and the F-statistic is computed as a function of the restricted and unrestricted residual variances."

4. Empirical results and discussions

4.1. Data descriptions

To examine the relationship between economic structural transformation and unemployment across short, medium and long-term horizons, this study employs annual time series data spanning from 2003 to 2023. The selected variables include the Lilien index (1982), denoted as $llindex_t$, and the unemployment rate, denoted as $unemr_t$.

Table 2. Data description

Variable	$uemr_t$	$liindex_t$
Obs	21	21
Mean	1.710	0.179
Median	1.848	0.106
Standard deviation	0.422	0.187
Std. dev. Coeff. of variation (CV)	0.247	1.045
Skewness	-0.362	1.943
Kurtosis	1.904	5.155
Min	0.999	0.058
Max	2.385	0.663

The findings presented in Table 2 indicate that the dataset comprises 21 annual observations, covering the period from 2003 to 2023. The variable $unemr_t$ exhibits a mean value of 1.710 with a standard deviation of 0.422, suggesting a moderate dispersion around the average. The coefficient of variation is 0.247, which is below unity, reflecting relatively low volatility. A skewness of -0.362 implies a left-skewed distribution, while a kurtosis of 1.904 indicates a slightly platykurtic shape compared to the normal distribution. The minimum and maximum values are 0.999 and 2.385, respectively, suggesting a reasonably narrow range of variation.

The variable $llindex_t$ has a mean value of 0.179 and a standard deviation of 0.187. Its coefficient of variation reaches 1.045, indicating a high level of volatility relative to the mean. The skewness of 1.943 and kurtosis of 5.155 suggest a strongly right-skewed distribution with a pronounced peak, reflecting a concentration of data at lower levels alongside a few unusually high values. The range, spanning from 0.058 to 0.663, further illustrates substantial dispersion. Overall, llindextt demonstrates greater variability compared to $unemr_t$.

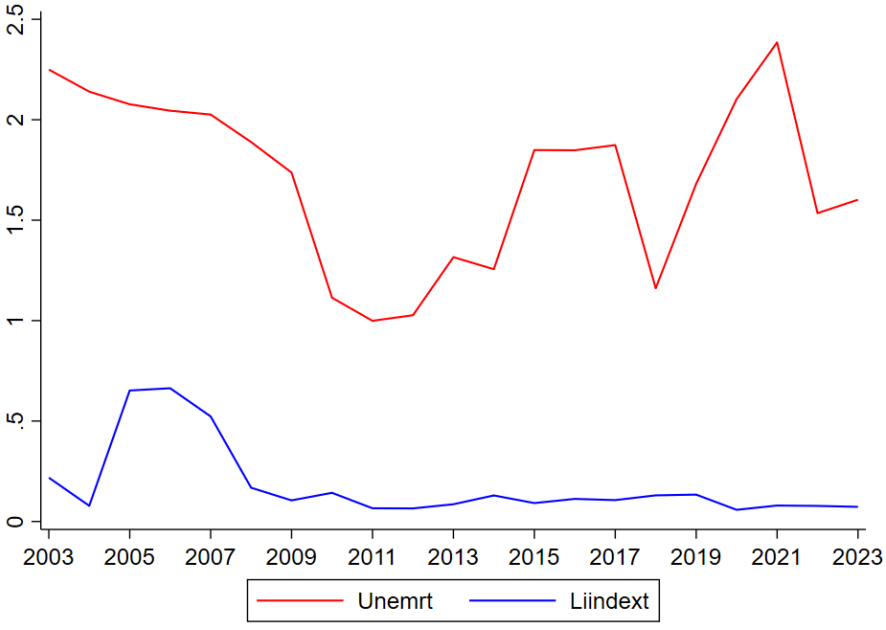

Figure 1. Trend dynamics of $liindex_t$ and $unemr_t$

The combined chart illustrating Vietnam's unemployment rate and the Lilien index from 2003 to 2023 offers a nuanced perspective on the interplay between labor market restructuring and unemployment. The Lilien index, introduced by Lilien (1982), quantifies the dispersion of employment changes across sectors, thereby capturing structural imbalances in labor allocation. An increase in this index signals significant sectoral shifts some industries expand hiring while others contract sharply potentially leading to both short-term and long-term unemployment.

As observed in the chart, periods such as 2008-2010 and 2020-2021, marked by elevated Lilien index values, coincide with spikes in unemployment. This correlation suggests that unemployment during these years was not solely driven by aggregate demand shocks but

also by structural mismatches, where workers were unable to swiftly adapt their skills to meet the demands of emerging sectors. For instance, during the COVID-19 pandemic, service industries such as hospitality, food services, and transportation experienced severe contractions, while sectors like healthcare and technology saw increased labor demand. This divergence contributed to a rise in the Lilien index and a corresponding increase in unemployment.

Conversely, the period from 2011 to 2015, characterized by relatively low Lilien index values, aligns with lower unemployment rates, indicating a more stable distribution of labor across sectors. These findings underscore the critical role of labor market policies particularly retraining programs, vocational transition support, and improved labor market information systems in mitigating structural unemployment and enhancing workforce adaptability.

4.2. Frequency domain causality analysis

To investigate the causal relationship between labor market structural transformation ($liindex_t$) and the unemployment rate ($uemr_t$), this study employs the frequency domain approach, also known as spectral analysis.

Case 1: Null hypothesis (H_0):"$liindex_t$ does not Granger cause $uemr_t$"

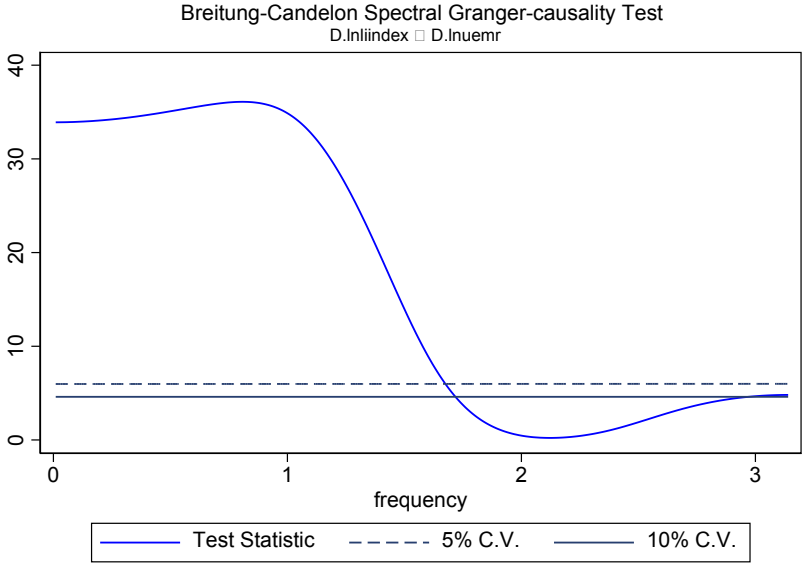

Figure 2. Results of the Granger causality test between $liindex_t$ and $uemr_t$

The results presented in Figure 2 indicate that the calculated t-statistic exceeds the critical values at both the 5% and 10% significance levels (approximately 1.67 and 1.71, respectively). This outcome leads to the rejection of the null hypothesis (H_0), thereby providing statistical evidence of a causal relationship from liindext to uemrt. In other words, structural shifts in the labor market appear to exert a significant influence on the unemployment rate.

Case 2: Null hypothesis (H_0):"$uemr_t$ does not Granger cause $liindex_t$"

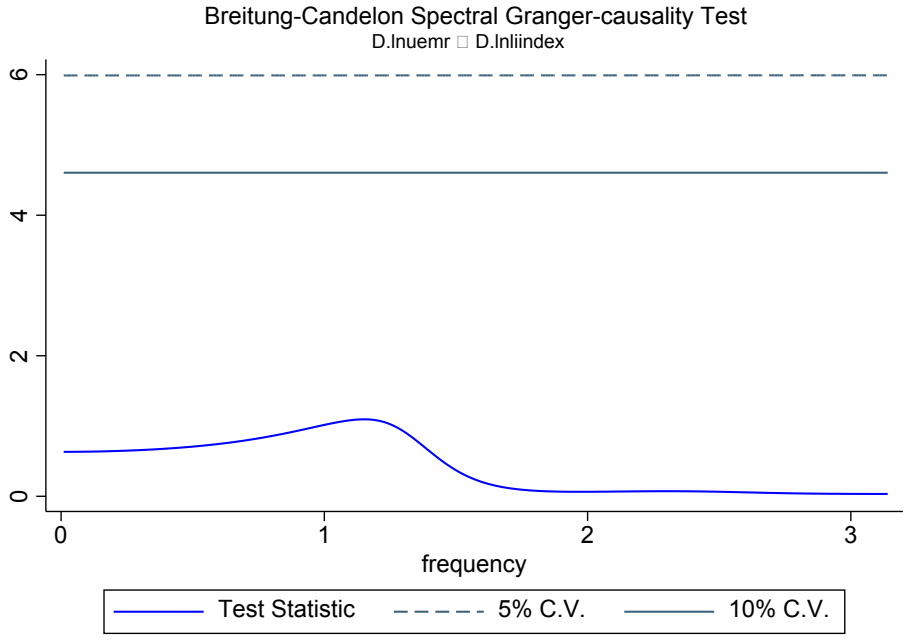

Figure 3. Results of the Granger causality test between $unemr_t$ and $liindex_t$

Similarly, the results shown in Figure 3 reveal that the t-statistic falls below the critical thresholds at the 5% and 10% significance levels. Consequently, the null hypothesis (H_0) cannot be rejected. This suggests that there is insufficient statistical evidence to support a causal relationship from $uemr_t$ to $liindex_t$. In other words, unemployment does not appear to drive changes in labor market structure.

Table 3. Results of the frequency domain analysis between the $liindex_t$ and $uemr_t$

Null hypothesis H_0	**Time domain**	**Frequency domain**					
		Long term		**Medium term**		**Short term**	
		ω = 0.01	ω = 0.05	ω = 1.0	ω = 1.5	ω = 2.0	ω = 2.5
$liindex_t \neq> uemr_t$	0.11	33.923***	33.935***	34.895***	13.995***	0.482	1.911
$uemr_t \neq> liindex_t$	0.570	0.635	0.636	0.638	0.374	0.066	0.067

*Notes: Symbole *** p<0.01, ** p<0.05, * p<0.1*

Table 3 presents the results of causality testing using two approaches: the time domain and the frequency domain. Based on the frequency values, the corresponding cycle periods (in years) can be inferred. According to Ozer and Kamisli (2015), Gül and Özer (2018), Özer et al. (2022), and Suresh et al. (2018), the cycle period T is typically divided into three phases depending on the frequency range: short-term when the frequency is high (corresponding to cycles of up to approximately 3 years), medium-term when the frequency is moderate (cycles ranging from 3 to 6 years), and long-term when the frequency is low (cycles spanning from around 6 to 125 years).

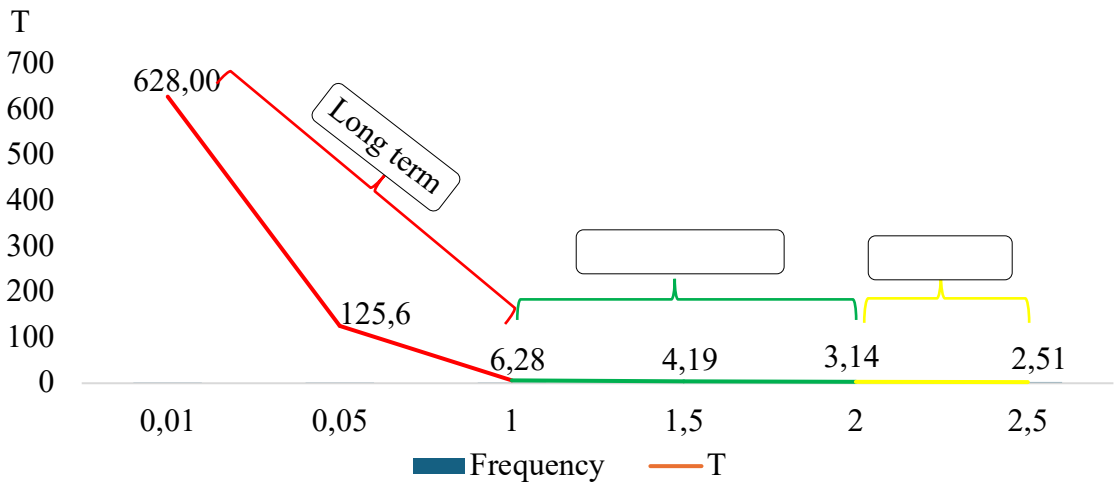

Figure 4. The cycle period T corresponds to the frequency ω

The results obtained from both the time domain and frequency domain approaches consistently confirm that the variable $liindex_t$ has a significant impact on $uemr_t$ in the medium and long term, as evidenced by statistically significant results at the 1% level. However, no causal relationship is observed in the short term. This implies that structural changes in the labor market influence unemployment over the medium and long run, while no such effect is detected in the short run.

4.3. Discussion of research findings

The empirical results derived from the frequency-domain causality analysis offer critical insights into the temporal dynamics between labor structural transformation and unemployment in Vietnam. Notably, the Modified Lilien Index (MLI), which captures sectoral labor reallocation, demonstrates a statistically significant causal influence on the unemployment rate in both the medium and long term. This finding aligns with theoretical expectations and international evidence suggesting that structural shifts in labor allocation-particularly transitions from low-productivity sectors such as agriculture to higher-productivity sectors like industry and services do not yield immediate labor market adjustments but instead manifest their effects over extended periods.

The absence of short-term causality implies that labor market responses to structural transformation are inherently gradual. This can be attributed to several factors. First, sectoral transitions often require workers to acquire new skills, relocate geographically, or adapt to different working conditions, all of which entail time and institutional support. Second, short-term unemployment fluctuations are more likely to be driven by cyclical macroeconomic shocks such as financial crises or pandemics rather than by underlying structural changes. Therefore, the short-term unemployment rate may obscure the latent effects of labor reallocation, which only become evident once transitional frictions are resolved.

Furthermore, the lack of reverse causality from unemployment to labor structural transformation suggests that rising unemployment does not, in itself, trigger significant changes in labor allocation across sectors. This asymmetry reinforces the notion that structural transformation is primarily driven by broader economic forces such as industrialization, technological advancement, and policy reforms rather than by reactive labor

market pressures. In the context of Vietnam, where economic modernization has been state-led and regionally uneven, labor reallocation appears to follow a top-down trajectory, shaped more by investment patterns and sectoral development strategies than by spontaneous labor market adjustments.

The medium-term causality observed in the analysis is particularly relevant for policy formulation. It indicates that interventions aimed at facilitating labor mobility such as vocational training, infrastructure development, and labor market information systems may not yield immediate reductions in unemployment but are essential for achieving sustainable labor market outcomes. This finding underscores the importance of adopting a long-term perspective in labor policy design, especially in transitioning economies where institutional capacity and labor market flexibility remain constrained.

Moreover, the long-term causal relationship between MLI and unemployment highlights the structural nature of labor market imbalances in Vietnam. As the economy continues to shift toward services and high-tech industries, mismatches between labor supply and demand are likely to persist unless proactive measures are taken to align workforce skills with evolving sectoral needs. Empirical evidence thus supports the argument for comprehensive labor market reforms, including the expansion of retraining programs, the promotion of intersectoral mobility, and the strengthening of social protection mechanisms.

In sum, the findings of this study contribute to a nuanced understanding of how labor structural transformation influences unemployment over time. By employing frequency-domain analysis, the research moves beyond conventional time-series approaches and captures the cyclical and lagged nature of labor market adjustments. This methodological innovation not only enhances the robustness of the empirical results but also provides a more accurate basis for policy recommendations. The Vietnamese experience, as documented in this study, offers valuable lessons for other developing economies undergoing structural change, emphasizing the need for strategic, long-term planning in labor market governance.

5. Conclusion and recommendations

5.1. Conclusion

This study employs frequency-domain analysis to investigate the causal relationship between labor structural transformation measured by the MLI index and the unemployment rate in Vietnam over the period 2003-2023. The empirical findings reveal that labor structural transformation Granger-causes unemployment in the medium and long term, while no significant causal effect is observed in the short term. Conversely, unemployment does not exhibit any reverse causality toward labor structural transformation. These results are consistent with international studies (Ansari et al., 2014; Dieppe & Matsuoka, 2021; Lilien, 1982) which emphasize that labor reallocation is a key driver of productivity convergence and sustainable unemployment reduction in developing economies. However, such effects tend to be delayed, requiring time for reskilling policies, occupational transition support, and infrastructure investment to take full effect.

5.2. Recommendations

Based on the empirical findings, several policy recommendations are proposed to maximize the benefits of labor structural transformation and mitigate unemployment. *First,* it is crucial to enhance reskilling and upskilling initiatives. The government and educational institutions should develop retraining and occupational transition programs aligned with the evolving demands of modern industries and service sectors. Particular emphasis should be placed on cultivating digital competencies, soft skills,

and creative thinking to enable workers to adapt swiftly to labor market changes. Collaboration between enterprises and educational institutions in designing training curricula can help bridge the gap between skill supply and demand more effectively.

Second, government agencies and labor institutions should prioritize the development of a modern labor market information system that delivers timely, reliable, and accessible data to support workforce planning and policy formulation. A transparent and regularly updated system that provides insights into recruitment needs, industry trends, and required skill sets will empower workers to make informed career choices and improve their competitiveness. In addition, career counseling and job-matching services should be expanded, particularly in rural areas and regions undergoing significant structural transformation.

Third, policymakers should implement measures that facilitate the movement of labor from agricultural sectors into industrial and service-based occupations, thereby enhancing productivity and supporting structural economic transformation. Investment incentives, infrastructure development, and the establishment of industrial and service zones in rural and transitioning regions are essential to attract labor. Concurrently, financial support, credit access, and entrepreneurship programs should be provided to facilitate occupational transitions and help workers integrate into new sectors.

Fourth, government institutions should reinforce social safety nets and expand unemployment insurance coverage to ensure that displaced workers receive adequate support while transitioning between sectors. During the structural transformation process, a segment of the workforce may face temporary unemployment. Therefore, it is necessary to improve the unemployment insurance system and provide financial assistance, counseling, and retraining opportunities to affected workers, enabling them to re-enter the labor market promptly.

Fifth, government institutions should reinforce social safety nets and expand unemployment insurance coverage to ensure that displaced workers receive adequate support while transitioning between sectors. Regulatory agencies should invest in research and forecasting tools to anticipate trends in labor structural transformation, skill demand, and labor market dynamics. This will support the proactive formulation of policies aimed at minimizing the risks of structural unemployment.

Finally, advancing digital technologies and promoting innovation throughout various industries is essential for modernizing the economy and adapting the workforce to future labor market demands. Digitalization not only creates new employment opportunities but also requires continuous skill upgrading among the workforce. Thus, enterprises should be encouraged to invest in technology, innovation, and digital workforce development, contributing to productivity growth and long-term unemployment reduction.

Declaration for using AI

During the preparation of this manuscript, the author partially used ChatGPT to assist with language editing. The author has carefully reviewed and revised the content and takes full responsibility for the final version of the articles.

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