

Dynamic Links among Stock Market Index, Purchasing Managers' Index, and China's Foreign Exchange Reserves

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Abstract. In post-pandemic China, the expanding weight of services in overall economic activity and the stabilising role of official foreign exchange reserves (FER) elevate the informational value of high-frequency business surveys for interpreting equity market conditions. This study investigates the dynamic relations among China's stock market index, the Manufacturing and Non-Manufacturing Purchasing Managers' Index (PMI), and official FER using monthly data from April 2022 to July 2025. All series are log-transformed. Stationarity is assessed via Augmented Dickey-Fuller (ADF) tests to determine that all variables enter the model as first differences. A reduced-form vector autoregression (VAR) with a constant and four lags is estimated, followed by in-system Granger causality tests, orthogonalized impulse-response functions under a Cholesky scheme, and forecast-error variance decomposition (FEVD). Results indicate short-run mean reversion in the stock market index and limited immediate pass-through from manufacturing PMI and FER, while the non-manufacturing PMI exhibits the clearest medium-horizon influence. The FEVD results show that own shocks dominate at very short horizons, with services PMI gaining prominence over 6-12 months and reserves contributing moderately. However, manufacturing PMI accounts for the smallest share of the variance. Granger causality tests suggest that both PMI and FER impact the stock market index, while no causal relationship is found from the stock market index to these variables. These results highlight the role of services-sector signals for monitoring economic trends at medium horizons, with reserves primarily viewed as a stability indicator.

Keywords: Stock market index; non-manufacturing PMI; manufacturing PMI; FER; VAR.

1. Introduction

China's PMI, compiled from monthly enterprise surveys, has long been treated as a timely barometer of business conditions and a leading indicator of macro activity [1]. A growing literature also documents close co-movements between PMIs and financial conditions, including equity prices, credit spreads and the US dollar, suggesting that PMI and markets share common information about macroeconomic sentiment [2-4]. For China specifically, prior studies report asymmetric stock-market reactions to PMI announcements, with positive PMI news eliciting stronger equity responses than negative news [5]. At the same time, China manages the world's largest stock of official FER, which play a stabilising role for balance-of-payments management and economic stability [6-7]. Yet, despite these strands, there remains a gap on the joint dynamics linking China's stock market with both manufacturing and non-manufacturing PMI and official FER within a unified time-series system over the post-pandemic period.

Against this backdrop, the paper asks three questions, (i) Do manufacturing and non-manufacturing PMIs trigger changes in China's stock market index, or do equity conditions impact PMI? (ii) Do innovations in FER transmit to equity returns (or vice versa), after controlling for PMI signals? (iii) What are the magnitudes and persistence of these dynamic effects? Methodologically, this study employs a VAR to model feedback across the stock market index, PMI and FER, conducts Granger causality tests to establish causality direction, and uses impulse-response functions with FEVD for dynamic interpretation [8-9].

The study contributes in three ways. First, it uses both manufacturing and non-manufacturing PMIs to capture the breadth of China's business cycle, rather than relying on a single manufacturing index [1, 5]. Second, it focuses on official FER, a policy-relevant balance-sheet variable distinct from the foreign exchange rate, thereby linking sentiment (PMI), reserve buffers (policy reserves) and

market pricing (equities) in one system [6, 10]. Third, by analysing monthly data from April 2022 to July 2025, it concentrates on a period featuring reopening dynamics, property-sector stress and evolving macro-financial conditions, when the information content of PMI relative to markets may differ from earlier decades [2, 11]. The results aim to inform both investors who use PMI tactically and policymakers who interpret stock-market moves alongside reserve management signals.

2. Method

This study examines the dynamic links among China's stock market, business-cycle signals, and external buffers using monthly data from April 2022 to July 2025. The system contains four endogenous series constructed from official releases (Table 1), the stock market level (Shanghai Composite), the Manufacturing and Non-Manufacturing PMI, and official foreign-exchange reserves [5, 12-16]. All variables are first log-transformed, then differenced to obtain the first differences in order to ensure stationarity, and shocks are interpreted as approximate percentage changes. Table 1 summarises the variables and coding used in the empirical analysis.

Table 1. Variables and definitions.

Symbol in text	Code name (R)	Definition	Source
$\log SI_t$	l_sh	Logarithm of China stock market index (Shanghai Composite, month-end or monthly average)	Shanghai Stock Exchange (SSE)
$\log PMI_t^M$	l_pmi_manu	Logarithm of Manufacturing Purchasing Managers' Index	National Bureau of Statistics of China (NBS of China)
$\log PMI_t^{NM}$	l_pmi_non	Logarithm of Non-Manufacturing Purchasing Managers' Index	National Bureau of Statistics of China (NBS of China)
$\log FER_t$	l_fx	Logarithm of Official foreign-exchange reserves (stock)	China Foreign Exchange Trade System (CFETS)

For VAR estimation suitability, ADF tests are employed for logged series [17-18]. Following the results of the ADF test, all variables are included in the model as first differences (interpretable as monthly growth rates) to ensure stationarity. It then estimates a VAR of order p with all four variables treated as endogenous in the following equation (1):

$$y_t = c + A_1 y_{t-1} + \dots + A_p y_{t-p} + u_t, y'_t = [\log PMI_t^M, \log PMI_t^{NM}, \log FER_t, \log SI_t] \quad (1)$$

Where u_t is a zero-mean vector white-noise process with covariance matrix $\sum u$. The lag length p is selected from a small grid suitable for monthly data (e.g., $p \in \{1, 2, 3, 4\}$) using information criteria, with the final choice favouring parsimony. A constant term is included to absorb deterministic means. No exogenous regressors are added so that innovations are defined strictly within the system [8-9]. Definitions of other variables are seen in Table 1.

Granger causality is examined via tests conducted within the VAR. For each ordered pair (x, y) , the null hypothesis states that lagged values of x do not enter the equation for y . It reports Wald (or F) statistics and p-values for the joint significance of the relevant lag coefficients at conventional levels (10%, 5%, 1%).

Dynamic transmission is assessed using orthogonalized impulse-response functions (IRFs) and FEVDs. Identification follows a Cholesky decomposition of $\sum u$ with the ordering $(PMI_t^M, PMI_t^{NM}, FER_t, SI_t)$. This ordering allows PMI (business-survey information) and FER (reserve buffers) to contemporaneously affect equity index, while equity shocks do not contemporaneously affect the other variables within the same month. IRFs are computed within 12 months to capture short- and medium-run effects, with confidence bands obtained by bootstrap resampling. FEVDs quantify the contribution of each orthogonal shock to the forecast-error variance of each variable. In reporting, it emphasises the decomposition for the stock-market variable while the model remains fully multivariate.

3. Results

3.1. Descriptive Statistics and ADF Test

The sample (Table 2) covers 40 monthly observations. Relative variability in the equity index is higher compared with foreign-exchange reserves, which remain extremely stable. Both groups of mean PMI groups are close to 50. However, their spread is tighter in manufacturing but wider in non-manufacturing with less than 50.

Table 2. Descriptive statistics to variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
SI_t	40	3173.99	173.28	2788.55	3573.21
FER_t	40	31915.06	752.81	30289.55	33174.22
PMI_t^M	40	49.58	0.98	47.00	52.60
PMI_t^{NM}	40	51.01	3.13	41.60	58.20

The ADF unit-root tests are reported in Table 3. All variables are transformed by the logarithm and then entered as first differences. The ADF tests indicate that all variables are $I(1)$, which justifies the use of first differences for the VAR estimation in stationary form.

Table 3. ADF unit-root tests (logged series).

Variable	First diff. p-value	5% decision
$\log FER_t$	0.031	$I(1)$
$\log SI_t$	0.010	$I(1)$
$\log PMI_t^M$	0.010	$I(1)$
$\log PMI_t^{NM}$	0.034	$I(1)$

3.2. VAR Results

The VAR results are summarized as follows, in terms of Monthly VAR with four endogenous variables $\Delta \log(FER)$, $\Delta \log(SI)$, $\Delta \log(PMI_M)$, $\Delta \log(PMI_NM)$. Information criteria choose $p=4$ for AIC, HQ and FPE, while SC suggests $p=1$. This study retains VAR (4). Effective sample after lags, in terms of $T = 35$ months (2022-04 to 2025-07). All roots of the characteristic polynomial lie inside the unit circle (max modulus approximately 0.997), indicating stability.

In the stock index equation (Table 4), $\Delta \log(SI)$ shows significant short-run mean reversion, with notable negative effects at lag 1. Cross-variable lags and FER lags are weak, and PMI terms are significant only sporadically. In the FER equation, own dynamics dominate, with a significant negative lag-4 and negligible cross-effects. Manufacturing PMI shows strong persistence at lags 2–3 with limited spillover from services PMI. The non-manufacturing PMI equation shows few significant coefficients.

Table 4. VAR results of stock index (SI) equation.

Lag	Variable	Coefficient	p-value
1	d_fx	-1.071	0.131
1	d_sh	-0.588*	0.012
1	d_pmi_manu	-0.803	0.177
1	d_pmi_non	0.193	0.243
2	d_fx	-1.170	0.121
2	d_sh	-0.198	0.336
2	d_pmi_manu	-1.081	0.065
2	d_pmi_non	0.551*	0.012
3	d_fx	-2.065*	0.011
3	d_sh	-0.054	0.772
3	d_pmi_manu	-1.354*	0.045

3	d_pmi_non	0.721**	0.007
4	d_fx	-1.085	0.235
4	d_sh	-0.237	0.183
4	d_pmi_manu	-0.901	0.184
4	d_pmi_non	0.316	0.216

Note: d_fx= The first difference of logarithm of FER; d_pmi_non= The first difference of logarithm of Non-manufacturing PMI; d_pmi_manu= The first difference of logarithm of Manufacturing PMI; d_sh= The first difference of logarithm of stock market index

*p< 0.05, **p< 0.01, ***p< 0.001

Impulse-response results are reported in Figure 1. The figure depicts the stock index's responses ($\Delta \ln SI$) to shocks in each variable. Overall, fluctuations are dominated by own shocks, with external variables contributing little. After an own shock, the index shows a marked positive response that gradually oscillates back toward zero, indicating clear self-driven, inertial dynamics. By contrast, shocks to FER have virtually no significant effect. In specific, the response stays within the confidence bands throughout, implying no direct short-run transmission to equities. Shocks to the manufacturing PMI are likewise weak, though the path wiggles, it generally remains inside the significance bands, suggesting limited direct pass-through. The non-manufacturing PMI exhibits a clearer pattern. That is, the response rises and then falls, followed by a rebound. Meanwhile, a negative effect appears around horizon 6, turning positive again around horizons 9–10. Although some points do not fully breach the confidence bands, the overall trajectory suggests that the non-manufacturing PMI exerts a dynamic influence on the stock index.

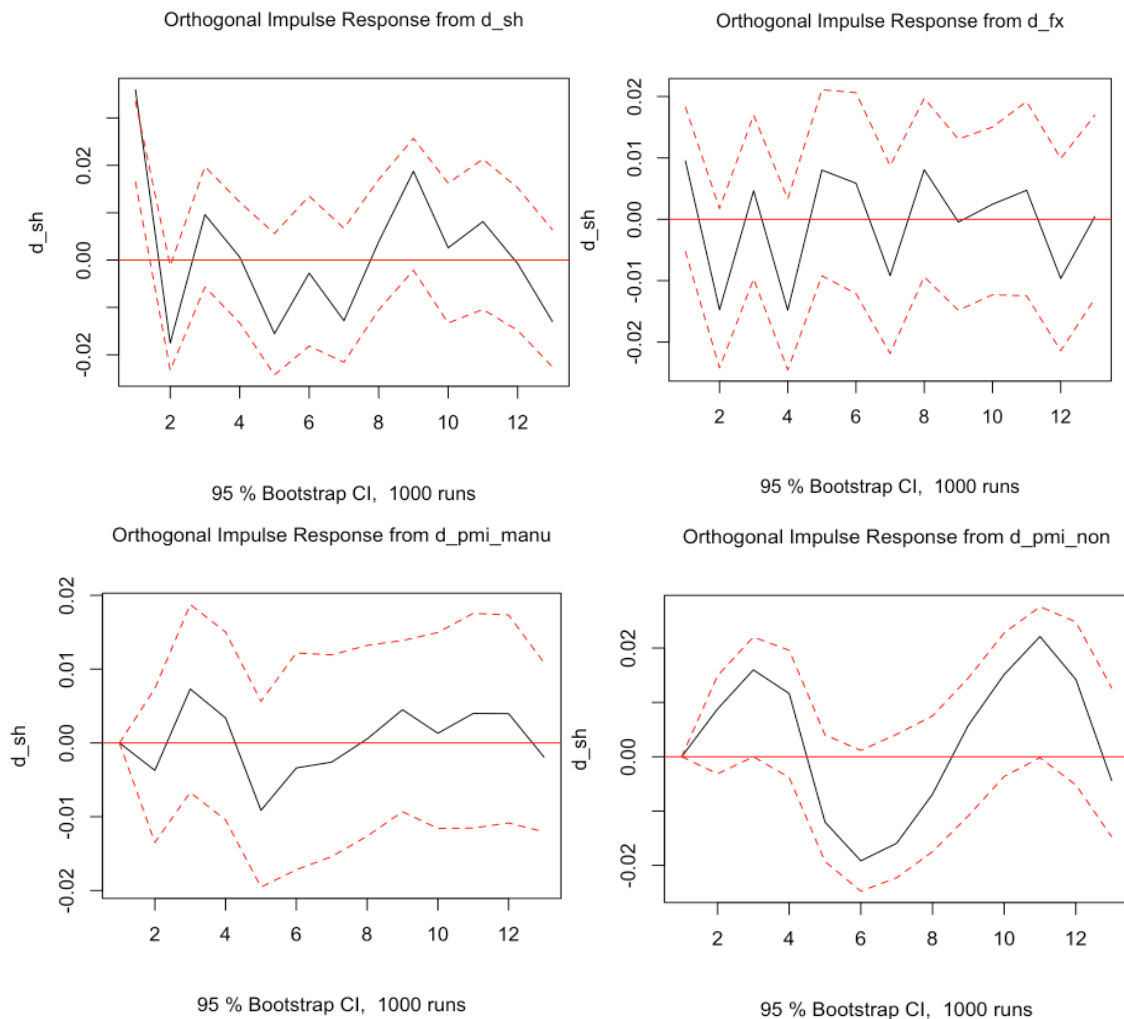


Fig 1. Impulse response functions.

The FEVDs of stock index are shown in Figure 2. The decomposition clarifies the relative contributions to Shanghai Composite fluctuations. At the short horizon (period 1), own shocks account for approximately 93%, implying that very near-term movements are almost entirely inertia driven. As the horizon lengthens, the own share declines to approximately 43% by period 12, indicating growing influence from external factors. Among them, the non-manufacturing PMI is most prominent. That is, its share rises from < 4% at period 2 to about 38% by period 12, becoming the largest external source of variation and pointing to a persistent, strengthening impact from services or consumption activity. FER shows a quicker short-run presence, for instance, approximately 15% at period 2, then broadly 15%– 20% thereafter, consistent with a stabilising role for liquidity and expectations. The manufacturing PMI contributes the least, staying below 5% over the entire forecast horizon. Overall, own shocks dominate in the short run, the non-manufacturing PMI increasingly matters at longer horizons, FER maintains a medium contribution, and the direct role of manufacturing PMI is weakest.

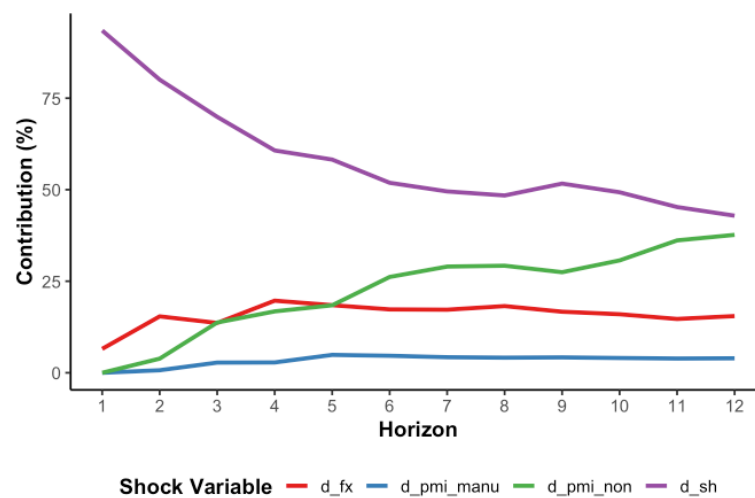


Fig 2. FEVDs of Shanghai stock composite index.

3.3. Granger Causality Test

The Granger Causality test results are reported in Table 5. At the 5% level, FER causes the system (including the stock index and both PMIs), and non-manufacturing PMI also causes the system. By contrast, neither the stock index nor manufacturing PMI causes other variables. Directionally, predictive content appears to run from services-side sentiment and FER toward equities rather than the reverse, consistent with the equation-level estimates.

Table 5. Granger causality test results.

Null hypothesis (H0)	F-stat	p-value	Decision (5%)
d_fx does not Granger cause d_sh	2.582	0.007	Reject
d_fx does not Granger cause d_pmi_manu	2.582	0.007	Reject
d_fx does not Granger cause d_pmi_non	2.582	0.007	Reject
d_sh does not Granger cause d_fx	1.076	0.393	Accept
d_sh does not Granger cause d_pmi_manu	1.076	0.393	Accept
d_sh does not Granger cause d_pmi_non	1.076	0.393	Accept
d_pmi_manu does not Granger cause d_fx	0.924	0.523	Accept
d_pmi_manu does not Granger cause d_sh	0.924	0.523	Accept
d_pmi_manu does not Granger cause d_pmi_non	0.924	0.523	Accept
d_pmi_non does not Granger cause d_fx	2.002	0.036	Reject
d_pmi_non does not Granger cause d_sh	2.002	0.036	Reject
d_pmi_non does not Granger cause d_pmi_manu	2.002	0.036	Reject

Note: d_fx= The first difference of logarithm of FER; d_pmi_non= The first difference of logarithm of Non-manufacturing PMI; d_pmi_manu= The first difference of logarithm of Manufacturing PMI; d_sh= The first difference of logarithm of stock market index

4. Discussion

The VAR results indicate that The VAR results show that monthly changes in the stock market index in China are characterised by short-run mean reversion and only modest contemporaneous pass-through from macro variables, as own shocks dominate at short horizons while external influences accumulate gradually. This pattern is in line with the argument that survey-based macro signals and financial conditions co-move rather than one mechanically leading to or predicting the other, and there are responses accompanied by lags as information is absorbed [2, 5, 10, 19]. Within a reduced-form model, such lagged propagation and persistence are normal when there are common shocks between markets and macro indicators which diffuse over horizons [8, 18].

A notable asymmetry in the estimates is that the non-manufacturing PMI provides the clearest predictive signal and a growing share of variance at medium horizons. This is economically plausible given China's ongoing shift towards services. The tertiary sector now accounts for the majority of value-added, meaning that services-sector sentiment may better reflect firms' revenue expectations and household demand than manufacturing conditions. Recent official revisions estimate that the tertiary sector contributes approximately 56% of GDP in 2023, with international datasets also showing services surpassing half of GDP [1, 20]. This structural shift helps explain why the services PMI, rather than the manufacturing PMI, is more strongly associated with equity dynamics in the post-pandemic sample of this study [19].

This services-driven result aligns with a substantial body of literature that recognises PMI as a timely, forward-looking indicator. PMI innovations are commonly used to assess real-time growth and likely policy direction, particularly in the United States. The BIS has documented strong links between PMIs and global financial conditions [2]. In China, studies using announcement windows also find that equities react to PMI news, often with asymmetric effects, where positive PMI surprises prompt stronger market reactions than negative ones. The dynamic findings in this study, where the services PMI shock gains significance over several months, complement these announcement results by demonstrating that the information contained in surveys persists and continues to influence equity pricing as macroeconomic conditions evolve.

In contrast, FER exhibits limited impulse effects on equities, despite accounting for a moderate share of equity variance at certain horizons. This is consistent with reserves acting primarily as an insurance buffer, rather than a high-frequency driver of corporate cash flows. Shocks to reserves signal policy capacity and external liquidity more clearly than they affect direct equity demand [12-13]. Cross-country evidence from the recent US tightening cycle shows that higher FER buffers systematically reduced exchange-rate depreciation, highlighting their stabilisation role. In this study, the reserves-to-equity channel is likely indirect, functioning through expectations of currency and macro stability, while the direct mechanical pass-through to monthly equity returns remains small.

The monthly sample used in this study is relatively short and spans a period of structural adjustment. The coefficients may be sensitive to regime shifts, calendar effects, or changes in disclosure practices. The identification relies on a recursive ordering, which could be complemented by sign-restricted or narrative Structural VAR models, as well as by local projections that allow for state-dependent impulse responses without committing to a fixed dynamic law [8-9]. Additional channels, such as exchange-rate returns, term-structure shocks, and global risk-on/off proxies, could be included to test whether the services PMI continues to dominate once external financial conditions are accounted for. Extending the sample to include pre-pandemic periods and combining the VAR with high-frequency event studies on PMI and FER releases would provide a better understanding of how information effects and transmission mechanisms interact.

5. Conclusion

This paper compiles a post-pandemic monthly dataset (2022–2025) and examines, within a unified framework, the dynamic relationships between China's equity market, manufacturing and non-manufacturing PMIs, and official FER, integrating business sentiment, policy buffers, and

market pricing. Methodologically, a stationarity-consistent VAR (4) model is employed, incorporating Granger causality tests, orthogonalized impulse responses, and variance decomposition, providing a transparent approach for small macro-finance systems. The paper documents, firstly, short-run mean reversion in equity returns with weak contemporaneous pass-through. Secondly, a services-driven information channel, where the non-manufacturing PMI both causes the system and accounts for a growing share of equity variance at medium horizons. Thirdly, FER is as an indirect stabilizer, with small impulse effects but a persistent role in supporting expectations and liquidity.

The findings indicate that Chinese equity indices exhibit short-term mean reversion, with the best medium-horizon signal coming from the non-manufacturing PMI. The manufacturing PMI adds limited value at horizons beyond one month, while FER serves more as a stabiliser than a direct driver. These results have significant practical implications. Investors should focus on medium-term positioning (6-12 months) based on service-PMI surprises and trends, while intraday trading should prioritise price movements over macroeconomic indicators. Execution strategies should align with the monthly release calendar (often outside trading hours), combining services-PMI signals with disciplined entry and exit rules to capitalise on short-term reversals in returns. Scenario tests should emphasise demand shocks in the services sector rather than manufacturing-specific disruptions, and portfolio risk should reflect the growing variance contribution of services-PMI innovations over medium horizons

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