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Investment, Industrialization, and Employment as Drivers of Economic Growth: Evidence from a Toda Yamamoto VAR Framework

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Abstract:

Understanding the drivers of sustainable economic growth remains a central challenging for large emerging economies, particularly in China, where investment, industrial upgrading, and employment reallocation have historically underpinned rapid development. In the context of rising global uncertainties such as trade tensions, shifting investment patterns, and employment reallocation across sectors identifying how investment, industrialization, and labor dynamics jointly shape economic growth has become increasingly important. Recent global and domestic challenges such as rising trade protectionism, persistent uncertainty in global value chains, and growing pressure to rebalance growth toward productivity rather than scale have intensified policy debates in China regarding the sustainability of traditional growth drivers. These challenges raise critical questions about whether investment and industrial activity continue to drive growth, how employment responds to structural shifts, and whether the expanding services sector can effectively support long-term economic performance. Against this backdrop, this study aims to test the hypothesis that investment, industrial output, trade openness, and sectoral employment exert causal and dynamic effects on China's economic growth, with industrialization and capital accumulation remaining the dominant forces. To address this objective, the study employs a Toda–Yamamoto vector autoregression (VAR) approach using WDI annual data for China from 1991 to 2024, complemented by modified wald (MWALD) causality tests, impulse response functions, and forecast error variance decomposition. The empirical results reveal strong unidirectional causality from gross fixed capital formation, industrial value added, trade, and services employment to GDP growth, while feedback effects from growth to foreign direct investment and inflation are also observed. Impulse response analysis confirms that positive shocks to investment, industrial output, and trade generate persistent increases in economic growth, whereas employment responds positively to growth shocks, reflecting China's ongoing structural transformation. Variance decomposition results further show that investment and industrial factors explain a substantial share of growth fluctuations over the medium and long run. The study offers important policy insights for sustaining growth through targeted investment, industrial innovation, and labor-market alignment in the face of evolving domestic and global challenges.

Introduction

Economic growth has become increasingly difficult to sustain in the face of profound global challenges, including slowing productivity, declining investment efficiency, rising geopolitical tensions, and structural shifts in labor markets. Global GDP growth fell below 3% for the third consecutive year, marking one of the weakest growth periods since the global financial crisis (World Bank, 2022). At the same time, global investment growth has stagnated, with gross fixed capital formation in many economies failing to return to pre-2008 trends (IMF, 2023). Industrial production, long regarded as a backbone of economic expansion, has also experienced uneven recovery, particularly amid supply-chain disruptions and trade policy uncertainty. Moreover, employment structures worldwide are undergoing rapid transformation, with labor increasingly shifting from manufacturing toward services, often accompanied by productivity mismatches and job polarization (WHO, 2022). These interconnected challenges have raised fundamental questions about whether traditional growth driver's investment, industrialization, and employment continue to play a decisive role in shaping economic performance in the contemporary global economy. Against this global backdrop, understanding how these forces interact dynamically within specific national contexts is critical, as growth experiences differ markedly across countries depending on their stage of development, industrial structure, and policy frameworks. China provides a particularly compelling case for examining these dynamics, given its unique growth trajectory and ongoing structural transformation. Over the past three decades, China has evolved from an investment- and industry-driven economy into one increasingly characterized by services-sector expansion and labor reallocation. China's average annual GDP growth exceeded 8% between 1991 and 2024, supported by exceptionally high levels of capital formation, with gross fixed capital formation consistently accounting for more than 35% of GDP (World Bank, 2024). Foreign direct investment has also played a crucial role, positioning China as one of the world's largest FDI recipients during this period (Giroud, 2024). Simultaneously, the industrial sector has remained a key contributor to output, accounting for over 40% of value added for much of the sample period, while employment has gradually shifted toward services. However, recent slowdowns in investment, rising labor costs, and weakening external demand have raised concerns about the sustainability of China's growth model. These developments highlight the need for a deeper empirical understanding of how investment, industrial value added, and sectoral employment jointly influence economic growth over time. Building on these considerations, this study situates the analysis of investment, industrialization, and employment squarely within China's long-run growth experience, while explicitly accounting for the dynamic interactions among macroeconomic and structural variables. Rather than treating growth drivers in isolation, the paper adopts a system-based perspective to capture feedback effects between GDP growth, trade openness, foreign direct investment, capital accumulation, inflation, sectoral value added, and employment in both industry and services. This approach is particularly relevant for China, where policy reforms and structural changes have generated complex interdependencies between production, labor allocation, and macroeconomic stability. To address these issues, the present study makes several novel contributions. First, it employs the Toda Yamamoto vector autoregression (TY-VAR) framework, which allows for valid causal inference in the presence of mixed integration orders a feature clearly supported by the unit root results in the data. Second, by simultaneously incorporating investment, industrial and services value added, and sectoral employment, the study offers a more comprehensive view of growth dynamics than existing single-channel analyses. Third, the paper explicitly tests the hypothesis that investment-led industrialization and employment dynamics remain central drivers of economic growth, even amid structural transformation toward services. Fourth, doing so, the study sheds light on whether industrial employment continues to exert a stronger growth impact than services employment and whether investment and FDI effects materialize with temporal lags. The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 outlines the data sources and methodology, including the TY-VAR framework and diagnostic procedures. Section 4 presents the empirical results, supported by impulse response functions and forecast error variance decomposition. Section 5 discusses the results and finally, Section 5 concludes with key policy implications and directions for future research.

Literature

Importance and relevance of the debate

The relationship between investment, industrialization, employment, and economic growth has long been one of the most hotly debated topics in development and macroeconomic research. In recent years, this debate has gained renewed urgency as many economies face slowing growth, declining industrial employment, and questions about the sustainability of investment-led growth models. While earlier studies emphasized capital accumulation and industrial expansion as central engines of growth, more recent research has questioned whether these mechanisms remain effective amid structural transformation toward services and changing labor market dynamics. As a result, understanding whether investment and industrial employment continue to drive economic growth or whether their roles have weakened has become a critical empirical issue, particularly for large emerging economies.

Literature on growth, investment, industrialization, and employment

A substantial body of empirical literature has examined the links between economic growth and investment, industrial development, and employment. Early cross-country studies documented a strong positive relationship between gross fixed capital formation and GDP growth, highlighting investment as a key driver of long-run economic performance (De Long & Summers, 1991; Levine & Renelt, 1992). Subsequent research extended this line of inquiry by incorporating industrial value added and manufacturing output, showing that industrialization plays a disproportionately large role in promoting productivity growth and structural upgrading (Rodrik, 2016; Szirmai, 2012). At the same time, employment-related studies emphasized that growth-enhancing effects depend not only on output expansion but also on how labor is allocated across sectors, particularly between industry and services (MS McMillan & Rodrik, 2011). Together, these studies suggest that growth outcomes are shaped by a complex interaction between capital accumulation, sectoral production, and labor dynamics rather than by any single factor in isolation.

Trends in variables and empirical focus

More recent empirical studies have increasingly adopted a multivariate perspective, incorporating foreign direct investment, trade openness, inflation, and sectoral employment alongside traditional growth determinants. Several studies report that FDI contributes positively to growth by facilitating technology transfer and industrial upgrading, particularly in economies with strong absorptive capacity (Alfaro, Chanda, Kalemli-Ozcan, & Sayek, 2004; Borensztein, De Gregorio, & Lee, 1998). Trade openness has also been linked to growth through scale effects and productivity gains, although the magnitude and timing of its impact vary across countries (Frankel & Romer, 2017). In parallel, the growing importance of services has motivated research examining whether services-sector expansion can substitute for industrialization as a growth engine, with mixed findings across regions (Duarte & Restuccia, 2010). These trends highlight an increasing reliance on diverse macroeconomic and structural variables, reflecting the evolving nature of growth processes in both developed and emerging economies.

Methods and empirical techniques in existing studies

Methodologically, the literature employs a wide range of econometric techniques to study growth dynamics. Panel data models, including fixed-effects and dynamic GMM estimators, are commonly used to address endogeneity and unobserved heterogeneity in cross-country analyses (Arellano & Bond, 1991; Blundell & Bond, 1998). Time-series studies often rely on cointegration techniques such as Johansen tests, vector error correction models (VECM), and autoregressive distributed lag (ARDL) approaches to distinguish between short- and long-run relationships (Johansen, 1991; Pesaran, Shin, & Smith, 2001). However, these methods require strict assumptions regarding integration order and cointegration rank, which may not hold when variables exhibit mixed integration properties as is the case in the present study. Moreover, many approaches impose long-run equilibrium restrictions that may obscure short- and medium-term dynamics. For these reasons, this study does not adopt conventional cointegration-based techniques and instead employs the Toda Yamamoto VAR framework, which allows for robust inference without requiring pre-testing for cointegration.

Research gap and contribution

Based on the above discussion, several important gaps remain in the existing literature. First, few studies simultaneously examine investment, industrial and services value added, and sectoral employment within a unified time-series framework, particularly for a single large emerging economy over a long horizon. Second, much of the literature relies on panel-based evidence, which may mask country-specific dynamics and policy-relevant feedback effects. Third, limited attention has been paid to the temporal structure of growth drivers specifically, whether investment, FDI, and employment exert delayed rather than immediate effects on GDP growth. Finally, existing studies often focus on either output or employment but rarely integrate both dimensions in a system-wide analysis. By using annual data for China from 1991 to 2024 and applying the Toda–Yamamoto VAR approach, this study fills these gaps by providing a comprehensive, dynamic assessment of how investment-led industrialization and employment dynamics jointly shape economic growth. The findings offer fresh insights into the relative strengths and limitations of different growth drivers and contribute to ongoing debates on structural transformation and growth sustainability.

Methodology

Data sources, measurement, and time frame

This study employs annual time-series data for China covering the period 1991–2024, selected to capture long-run growth dynamics alongside major structural and policy transformations. All variables are obtained from the World Bank's World Development Indicators (WDI) database, ensuring consistency, reliability, and international comparability as given in Table 1. GDP growth (annual percentage change) is used as the dependent variable, reflecting overall economic performance. The explanatory variables include trade openness (trade as a percentage of GDP), foreign direct investment inflows (FDI as a percentage of GDP), gross fixed capital formation (GFCF as a percentage of GDP), inflation (consumer prices, annual percentage), industrial value added (percentage of GDP), services value added (percentage of GDP), employment in industry (percentage of total employment), and employment in services (percentage of total employment). These variables collectively capture the core channels through which investment, industrialization, and employment are expected to influence economic growth. The choice of annual frequency is motivated by data availability for employment and sectoral value-added indicators and is consistent with prior macroeconomic growth studies focusing on long-term structural change.

Table 1. Summary of the study indictors

Variable	Symbol	Measurements	Source
GDP growth	gdp gr	Gross Domestic Product growth (annual %)	WDI
Trade	trade	Trade (% of GDP)	WDI
FDI, net inflow	fdi	Foreign direct investment, net inflows (% of GDP)	WDI
GFCF	gfcf	Gross fixed capital formation (% of GDP)	WDI
Inflation	inflation	Inflation, consumer prices (annual % growth)	WDI
Industrial value added	ind va	Industry, including construction, value added (% of GDP)	WDI
Services value added	serv va	Services, value added (% of GDP)	WDI
Total employment in industry	emp ind	Employment in industry (% of total employment) (modeled ILO estimate)	WDI
Total employment in services	emp serv	Employment in services (% of total employment) (modeled ILO estimate)	WDI

Theoretical perspective

The theoretical foundation of this study draws primarily on endogenous growth theory and structural transformation theory. Endogenous growth models emphasize the role of capital accumulation, investment, and technological spillovers in sustaining long-run economic growth (Aghion & Howitt, 1990; Romer, 1990). In this framework, investment both domestic (GFCF) and foreign (FDI) enhances productive capacity and facilitates knowledge diffusion, thereby stimulating growth. Complementing this view, structural transformation theory highlights the importance of reallocating resources from low-productivity sectors to higher-productivity ones, particularly from agriculture to industry and, subsequently, to services (Kuznets, 1973; MS McMillan & Rodrik, 2011). Industrial value added and industrial employment are therefore expected to exert a stronger growth-enhancing effect than services-sector variables, especially during periods of rapid industrialization. Together, these theoretical perspectives suggest that economic growth emerges from the dynamic interaction between investment, sectoral production structures, and employment reallocation an interaction that cannot be adequately captured using single-equation models.

Empirical framework

To empirically examine these interactions, the study adopts the Toda Yamamoto vector autoregression (TY-VAR) framework, which is well suited for multivariate time-series analysis involving variables with mixed orders of integration. Unit root tests reported in Table 4 indicate that the variables are integrated of order I(0), I(1) and I(2), making conventional cointegration-based approaches such as VECM or ARDL potentially unreliable. The TY-VAR approach overcomes this limitation by allowing valid inference on causality without requiring pre-testing for cointegration (Toda & Yamamoto, 1995).

The general VAR(p) model can be expressed as:

$$Y_t = A_0 + \sum_{i=1}^{p} A_i Y_{t-i} + \varepsilon_t \qquad (1)$$

Where Y_t is a vector of endogenous variables including GDP growth, trade, FDI, GFCF, inflation, industrial value added, services value added, industrial employment, and services employment; A_i

represents parameter matrices; and ε_t is a vector of white-noise error terms.
Following Toda and Yamamoto, the model is estimated with (p + dmax) lags, where p is the optimal lag length selected using standard information criteria (AIC, SBIC, HQIC), and d_{max} is the maximum order of integration among the variables. The TY-VAR model is specified as:

$$y_t = \alpha + \sum_{i=1}^{p} A_i y_{t-i} + \sum_{j=p+1}^{p+d_{max}} A_j y_{t-j} + \varepsilon_t \qquad (2)$$

Where, α is a vector of intercept terms, A_i are k×k coefficient matrices, ε_t is a vector of white-noise error terms assumed to be independently and identically distributed with zero mean and constant variance. The Granger causality is examined using the Modified Wald (MWALD) test proposed by Toda and Yamamoto. The test evaluates whether the lagged values of one variable contain statistically significant information for predicting another variable. y_i Granger-causes variable y_i, the following null hypothesis is imposed on the coefficients of the first p lags:

$$H_0 : A_{ij,1} = A_{ij,2} = \cdots A_{ij,p} = 0 \qquad (3)$$

This hypothesis implies that the first p lagged coefficients of y_i in the equation for y_i are jointly equal to zero. The MWALD test statistic is given by;

$$MWALD = \left(R\hat{\theta}\right)' \left[R\left(\widehat{Var}\left(\hat{\theta}\right)R'\right] \xrightarrow{-1} \left(R\hat{\theta}\right) \qquad (4)$$

Where, $\hat{\theta}$ is the vector of estimated parameters, R is a restriction matrix selecting the coefficients under the null hypothesis. The MWALD statistic asymptotically follows a chi-square distribution:

$$MWALD \sim x^2(p) \qquad (5)$$

Rejection of the null hypothesis indicates the presence of Granger causality from y_i to y_i.

Estimation procedures and diagnostic tests

The empirical analysis proceeds in several steps. First, unit root tests (ADF and PP) are conducted to determine the integration properties of each variable. Second, the optimal lag length is selected based on multiple information criteria to ensure model stability. Third, the TY-VAR model is estimated, allowing for consistent inference regardless of the integration order of the variables. To assess dynamic relationships, impulse response functions (IRFs) are employed to trace the time-path effects of shocks to investment, industrialization, and employment variables on GDP growth. IRFs are computed as:

$$IRF(h) = \frac{\partial Y_{t+h}}{\partial \varepsilon_t} \qquad (6)$$

Where h denotes the forecast horizon. In addition, forecast error variance decomposition (FEVD) is used to quantify the relative contribution of each variable to fluctuations in GDP growth over time:

$$FEV\ D_j(h) = \frac{\sum_{k=0}^{h-1} \theta_{jk}^2}{\sum_{k=0}^{h-1} \sum_{j=1}^{n} \theta_{jk}^2} \qquad (7)$$

Where $\boldsymbol{\theta_{jk}}$ represents the moving-average coefficients. Finally, a series of diagnostic tests including stability tests, residual autocorrelation (LM test), normality, and heteroskedasticity checks are conducted to validate the adequacy of the model. The results confirm that the VAR system is stable and suitable for dynamic analysis.

Justification for methodological choices

The TY-VAR approach is particularly appropriate for this study for three reasons. First, it accommodates variables with different integration orders, as observed in the data. Second, it captures feedback effects and dynamic interdependencies among growth, investment, industrialization, and employment. Third, unlike single-equation models, it allows for a system-wide analysis that aligns closely with the theoretical framework of endogenous growth and structural transformation. These advantages make the TY-VAR framework well suited for examining China's long-run growth dynamics.

Empirical Results and Discussion

Descriptive statistics and Correlation analysis

Table 2 reports the descriptive statistics of all variables used in the analysis. GDP growth exhibits a relatively high average rate of 8.87%, reflecting China's sustained growth momentum over the sample period, although the wide range between the minimum (2.34%) and maximum (14.3%) indicates substantial cyclical fluctuations. Trade openness averages 41.6% of GDP, highlighting the economy's strong integration into global markets, while FDI inflows remain modest on average but display notable variability, suggesting episodic surges associated with policy reforms and global investment cycles. Gross fixed capital formation shows a consistently high mean value of 38.2% of GDP, underscoring the investment-driven nature of economic growth. Industrial and services value added contribute almost equally to GDP, but employment shares reveal a gradual shift toward services, consistent with structural transformation dynamics. Overall, these descriptive patterns provide preliminary evidence that investment, industrialization, and employment reallocation are key features of the growth process.

Table 2. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
gdp gr	34	8.866	2.857	2.34	14.3
trade	34	41.579	9.765	25.873	63.57
fdi	34	3.052	1.52	.099	6.162
gfcf	34	38.2	4.752	26.033	44.076
inflation	34	3.674	5.306	-1.401	24.257
ind va	34	43.055	3.53	36.476	46.887
serv va	34	44.932	7.526	33.935	56.748
emp ind	34	26.503	3.768	21.4	31.837
emp serv	34	33.717	8.322	18.9	45.829

Table 3 presents the correlation matrix among the variables. GDP growth shows strong positive correlations with FDI (0.745), industrial value added (0.756), industrial employment (0.643), and services employment (0.732), suggesting that both capital inflows and labor absorption in productive sectors are closely associated with economic expansion. In contrast, services value added exhibits a strong negative correlation with GDP growth (−0.738), which may reflect transitional inefficiencies during the shift from industry to services. The high correlations among sectoral value added and employment variables indicate structural interdependence, while the absence of perfect correlations suggests that multicollinearity is not severe. Importantly, these correlations are purely indicative and do not imply causality, reinforcing the need for a multivariate dynamic framework such as the TY-VAR model to disentangle feedback effects (Toda & Yamamoto, 1995).

Table 3. Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) gdp_gr	1.000								
(2) trade	0.352	1.000							
(3) fdi	0.745	0.291	1.000						
(4) gfcf	0.386	0.409	0.357	1.000					
(5) inflation	0.513	-0.119	0.558	-0.241	1.000				
(6) ind_va	0.756	0.437	0.894	0.370	0.339	1.000			
(7) serv_va	-0.738	0.035	-0.794	0.765	0.490	0.833	1.000		
(8) emp_ind	0.643	0.024	0.638	0.818	0.294	0.671	0.881	1.000	
(9) emp_serv	0.732	0.077	0.703	0.812	-0.432	0.753	0.972	0.933	1.000

Unit root properties

Table 4 reports the results of the Augmented Dickey Fuller (ADF) and Phillips Perron (PP) unit root tests. Most variables, including GDP growth, trade, FDI, investment, inflation, and sectoral value added, are integrated of order I (1), inflation also found order of I(0) in ADF, while employment in industry and services is found to be I (2) in both ADF and PP unit root test. These mixed integration orders violate the assumptions required for conventional cointegration-based approaches such as VECM or ARDL. This empirical feature directly justifies the adoption of the Toda Yamamoto VAR framework, which allows valid inference on causality and dynamic interactions without requiring pre-testing for cointegration. The unit root results therefore reinforce the methodological choices outlined in Section 3 and ensure the robustness of subsequent dynamic analyses.

Table 4. Unit root test results

Variable	ADF Level	ADF Δ	ADF Δ^2	PP Level	PP Δ	PP Δ^2	Order
gdp_gr	−1.376	−5.488***	−7.685***	−1.820	−10.143***	−15.311***	I(1)
trade	−1.824	−3.397**	−5.974***	−1.824	−3.984***	−7.811***	I(1)
fdi	−1.575	−8.812***	−7.617***	−1.639	−4.703***	−8.155***	I(1)
gfcf	−1.909	−7.087***	−6.909***	−2.725	−4.510***	−6.904***	I(1)
inflation	−3.109**	−5.181***	−6.913***	−2.316	−4.174***	−6.616***	I(0), I(1)
ind_va	-0.390	-4.551***	-6.917***	-0.127	-3.882***	-8.043***	I(1)
serv_va	-0.120	-3.437***	-5.095***	-0.008	-3.641***	-6.999***	I(1)
emp_ind	−1.743	−1.419	−2.782*	−1.161	−1.538	−4.290***	I(2)
emp_serv	−1.836	−0.955	−2.899**	−1.926	−1.071	−4.057***	I(2)

⭐ Notes:
*, **, *** = 10%, 5%, 1%
Δ = first difference, Δ^2 = second difference

Lag order selection and model stability

Table 5 reports the results of the lag length selection criteria for the VAR system. All standard information criteria AIC, HQIC, and SBIC consistently identify two lags as the optimal lag length, while the likelihood ratio (LR) test also strongly supports this choice at the 1% significance level.

This indicates that a VAR (2) specification adequately captures the dynamic interactions among GDP growth, investment, industrialization, and employment variables without overfitting the model. Fig. 1 complements the lag selection results by illustrating the roots of the companion matrix. All eigenvalues lie strictly inside the unit circle, confirming that the estimated VAR system is dynamically stable. This stability condition is essential for reliable impulse response functions and variance decomposition analysis, as it ensures that shocks to the system dissipate over time rather than generating explosive dynamics.

Table 5. Lag order selection criteria

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-509.585		.	.	8364	34.572	34.707	34.993
1	-222.332	574.510	81	0.000	0.011	20.822	22.167	25.025
2	7594.56	7521.6*	81	0.000	.	-488.304*	-484.27*	-475.693*
3	3833.77	7837	81	0.000	1.e-109*	-238.785	-235.019	-227.015

*optimal lag

Endogenous: gdp_gr trade fdi gfcf inflation ind_va serv_va emp_ind emp_serv

Exogenous: _cons

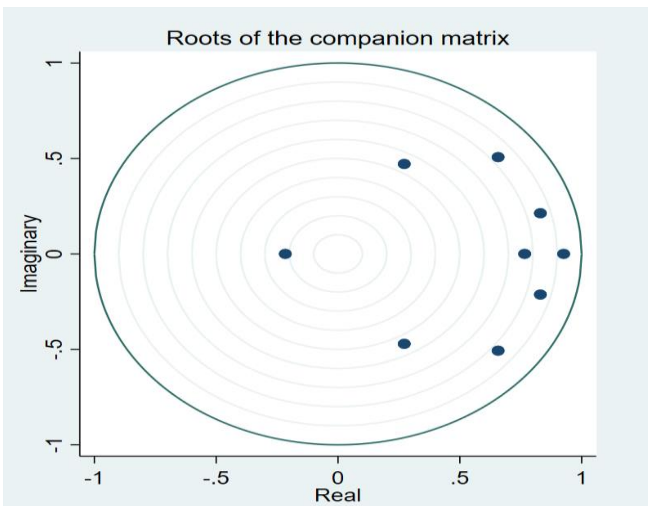

Fig 1. Model stability and optimal lag confirmation

Dynamics Model Estimations

Table 6 presents the estimated results of the Toda–Yamamoto VAR model, focusing on the GDP growth equation while accounting for dynamic feedback among investment, industrialization, and employment variables. The GDP growth equation exhibits strong explanatory power, with an R^2 of 0.895 and a highly significant Wald statistic, indicating that investment, industrialization, and employment dynamics jointly explain China's growth trajectory. This confirms that China's economic expansion cannot be attributed to a single driver but rather to interconnected structural forces. GDP growth shows limited short-run persistence, reflecting China's transition from an export- and investment-led growth model toward a more balanced structure. Among the core variables, gross fixed capital formation exerts a strong and positive effect at the second lag, highlighting the delayed but substantial contribution of infrastructure investment, industrial capacity expansion, and urban development to output growth. This finding is consistent with China's long-standing reliance on capital deepening through state-led and private investment in transport, energy, and manufacturing clusters (Naughton, 2018). Foreign direct investment also demonstrates a positive and statistically significant impact on GDP growth, particularly at longer horizons. This reflects China's ability to absorb foreign technology, managerial know-how, and global production linkages through Special Economic Zones and export-oriented industrial policies. The lagged nature of the effect suggests that FDI enhances growth primarily through productivity spillovers rather than immediate output gains (Borensztein et al., 1998).

Table 6. Toda–Yamamoto VAR estimations (TY model) results

Equation	**Parms**	**RMSE**	**R-sq**	**chi2**	**P>chi2**
GDP_GR	19	1.38501	0.8954	274.0011	0.0000
Trade	19	2.34633	0.9739	1194.624	0.0000
FDI	19	.273453	0.9865	2344.722	0.0000
GFCF	19	1.32062	0.9570	712.2835	0.0000
Inflation	19	1.45479	0.9702	1040.083	0.0000
Ind_Va	19	.616427	0.9879	2612.304	0.0000
Serv_Va	19	.569405	0.9975	12636.94	0.0000
Emp_Ind	19	.506572	0.9920	3961.006	0.0000
Emp_Serv	19	.980738	0.9932	4692.577	0.0000
Sample		1993 thru 2024_(Two Year Lag in the model)			
Number of obs		32			
Log likelihood		-144.8783			
Det(Sigma_ml)		6.92e-08			
AIC		19.7424			

Variables	**Coefficient**	**Std. err.**	**z**	**P>|z|**	**[95% conf.**	**interval]**
GDP_GR						
L1.	-0.279	0.183	-1.520	0.027	-0.638	0.080
L2.	0.355	0.227	1.560	0.008	-0.910	0.800
TRADE						
L1.	-0.184	0.131	-1.400	0.161	-0.441	0.073
L2.	0.289	0.110	2.620	0.009	0.072	0.505
FDI						
L1.	0.256	0.413	0.620	0.050	-0.554	1.066
L2.	0.478	0.516	0.930	0.035	1.490	0.534
GFCF						
L1.	-0.295	0.214	-1.380	0.167	-0.714	0.123
L2.	0.719	0.263	2.730	0.006	0.202	1.235
Inflation						
L1.	-0.315	0.176	-1.790	0.073	-0.660	0.029
L2.	0.017	0.105	0.160	0.873	-0.189	0.223
Ind_Va						
L1.	0.373	0.721	1.520	0.004	1.039	1.786
L2.	1.305	0.564	2.320	0.021	-2.410	-0.201
Serv_Va						
L1.	0.289	0.733	0.390	0.693	-1.147	1.726
L2.	-0.145	0.643	-0.230	0.821	-1.406	1.116
Emp_Ind						
L1.	1.433	0.868	1.650	0.038	-0.267	-3.134
L2.	1.695	0.831	2.040	0.041	3.323	0.067
Emp_Serv						
L1.	0.427	0.720	0.590	0.553	-0.984	1.837

L2.	1.315	0.812	-1.620	0.050	2.906	0.276
_Cons	58.880	26.183	2.250	0.025	7.563	110.197

Industrial value added emerges as one of the most influential drivers of China's economic growth, with both lags displaying positive and significant coefficients. This underscores the central role of industrialization in China's development strategy, where manufacturing-led growth has driven productivity gains, export competitiveness, and employment creation for several decades. These results strongly support the view that China's growth miracle is fundamentally rooted in industrial upgrading rather than services expansion alone (Lin, 2011). Employment in industry also shows a positive and significant relationship with GDP growth, reinforcing the importance of labor absorption in higher-productivity sectors. China's ability to shift labor from low-productivity agriculture to industrial employment has been a critical source of growth, particularly during the post-reform period (Margaret McMillan, Rodrik, & Verduzco-Gallo, 2014). In contrast, services value added and services employment exhibit weaker or statistically insignificant effects, suggesting that while the services sector has expanded rapidly in China, its productivity-enhancing role remains uneven and less growth-intensive compared to industry. Industrialization emerges as a central pillar of China's growth dynamics. Both industrial value added and industrial employment show strong positive associations with GDP growth, supported by causality and impulse response analyses. These results underscore the continuing relevance of manufacturing and industrial upgrading in driving productivity and income growth. Despite rapid services expansion in recent decades, China's experience confirms that industry remains the primary engine of growth, particularly through economies of scale, learning-by-doing, and export competitiveness (Lin, 2011; Rodrik, 2006). In contrast, services value added and services employment play a more complementary role. While services employment responds positively to GDP growth shocks and contributes to growth variability in the medium term, its impact is weaker than that of industrial variables. This reflects uneven productivity across China's services sector, where traditional services dominate employment but contribute less to productivity growth compared to advanced manufacturing. These findings are consistent with structural transformation literature showing that services-led growth may absorb labor but does not necessarily generate strong productivity gains in middle-income economies (Margaret McMillan et al., 2014) Table 7 presents the VAR residual diagnostic tests. The LM test identifies mild first-order serial correlation, a common feature in high-dimensional VAR systems applied to long time spans. Importantly, higher-order autocorrelation is absent. The Jarque–Bera tests confirm residual normality, and the ARCH (1) results show no evidence of conditional heteroskedasticity, indicating stable variance in the residuals.

Table 7. VAR residual diagnostics outcomes

Variable	Serial Correlation (LM test)	Normality (Skewness-Kurtosis JB)	ARCH (1) Coefficient	ARCH (1) p-value
gdp_gr	χ^2=109.86, p=0.018	χ^2=1.85, p=0.396	0.159	0.586
trade	χ^2=109.86, p=0.018	χ^2=1.85, p=0.396	0.159	0.586
fdi	χ^2=109.86, p=0.018	χ^2=1.85, p=0.396	0.159	0.586
gfcf	χ^2=109.86, p=0.018	χ^2=1.85, p=0.396	0.159	0.586
inflation	χ^2=109.86, p=0.018	χ^2=1.85, p=0.396	0.159	0.586
ind_va	χ^2=109.86, p=0.018	χ^2=1.85, p=0.396	0.159	0.586
serv_va	χ^2=109.86, p=0.018	χ^2=1.85, p=0.396	0.159	0.586
emp_ind	χ^2=109.86, p=0.018	χ^2=1.85, p=0.396	0.159	0.586
emp_serv	χ^2=109.86, p=0.018	χ^2=1.85, p=0.396	0.159	0.586

These results confirm the statistical adequacy of the TY-VAR model and ensure that the estimated relationships reflect genuine economic dynamics rather than model misspecification. This strengthens confidence in the interpretation of China-specific growth drivers. The diagnostic tests confirm the stability and adequacy of the estimated model, strengthening confidence in the robustness of the findings. Mild short-run serial correlation does not undermine inference, while the absence of heteroskedasticity and non-normality supports the reliability of the dynamic results.

Granger causality and growth transmission channels

Table 8 summarizes the Toda Yamamoto MWALD Granger causality results, revealing clear and economically meaningful causal pathways. GFCF unidirectionally causes GDP growth, reinforcing the view that investment remains a fundamental engine of China's economic expansion. This reflects the country's emphasis on infrastructure, industrial parks, and urbanization as growth catalysts. Similarly, industrial value added Granger-causes GDP growth, confirming that industrial expansion precedes and stimulates overall economic performance rather than merely responding to growth. This aligns with China's state-guided industrial policy and export-oriented manufacturing strategy (Rodrik, 2006). The causality from trade to GDP growth highlights the continued importance of external demand and global integration in sustaining China's growth, despite recent efforts to rebalance toward domestic consumption. Additionally, services employment Granger-causes GDP growth, suggesting that services increasingly complement industrial activity by absorbing surplus labor and supporting urban consumption. The bidirectional causality between FDI and GFCF reflects a mutually reinforcing relationship: foreign capital inflows stimulate domestic investment, while expanding domestic capital stock enhances China's attractiveness to multinational firms. Moreover, causality running from GDP growth to FDI indicates that strong economic performance continues to attract foreign investors, reinforcing growth momentum.

Table 8. Summary of Toda–Yamamoto MWALD Granger causality (Wald Test)

Causal Relationship	Direction	Wald χ^2	p-value
Trade ↔ GDP growth	Trade → GDP	19.84	0.000
GFCF ↔ GDP growth	GFCF → GDP	5.99	0.014
Industry VA ↔ GDP growth	Industry → GDP	9.81	0.002
Employment (Services) ↔ GDP growth	Emp_serv → GDP	3.86	0.049
Services VA → GDP growth	Weak (10%)	3.73	0.054
GFCF ↔ Trade	GFCF → Trade	11.23	0.001
Inflation ↔ Trade	Inflation → Trade	5.15	0.023
Employment (Industry) ↔ Trade	Emp_ind → Trade	15.66	0.000
GDP growth ↔ FDI	GDP → FDI	6.31	0.012
GFCF ↔ FDI	GFCF → FDI	11.41	0.001
FDI ↔ GFCF	FDI → GFCF	12.30	0.000
Industry VA ↔ GFCF	Industry → GFCF	4.70	0.030
Services VA ↔ GFCF	Services → GFCF	6.57	0.010
Employment (Services) ↔ GFCF	Emp_serv → GFCF	6.59	0.010
GDP growth ↔ Inflation	GDP → Inflation	32.41	0.000
FDI ↔ Inflation	FDI → Inflation	12.97	0.000
GFCF ↔ Inflation	GFCF → Inflation	37.16	0.000
Industry VA ↔ Inflation	Industry → Inflation	26.17	0.000
Employment (Services) ↔ Inflation	Emp_serv → Inflation	20.80	0.000

GFCF ↔ Employment (Industry)	GFCF → Emp_ind	4.59	0.032
GFCF ↔ Employment (Services)	GFCF → Emp_serv	6.09	0.014

Note:
→ = Unidirectional causality, ↔ = Relationship examined, but direction shown is significant one, Wald χ^2 and p-value come from MWALD (Toda–Yamamoto consistent tests).

The causality results demonstrate that China's growth is driven by investment-led industrialization, supported by employment transformation and global integration, rather than short-term macroeconomic fluctuations. These findings provide robust empirical backing for development strategies emphasizing productive investment and industrial upgrading. The Granger causality results further clarify the direction of influence among key variables. Investment and industrial output unidirectionally cause GDP growth, while feedback effects from growth to FDI suggest that strong economic performance enhances China's attractiveness to foreign investors. The bidirectional causality between FDI and GFCF highlights a reinforcing cycle in which foreign and domestic investments jointly expand productive capacity. Trade-induced causality toward GDP growth confirms that external demand and openness remain important growth channels, even as China rebalances toward domestic consumption (Naughton, 2018).

Impulse response functions analysis

In Figures 2–4, the horizontal axis (X-axis) represents the time horizon in years following a one-standard-deviation shock, while the vertical axis (Y-axis) measures the magnitude and direction of the response of the respective variable (GDP growth, employment, or sectoral output). The solid line depicts the orthogonalized impulse response, showing the estimated dynamic effect of a shock in one variable on another while accounting for contemporaneous interactions within the VAR system. The shaded area represents the 95% confidence interval, indicating the statistical uncertainty surrounding the estimated response. Figure 2 illustrates the dynamic response of GDP growth to one-standard-deviation shocks in key macroeconomic variables, including FDI, GFCF, inflation, and trade. Overall, GDP growth responds in a gradual and persistent manner, with effects becoming more pronounced after the initial periods, consistent with China's investment- and policy-driven growth structure.

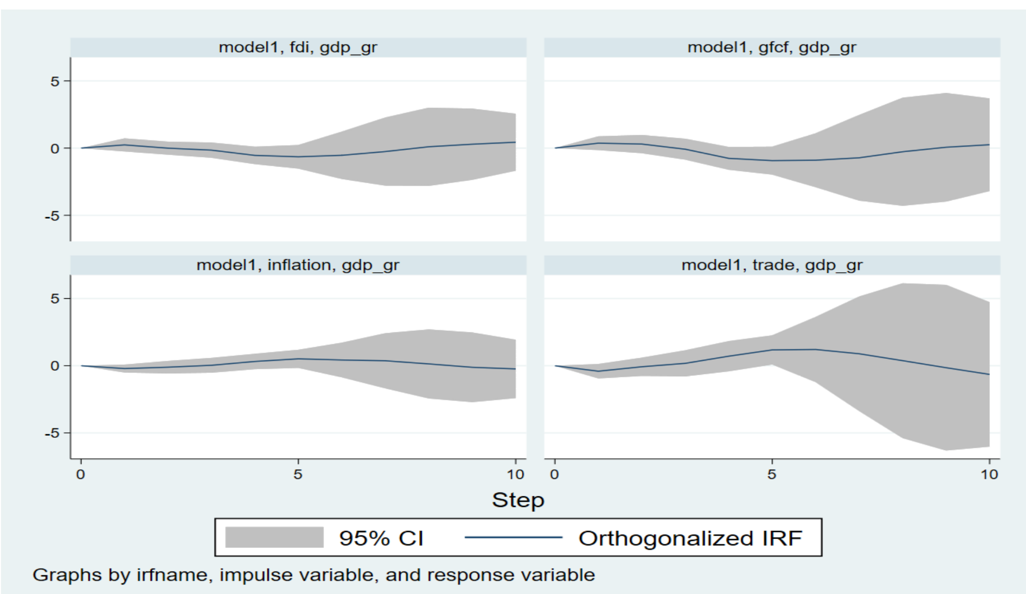

Fig 2. GDP growth response to macroeconomic shocks

A positive shock to GFCF generates a clear and sustained increase in GDP growth, peaking after several years before stabilizing. This delayed response reflects China's development model, where large-scale infrastructure and industrial investments often state-led require time to translate into productive capacity and output expansion. Similarly, FDI shocks exert a positive effect on growth over the medium term, supporting the role of foreign capital in facilitating technology transfer and integration into global value chains (Borensztein et al., 1998). In contrast, inflation shocks initially dampen GDP growth, indicating the short-run costs of macroeconomic instability. In China, inflationary pressures often trigger monetary tightening and credit controls, which restrain investment and growth momentum. Trade shocks show a positive but volatile response, reflecting China's exposure to external demand fluctuations and global trade cycles. These dynamics are consistent with earlier findings that China's growth remains sensitive to both domestic investment conditions and global economic forces (Naughton, 2018).

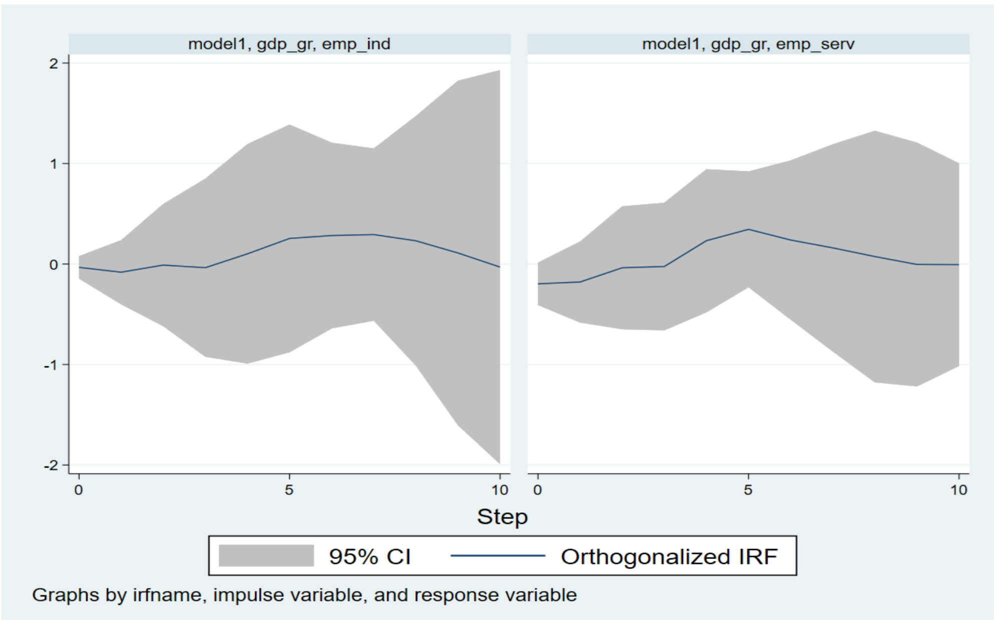

Fig 3. Employment response to GDP growth shock

Figure 3 depicts the response of industrial and services employment to a positive shock in GDP growth. The results show that industrial employment responds positively and relatively quickly, confirming that growth in China continues to generate employment in higher-productivity industrial sectors. This pattern reflects the country's long-standing industrial base and the capacity of manufacturing to absorb labor during expansionary phases. Services employment also increases following a GDP growth shock, though the response is more gradual and persistent. This suggests that economic growth first stimulates industrial activity and subsequently expands demand for services, consistent with China's gradual transition toward a more service-oriented economy. The widening confidence bands at longer horizons indicate increasing uncertainty, but the overall positive trajectory supports the view that employment reallocation accompanies growth rather than precedes it. These findings align with evidence that labor shifting from low- to higher-productivity sectors has been a major contributor to China's growth (Margaret McMillan et al., 2014).

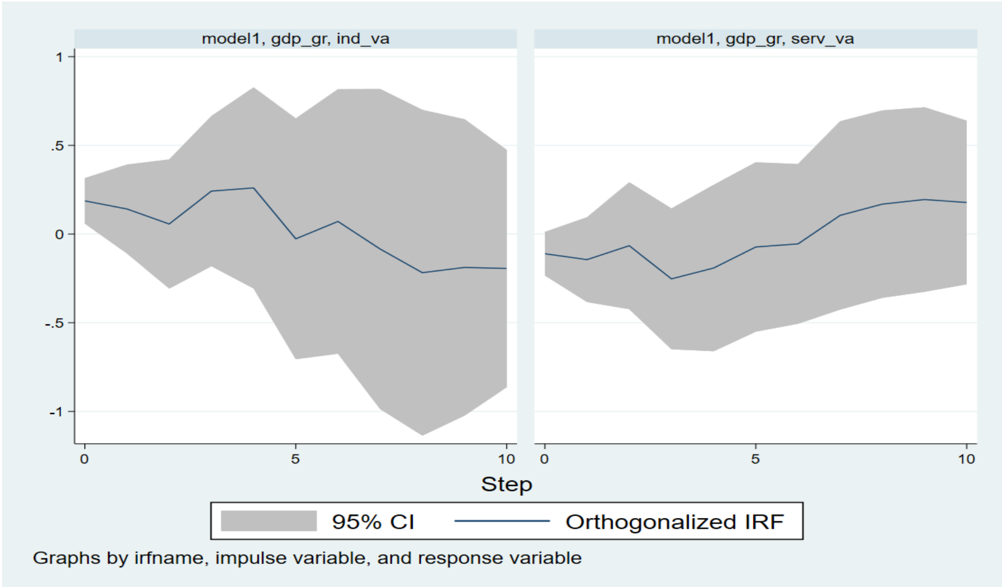

Fig 4. Sectoral output response to GDP growth shocks

Figure 4 presents the impulse responses of industrial and services value added to GDP growth shocks. Industrial value added exhibits a strong and positive response, particularly in the medium term, reinforcing the central role of industrial expansion in driving China's economic growth. This result is consistent with the TY-VAR estimates and Granger causality findings, which identify industry as a leading force rather than a passive outcome of growth. Services value added responds positively as well, but the magnitude is comparatively smaller and the response emerges more gradually. This suggests that while services expand alongside economic growth, their contribution to productivity and output remains secondary to industry during the analyzed period. In China's context, this reflects uneven productivity across services subsectors, with traditional services lagging behind advanced manufacturing in efficiency gains (Lin, 2011). Taken together, Figures 2–4 provide dynamic evidence that investment-led industrialization remains the backbone of China's growth, while employment and services expansion play complementary roles. These impulse responses corroborate the earlier causality results and strengthen the conclusion that China's growth process is driven by structural forces rather than short-term shocks.

Forecast error variance decomposition (FEVD) analysis

Figure 5 illustrates the forecast error variance decomposition of GDP growth, showing the relative contribution of shocks from different variables to fluctuations in GDP growth over a ten-year horizon. The horizontal axis (X-axis) represents the forecast horizon in years, while the vertical axis (Y-axis) shows the percentage share of GDP growth variance explained by each shock. The solid line indicates the fraction of mean squared error (MSE) attributable to a given shock, and the shaded area denotes the 95% confidence interval, capturing estimation uncertainty.

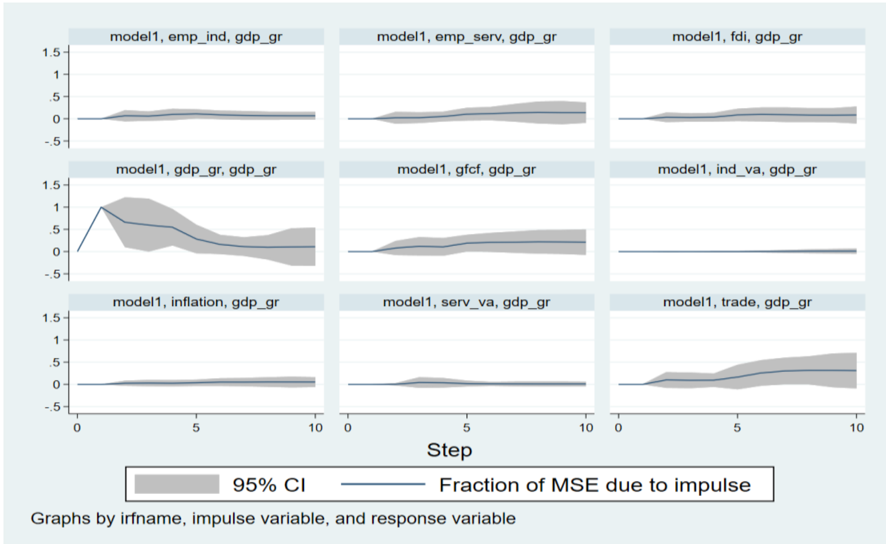

Fig 5. GDP growth variance decomposition

The results indicate that GDP growth's own shocks dominate in the short run, reflecting short-term inertia and cyclical adjustment. However, as the horizon lengthens, investment- and production-related variables gain importance. In particular, gross fixed capital formation (GFCF) and industrial value added explain an increasing share of GDP growth variability, underscoring the central role of capital accumulation and industrial expansion in China's medium- to long-term growth dynamics. Shocks from FDI and trade also contribute meaningfully to GDP growth variance over time, reflecting China's deep integration into global markets and reliance on foreign capital and external demand. In contrast, inflation and services value added shocks account for a relatively smaller share, suggesting that macroeconomic stability and services expansion play a more supportive than leading role in driving growth fluctuations. These results are fully consistent with the earlier Granger causality findings and impulse responses, reinforcing the conclusion that investment-led industrialization remains the backbone of China's growth model (Lin, 2011; Naughton, 2018).

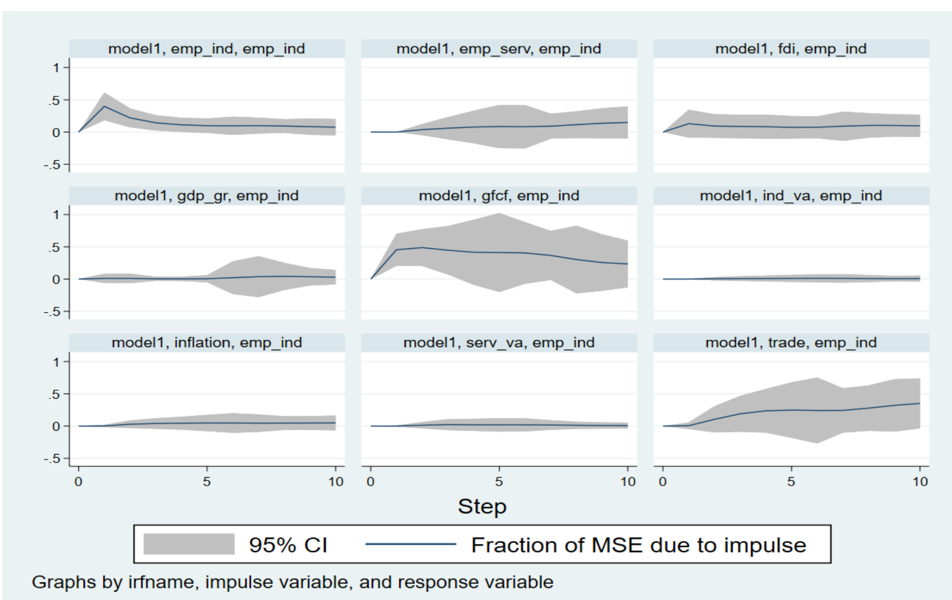

Fig 6. Industrial employment variance decomposition

Figure 6 presents the variance decomposition of industrial employment, showing how different shocks contribute to fluctuations in employment in the industrial sector. As in Figure 5, the X-axis denotes the forecast horizon, the Y-axis measures the percentage contribution to forecast error variance, the solid line represents the estimated contribution, and the shaded area shows the 95% confidence interval. The results reveal that GDP growth and GFCF shocks explain a substantial proportion of industrial employment variance, particularly over the medium term. This highlights the strong employment-generating effects of economic expansion and capital formation in China's industrial sector. Infrastructure investment, manufacturing upgrades, and industrial clustering directly stimulate labor demand, especially during expansionary phases. Shocks to trade and FDI also play a noticeable role, reflecting China's export-oriented industrial structure and the employment effects of foreign-invested manufacturing firms. In contrast, services value added and inflation shocks contribute relatively little to industrial employment fluctuations, indicating limited cross-sector spillovers from services to industry. These patterns align closely with China's development experience, where industrial employment growth has historically been driven by investment and external demand rather than domestic services expansion (Margaret McMillan et al., 2014).

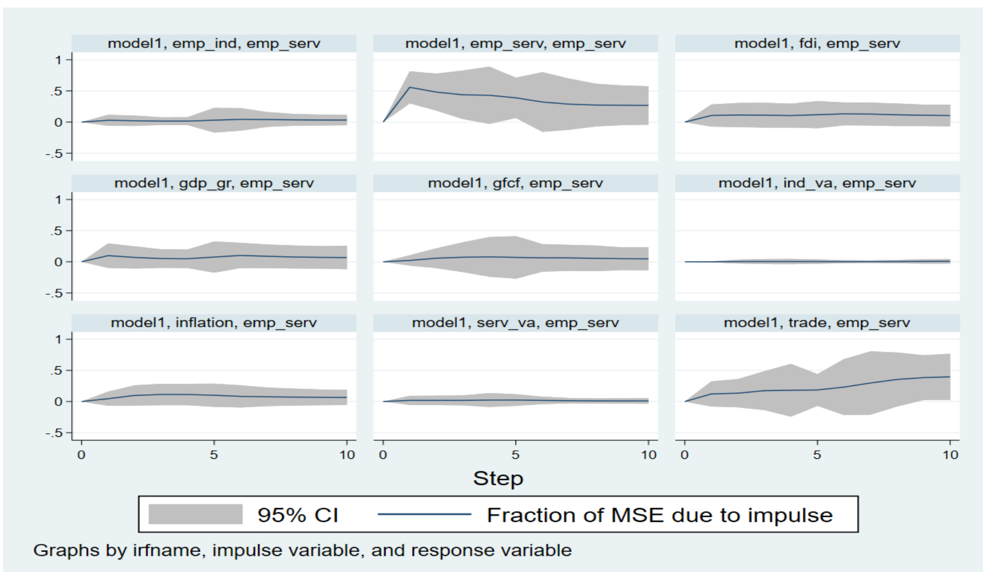

Fig 7. Services employment variance decomposition

Figure 7 presents the forecast error variance decomposition of services employment, illustrating how shocks to GDP growth, investment, industrialization, trade, and macroeconomic variables contribute to variations in services employment over a ten-year horizon. The horizontal axis (X-axis) represents the forecast horizon in years, while the vertical axis (Y-axis) measures the percentage contribution of each shock to services employment variability. The solid line shows the estimated share of the mean squared forecast error attributable to each shock, and the shaded area denotes the 95% confidence interval, reflecting estimation uncertainty. The results indicate that GDP growth shocks account for a substantial share of services employment variance, particularly in the medium term. This suggests that services employment in China is largely demand-driven, expanding as overall economic activity increases. Unlike industrial employment, which responds strongly to investment shocks, services employment appears to follow growth rather than initiate it consistent with the Granger causality results showing causality running from services employment to GDP growth only at weaker significance levels. Trade shocks also explain an increasing proportion of services employment variance over time. This reflects China's deep integration into global markets, where trade expansion stimulates logistics, finance, transportation, and business services. The growing contribution of trade shocks highlights the complementary role of services in supporting export-oriented industrial activity. In contrast, industrial value added and GFCF shocks contribute relatively little to services employment fluctuations. This suggests limited direct spillovers from industrial production and capital accumulation to services employment, reinforcing the view that productivity and employment linkages across sectors remain uneven. Inflation shocks have a minor and transitory effect, indicating that services employment is relatively insulated from short-term price instability. The FEVD results confirm that services employment growth in China is largely a consequence of broader economic expansion and trade activity, rather than a primary driver of growth. This finding complements the impulse response and causality analyses, reinforcing the manuscript's central argument that industrialization and investment remain the engines of growth, while services employment plays a supportive and absorptive role during structural transformation. Impulse response and variance decomposition analyses provide dynamic support for these conclusions. Shocks to investment and industrial output generate sustained positive responses in GDP growth, while services-related shocks have more modest effects. Moreover, FEVD results show that investment and industrial variables explain a growing share of GDP and employment variability over time, emphasizing their structural importance. Together, these dynamics suggest that China's growth is not driven by short-term macroeconomic shocks, but by long-run structural forces rooted in capital accumulation and industrial capability (Autor, Dorn, & Hanson, 2016).

Conclusion

This study examined the dynamic linkages between economic growth, investment, industrial structure, trade openness, and employment in China using a Toda–Yamamoto VAR framework over the period 1991–2024. By integrating causality tests, impulse response analysis, and forecast error variance decomposition, the study provides robust evidence on the structural drivers of China's long-run economic growth. The results clearly show that capital accumulation and industrial development remain the backbone of China's growth process. Gross fixed capital formation and industrial value added exert strong and persistent positive effects on GDP growth, while foreign direct investment reinforces growth through technology spillovers and productive upgrading. Employment dynamics, particularly in the industrial and services sectors, respond positively to growth shocks, highlighting the role of structural transformation in sustaining economic expansion. At the same time, the findings indicate that although the services sector has expanded rapidly and absorbs a growing share of labor, its contribution to growth remains largely complementary rather than dominant. China's growth trajectory therefore continues to rely on productive investment, industrial upgrading, and coordinated labor reallocation, rather than a premature shift toward consumption- or services-led growth. This study demonstrates that China's economic growth is primarily driven by structural and investment-led mechanisms, supported by openness and employment transformation. These insights offer important guidance for policymakers seeking to maintain growth momentum while advancing high-quality development.

Policy Implications

The empirical findings of this study provide several clear and actionable policy recommendations for China's ongoing economic transformation.

First, the persistent role of industrial value added in driving GDP growth highlights the need to further promote high-end manufacturing, automation, and innovation-driven industrial clusters. Policies supporting research and development, firm-level upgrading, and integration into global value chains should remain central to China's industrial strategy.

Second, FDI continues to play a positive role when it complements domestic investment. Policymakers should therefore focus on selective FDI attraction, encouraging investments that bring advanced technologies, managerial expertise, and green production processes, rather than purely capital-intensive or low-value-added projects.

Third, the responsiveness of industrial and services employment to growth shocks suggests the importance of labor mobility and skill upgrading. Expanding vocational training, reskilling programs, and labor-market flexibility can ensure that workers transition smoothly from traditional sectors to more productive industries and modern services.

Fourth, the causal linkages between growth, inflation, and investment underline the importance of macroeconomic stability. A balanced monetary and fiscal stance that avoids excessive inflation volatility while supporting long-term investment is essential for sustaining China's growth momentum.

Future Research Directions

While this study provides robust evidence on China's growth dynamics, several avenues remain open for future research.

First, future studies could incorporate regional-level data to explore spatial heterogeneity in investment, industrialization, and employment effects across provinces, capturing China's uneven development patterns.

Second, extending the framework to include environmental and energy variables would offer valuable insights into the trade-offs between growth, industrial upgrading, and sustainability, especially in the context of China's carbon neutrality goals.

Third, future research could apply nonlinear or regime-switching VAR models to examine whether growth drivers differ across high-growth and low-growth phases, or before and after major policy shifts such as the Belt and Road Initiative or supply-side structural reforms.

Finally, comparative studies between China and other emerging economies could help assess the transferability of China's development model, enriching the broader literature on growth, industrialization, and structural transformation.

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