

Supply Chain Concentration Is Not an Effective Predictor of A-Share Excess Returns—Negative Evidence Based on the Fama-MacBeth Method

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ABSTRACT

Does supply chain concentration (SC) constitute a pricing factor for stock excess returns? Using a sample of 4,302 Chinese A-share stocks from 2002 to 2024, this paper systematically tests the predictive power of one-year lagged supply chain concentration (lagged SC) for annual excess returns using the Fama-MacBeth two-pass cross-sectional regression method at annual frequency. The empirical results show that, after controlling for firm size, a one percentage point change in lagged SC is associated with a change in annual excess returns of about 5.5 bp per year — far below the one-way trading cost of about 10 bp in the A-share market. Although the coefficient for lagged SC is statistically significant in some model specifications ($t = 2.50$), its economic magnitude is close to zero, and the effect is not robust over time — a marginal signal ($p = 0.062$) appears only in the 2009–2015 sub-period and is insignificant in all other periods. Therefore, SC should not be regarded as an effective pricing factor in the A-share market. This study provides clear negative evidence for empirical research at the intersection of supply chain finance and asset pricing.

Keywords: Supply Chain Concentration; Annual Excess Returns; Fama-Macbeth; Asset Pricing; Negative Evidence

1. INTRODUCTION

Supply chain concentration — the degree of a firm’s dependence on its top five customers and suppliers — has long been regarded as an important source of operational risk ^[14]. Theoretically, a highly concentrated customer/supplier structure may give trading partners bargaining power and squeeze the firm’s profit margins ^[15]; conversely, it may reduce transaction costs through stable cooperative relationships ^[5]. These two opposing views raise an important asset pricing question: Is supply chain concentration priced by the market? That is, can the level of SC predict stock excess returns?

In international academia, existing research provides different answers. Some studies find that firms with higher supply chain concentration earn higher stock returns ^[13, 9], while others find a negative relationship ^[1] or a non-linear relationship ^[4]. In the Chinese A-share market, relevant empirical research is relatively limited and conclusions are inconsistent.

This paper aims to answer: Does supply chain concentration constitute a predictor of excess returns in the Chinese A-share market? Using the Fama-MacBeth ^[6] (1973) two-pass cross-sectional regression method on 4,302 A-share stocks from 2002 to 2024, the empirical results clearly point to a negative conclusion: the economic impact of SC is close to zero, it does not possess meaningful predictive power, and the effect is not robust over time.

The contributions of this paper are threefold. First, it provides methodologically rigorous negative evidence for the Chinese A-share market. Second, it distinguishes between statistical significance and economic significance in asset pricing research. Third, it shows that even after aligning the frequency of annual SC with annual returns and using a strict lagged predictive structure free of look-ahead bias, SC still lacks economically meaningful predictive power.

2. LITERATURE REVIEW

2.1 Supply Chain Concentration and Firm Performance

The impact of supply chain concentration on firm performance is a classic topic in strategic management and accounting. Early research, drawing on transaction cost economics, argues that highly concentrated customer relationships may create a hold-up problem, where suppliers accept unfavourable terms to maintain major customer relationships ^[10, 16]. However,

the relational view emphasises that deep cooperative relationships can generate relational rents through specific investments, knowledge sharing, and trust mechanisms ^[5].

Empirical studies also show divergence. Patatoukas ^[13] (2012) finds that customer concentration is positively correlated with firm profitability (return on assets), arguing that efficiency gains from large customers outweigh bargaining losses. Irvine et al. ^[9] (2016) find that firms with high customer concentration have higher earnings volatility and lower inventory levels. In the Chinese market, Tang ^[19] (2009) finds an inverted U-shaped relationship between customer concentration and firm profit margins; Wang et al. ^[20] (2014) find that supplier concentration is negatively correlated with corporate trade credit financing.

2.2 Supply Chain Concentration and Stock Returns

Whether supply chain concentration is reflected in stock returns is an interdisciplinary topic in asset pricing.

Evidence supporting pricing ability: Patatoukas ^[13] (2012) finds that firms with higher customer concentration earn higher stock returns and argues that the market fails to fully understand the positive effect of supply chain structure on operating efficiency. Irvine et al. ^[9] (2016) construct a supply chain concentration factor and find that it explains part of the cross-sectional variation in returns. Cohen and Frazzini ^[3] (2008), from a customer-supplier network perspective, find that changes in customer stock prices predict supplier stock returns.

Evidence questioning pricing ability: Campello and Gao ^[1] (2017) find that firms with high customer concentration perform worse during the financial crisis, suggesting that supply chain concentration is not a robust source of risk premiums. Dhaliwal et al. ^[4] (2016) find a non-linear relationship between customer concentration and the cost of equity capital — positive in the low-concentration range and turning negative in the high-concentration range ^[7].

Evidence from the Chinese A-share market: Domestic research is relatively limited. Chen et al. ^[17] (2018) find that customer concentration is positively correlated with firm risk, but they do not directly test its relationship with stock returns. Li et al. ^[18] (2019) find that supply chain concentration indirectly affects stock price synchronicity through the degree of information asymmetry, rather than directly predicting excess returns.

2.3 Negative Evidence in Asset Pricing

In asset pricing research, the “factor zoo” problem has become increasingly prominent ^[2, 8]. Harvey et al. ^[8] (2016) examine 316 stock return predictors and find that after multiple-testing corrections, most predictors lose significance. They emphasise that, against the background of numerous proposed factors, negative evidence is as important as positive evidence — it helps identify which variables genuinely represent risk compensations and which are chance discoveries within a sample.

This paper follows this tradition by providing methodologically rigorous negative empirical evidence on supply chain concentration.

3. THEORETICAL MECHANISMS AND RESEARCH HYPOTHESES

3.1 Possible Channels Through Which SC Affects Excess Returns

For SC to affect stock returns, it must operate through one or more of the following channels:

Risk compensation channel: High SC implies higher operational risk (customer loss risk, bargaining power imbalance), and investors demand a higher risk premium ^[11].

Efficiency channel: High SC may improve operational efficiency through stable relationships, economies of scale, and information sharing, thereby reducing risk or increasing profitability ^[5].

Information channel: SC reflects a firm’s supply chain structure and is fundamental information. If the market fails to fully absorb such information, predictable return patterns may emerge ^[3].

3.2 Research Hypotheses

Based on the above channels, competing hypotheses can be formulated:

H1 (pricing ability hypothesis): Supply chain concentration significantly predicts A-share annual excess returns, and stocks with high SC have different levels of returns.

H0 (null hypothesis): Supply chain concentration cannot predict A-share annual excess returns; its effect is neither statistically nor economically significant.

This paper aims to test whether H0 holds. Given the conflicting evidence in the literature and the information pricing characteristics of the A-share market, no directional prediction is made.

4. RESEARCH DESIGN

4.1 Data Sources and Sample Selection

All data are obtained from the CSMAR database, including:

Monthly individual stock returns and float market capitalisation (1991–2024)

Monthly risk-free interest rates (1990–2025)

Composite A-share float-weighted three factors (MKT, SMB, HML, 1990–2025)

Supply chain concentration data (2001–2023)

Sample selection steps:

1. Exclude financial industry stocks (banks, insurance, brokerages, trusts, futures; 98 stocks in total).
2. To mitigate the influence of outliers, monthly returns are winsorized at the 1% and 99% levels before annual aggregation.
3. Retain stocks with available SC data and at least 36 months of valid return history before their first inclusion.
4. Use an unbalanced panel to maximise sample size while ensuring data availability.

Final valid sample: 4,302 A-share stocks, with annual observations from 2002 to 2024 (23 years).

4.2 Variable Definitions

Dependent variable — annual excess return:

For stock i in year y , the annual excess return is the sum of monthly excess returns from January to December of that year:

$$R_{i,y}^{\text{annual}} = \sum_{m \in y} (R_{i,m} - R_{f,m}) \quad (1)$$

where $R_{f,m}$ is the monthly risk-free rate. This linear aggregation ignores compounding, which is negligible given the low level of risk-free rates in China.

Core independent variable — supply chain concentration (one-year lagged):

$$SC_{i,y} = \frac{\text{Proportion of sales to top five customers} + \text{Proportion of purchases from top five suppliers}}{2} \quad (2)$$

measured in percentage (%). Data are obtained from annual reports. To ensure a strictly predictive relationship with no look-ahead bias, all regressions use the one-year lagged value $SC_{i,y-1}$. That is, SC disclosed in the annual report of fiscal year $y - 1$ (released in the first half of year y) is used to predict annual excess returns of year y .

Factor exposures:

Factor exposures $\hat{\beta}_{\text{MKT},i,y}$, $\hat{\beta}_{\text{SMB},i,y}$, $\hat{\beta}_{\text{HML},i,y}$ are estimated using a rolling 60-month window to avoid look-ahead bias. For each year y , betas are estimated using only historical data available before the return prediction period, which is standard in empirical asset pricing.

Control variable — firm size:

Annual firm size $\ln(\text{Size}_{i,y})$ is the natural logarithm of year-end floating market capitalisation.

4.3 Descriptive Statistics

Table 1. Descriptive Statistics of Supply Chain Concentration, Firm Size, and Annual Excess Returns.

Statistic	SC (%)	Ln (Size)	Annual Excess Return
Mean	31.68	21.23	0.125
Median	29.03	21.05	0.082
Standard deviation	18.40	1.18	0.421
10th percentile	9.94	19.73	-0.316
90th percentile	56.83	22.69	0.584

The Pearson correlation between SC and ln (Size) is -0.078 , indicating a weak negative correlation.

4.4 Empirical Method: Annual Fama-MacBeth Regressions

To eliminate the frequency mismatch between annual SC and monthly returns, we aggregate monthly excess returns to the annual level. We then apply the two-pass Fama-MacBeth ^[6] (1973) procedure strictly at the annual frequency with rolling-window beta estimation to avoid look-ahead bias.

First pass (rolling-window time-series):

For each stock i and each prediction year y , we estimate factor exposures using a 60-month rolling window from January of year $y-5$ to December of year $y-1$:

$$R_{i,m} - R_{f,m} = \alpha_{i,y} + \beta_{MKT,i,y}MKT_m + \beta_{SMB,i,y}SMB_m + \beta_{HML,i,y}HML_m + \varepsilon_{i,m} \quad (3)$$

Only historical data prior to year y is used, ensuring no future information is included.

Second pass (annual cross-sections):

For each calendar year y , we run the cross-sectional regression:

$$R_{i,y}^{\text{annual}} = \gamma_{0,y} + \gamma_{1,y}\hat{\beta}_{MKT,i,y} + \gamma_{2,y}\hat{\beta}_{SMB,i,y} + \gamma_{3,y}\hat{\beta}_{HML,i,y} + \gamma_{4,y}SC_{i,y-1} + \gamma_{5,y}\ln(\text{Size}_{i,y}) + u_{i,y} \quad (4)$$

where $SC_{i,y-1}$ is the one-year lagged supply chain concentration.

Coefficient aggregation:

We compute the time-series average of annual coefficients:

$$\hat{\gamma}_k = \frac{1}{Y} \sum_{y=1}^Y \gamma_{k,y} \quad (5)$$

Standard errors are corrected for autocorrelation using the Newey-West ^[12] (1987) method with 2 lags, which is standard for annual panel data.

For comparison, we also estimated betas using the full sample; the economic magnitude and statistical significance of SC are nearly identical and do not change the conclusion.

5. EMPIRICAL RESULTS

5.1 Main Regression Results (Annual Fama-MacBeth)

Table 2. Annual Fama-MacBeth Regression Results: The Predictive Effect of Lagged Supply Chain Concentration on Excess Returns.

Coefficient	Model A	Model B	Model C
γ_0 (intercept)	0.031 (0.55)	0.031 (0.56)	-1.855 (-8.48)
γ_{MKT}	0.107 (1.10)	0.107 (1.10)	0.108 (1.14)
γ_{SMB}	0.006 (0.14)	0.006 (0.13)	0.138 (2.89)
γ_{HML}	-0.056 (-2.10)	-0.055 (-2.08)	-0.090 (-3.44)
γ_{SC} (lagged)	—	0.00006 (0.25)	0.00055 (2.50)
γ_{Size}	—	—	0.120 (8.88)
Average R^2	6.88%	7.04%	8.67%

Note: Newey-West t-values (2 lags) in parentheses. Factor betas are estimated using rolling 60-month windows before each year y to eliminate look-ahead bias. Annual cross-sections from 2002 to 2024 (23 years); average of 2,230 stocks per year, approximately 51,300 firm-year observations. The coefficient γ_{SC} corresponds to one-year lagged $SC_{i,y-1}$.

Interpretation of economic significance:

$\gamma_{SC} = 0.00055$ implies that a one percentage point increase in lagged SC is associated with a 5.5 basis point (bp) change in annual excess returns. This magnitude is less than half of the typical one-way trading cost (about 10 bp) in the A-share market and thus is not economically tradable. In contrast, the coefficient on firm size is approximately 200 times larger.

5.2 R^2 Decomposition: Contribution of SC to Explanatory Power

Table 3. Decomposition of the Incremental Explanatory Power of Lagged Supply Chain Concentration for Cross-Sectional Returns.

Model change	ΔR^2	Attribution
A $\rightarrow$ B (add lagged SC)	+0.16%	SC contributes almost no explanatory power
B $\rightarrow$ C (add firm size)	+1.63%	Explanatory power gains come almost entirely from size

The relatively high average R^2 in annual regressions reflects the strong explanatory power of persistent firm characteristics, especially size, which is common in Chinese A-share asset pricing studies. SC accounts for a negligible share of cross-sectional return variation.

5.3 Time-Series Robustness Tests

The sample is split into three sub-periods representing distinct market regimes:

2002–2008: Pre-crisis and share-structure reform period

2009–2015: Post-crisis stimulus and high-volatility period

2016–2024: “New normal” and stable market period

Table 4. Time-Series Robustness Tests of the Supply Chain Concentration Effect Across Different Market Periods.

Period	Years	Mean γ_{SC}	t-value	p-value	Significance
2002–2008	7	-0.00042	-1.03	0.305	Not significant
2009–2015	7	0.00067	1.90	0.062	Marginally significant

Table 4. (continued) Time-Series Robustness Tests of the Supply Chain Concentration Effect Across Different Market Periods.

Period	Years	Mean γ_{SC}	t-value	p-value	Significance
2016–2024	9	−0.00008	−0.25	0.806	Not significant

The SC effect is not robust across time. A only marginal signal appears in 2009–2015 and is fully insignificant in the other two periods.

6. DISCUSSION

6.1 Why is Lagged SC “Statistically Significant” in Model C?

In Model C, lagged SC shows $t = 2.50$ ($p = 0.013$), but this represents statistical significance without economic significance:

Large sample effect: With roughly 51,300 firm-year observations, even tiny coefficients can become statistically significant.

Dependence on size control: Without controlling for firm size, lagged SC is completely insignificant ($t = 0.25$).

Lack of temporal robustness: Full-sample significance is driven almost entirely by the 2009–2015 sub-period.

6.2 Why SC Is Not Suitable as a Return Predictor

After aligning to annual frequency and using a strict one-year lagged predictive structure with no look-ahead bias, the SC coefficient remains economically negligible at about 5.5 bp per year. Even with perfect frequency matching and clean identification, the return impact is far below practical investment thresholds. SC may affect corporate fundamentals such as earnings volatility and credit risk, but it does not serve as a meaningful cross-sectional predictor of stock returns.

6.3 Future Research Directions

Future research may focus on:

The impact of SC on earnings volatility and earnings persistence

The relationship between SC and corporate credit spreads or bond yields

Asymmetric effects of customer concentration versus supplier concentration

Supply chain risk exposure during external shocks (pandemics, trade frictions, etc.)

7. CONCLUSION

Using a sample of 4,302 Chinese A-share stocks from 2002 to 2024, this paper tests the predictive ability of supply chain concentration for annual excess returns using the annual Fama-MacBeth^[6] (1973) two-pass methodology with rolling 60-month betas and one-year lagged SC to ensure a pure predictive design free of look-ahead bias. The main conclusions are as follows:

1. The economic impact of SC is negligible. A one percentage point change in lagged SC implies a change of about 5.5 bp in annual excess returns, far below typical one-way trading costs of about 10 bp.
2. Statistical significance does not equal economic meaningfulness. The observed t-statistic arises from the large sample size rather than genuine investment value.
3. The SC effect lacks temporal robustness. A marginal signal appears only in 2009–2015 and is absent in other periods.

Supply chain concentration should not be regarded as an effective pricing factor or return predictor in the A-share market.

Limitations: This study does not incorporate industry fixed effects, alternative SC constructions (e.g., separate customer and supplier concentration), or the Fama-French five-factor model. All results are robust to rolling and full-sample beta estimation.

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