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The gap between you and your peers matters: The net peer momentum effect in China

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Abstract: We propose a new return predictive signal: the net peer momentum (NPM), defined as the excess return on analyst-connected firms (CF) over the focal firm. Examining its pricing effect in the Chinese equity market reveals a robust cross-sectional relationship: stocks with high NPM significantly outperform those with low NPM. Accordingly, a long-short strategy based on NPM quintiles earns over 1% per month. While both CF and NPM offer incremental pricing power, NPM exhibits a stronger effect, as it incorporates both information about peer firms and the degree of investor underreaction to such information.

Keywords: connected-firm momentum; asset pricing; analyst co-coverage; Chinese stock market

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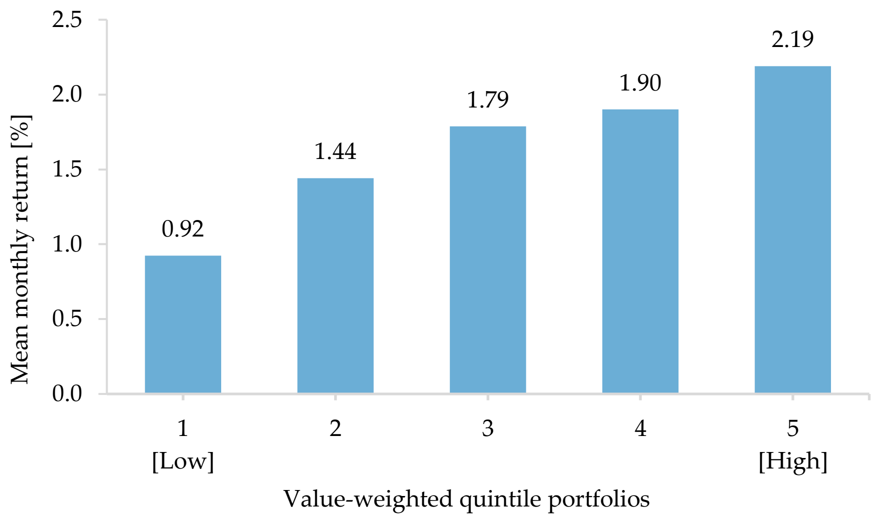
1. Introduction

The momentum spillover effects in stock returns are well documented across various types of firm relatedness, such as industry (Moskowitz & Grinblatt, 1999; Hou, 2007), geography (Parsons et al., 2020; Jin and Li, 2024), supply-chain (Cohen & Frazzini, 2008; Menzly & Ozbas, 2010), single- and multi-segment (Cohen & Lou, 2012), and technology linkages (Lee et al., 2019). Ali and Hirshleifer (2020) argue that these patterns result from analyst co-coverage, providing evidence that the analyst connected-firm (CF) momentum factor subsumes all other linkage effects. However, while acknowledging the role of short-term peer performance, their measure ignores that of the focal firm—which also matters, as short-term reversals are prevalent (Da et al., 2014), especially in Chinese stocks (Neszveda et al., 2022).

In light of this, we propose a new return predictive signal: the net peer momentum (NPM), defined as the excess return on analyst-connected firms (CF) over the focal firm. We hypothesize that the wider return gap between peers and the focal firm signals stronger momentum spillovers, translating into more powerful future return patterns. We verify this conjecture within a sample of over 4000 Chinese firms for the years 2004 to 2022.

We begin with univariate portfolio sorts. Our results reveal a powerful monotonic relation between the past NPM and future stock returns. Figure 1 summarizes the key findings. A value-weighted long-short portfolio constructed that buys the top NPM quintile and shorts the bottom one earns an average return of 1.26% per month and a six-factor alpha of 1.42%. Moreover, further bivariate sorts and cross-sectional regressions confirm that NPM contains incremental information about stock returns, beyond other common firm characteristics or industry reversals. Our findings are robust to alternative weighting schemes, accounting for different factor models, and many other modifications to the baseline methodology.

Figure 1. Average Excess Returns on *NPM* Quintile Portfolios



Note: This figure shows the average excess returns on quintile portfolios sorted by *NPM*. Quintile 1 contains stocks with the lowest *NPM* in the previous month, while quintile 5 comprises those with the highest *NPM* in the previous month. The portfolios are value-weighted and rebalanced monthly. The returns are presented in percentage terms. The sample consists of 4275 stocks, and the sample period is from January 2004 to December 2022.

One potential concern is that the stock return predictability by NPM merely arises from the predictability by CF. To tackle this question, we directly compare NPM to CF via a series of analyses, such as spanning tests. The results document that the factor portfolios formed on NPM returns generate significant and positive abnormal returns, even after controlling for the six factors from the Fama and French (2018) model and the CF factor. Although these two factors share some overlapping information in predicting stock returns, each of them offers incremental explanatory power not captured by the other, with the pricing effect of NPM being noticeably stronger. It results from the fact that NPM incorporates not only the information of peer firms that are covered by common analysts (as shown by Ali & Hirshleifer, 2020) but also captures the extent of investor underreaction to such information.

Our study contributes to several strands of literature. First, our paper is related to numerous studies on short-term momentum, short-term reversal, and momentum spillover effects (e.g., Hameed & Mian, 2014; Ali & Hirshleifer, 2020; Medhat & Schmeling, 2022). Against this background, we introduce a new measure, NPM, which combines analyst co-coverage momentum and short-term reversal. We find a robust and stronger pricing NPM effect controlling for all other factors explored in the aforementioned studies.

Second, our paper extends the debate on the role of security analysts in asset pricing. Lee and So (2017) suggest analyst coverage proxies contain information about expected returns. Ali and Hirshleifer (2020) also find that sell-side analysts incorporate news about linked firms sluggishly so that shared analyst coverage can unify other seemingly distinct momentum spillover effects. Consistent with these works, we corroborate the security analysts' role by extending the study of Ali and Hirshleifer (2020) to the Chinese stock market.

Third, our adds to the mounting evidence on cross-sectional predictability of stock returns in China (see, e.g., Jansen et al., 2021, Dai et al. 2023; Long et al., 2018). We offer a novel return predictor, NPM, to the best of our knowledge, which has not been explored in prior studies.

The remainder of the paper proceeds as follows. Section 2 discusses the data and variables. Section 3 presents the findings and the results of robustness checks. Section 4 analyzes the pricing effect of NPM versus CF. Finally, section 5 concludes.

2. Data and Variables

2.1. Research Sample

We collect analyst earning forecasts and stock return data from the China Stock Market & Accounting Research (CSMAR) database. Our sample consists of all Chinese A-shares with available data, including both currently listed and delisted firms to avoid survivorship bias. The full sample period ranges from January 2004 to December 2022. Our final sample comprises 4275 individual companies, with the number of companies varying over time, averaging 1492 firms per year. The risk-free rate is measured by the one-year deposit rate announced by the People's Bank of China.

2.2. Net peer momentum (NPM)

Ali and Hirshleifer (2020) propose a share-analyst connected-firm momentum factor and show that this factor return is driven by the underreaction of investors with limited attention. In this paper, we modify their measure by considering the extent to which investors underreact to the returns of their peers. Specifically, our key variable is the difference between returns on connected firms (CF) and the return on the focal firm (Ret), termed as the net peer momentum (NPM). For the focal firm i in month t, we calculate $NPM_{i,t}$ as follows:

$$NPM_{i,t} = CF_{i,t} - Ret_{i,t}\,, \tag{1}$$

where Ret_{jt} is the return of stock i during month t. CF_{it}, closely followed by Ali and Hirshleifer (2020), is the weighted average return of peer firms j (i.e., firms having the same analyst following as the focal firm), computed as follows:

$$CF_{i,t} = \frac{1}{\sum_{j=1}^{N} ln(n_{i,j}+1)} \sum_{j=1}^{N} ln(n_{i,j}+1)\, Ret_{j,t}, \tag{2}$$

where Ret_{jt} is the return of stock j during month t and $n_{i,j}$ is the number of analysts covering both firm i and firm j at the end of month t. To mitigate the influence of extreme values, we employ the natural logarithm transformation of the number of analysts. A pair of stocks is defined as “connected” peers if they are covered by at least one analyst who has issued at least one earnings forecast for both stocks in the past 12 months.

A higher value of the NPM implies either a higher peer return or a lower return on the focal firm. In other words, it indicates a greater extent of underreaction by investors. Therefore, we expect that the return of the focal firm will increase to catch up with its peers. Compared to CF, NPM accounts for the cross-asset momentum effect and the idea of mean reversion. Thus, we expect NPM to have stronger predictive power for future returns than CF.

2.3. Control Variables

We consider a number of control variables commonly used in cross-sectional asset pricing studies. These include market beta (*BETA*), the log market value (*LNMV*), the log book-to-market ratio (*LNBM*), short-term reversal (*REV*), momentum (*MOM*), Amihud’s (2002) illiquidity ratio (*ILLIQ*), turnover ratio (*TURN*), idiosyncratic risk (*IVOL*), co-skewness (*SKEW*), co-kurtosis (*KURT*), and the lottery-like factor (*MAX*). We also consider industry return reversal (*Ret_Ind*) and inter-industry reversal (*Ret_Mar*), which may have a similar effect to our key variable *NPM*. We follow seminal literature to construct these variables. Table 1 provides further details. The summary statistics for the main variables are displayed in Table 2.

Table 1. The Definitions of Control Variables

Variables	Definations
Market beta (BETA)	BETA is the estimated slope coefficient that is generated by the regressions of a stock's excess returns on the excess market return within a one-year window of daily data, which aligns with the Capital Asset Pricing Model (CAPM).
Size (LNMV)	LNMV is the natural logarithm of the market value of the listed company at the end of the previous month.
Book-to-market ratio (LNBM)	LNBM is the logarithm of the book-to-market ratio at the end of the last fiscal year.
Momentum (MOM)	MOM is calculated using the stock returns of the previous year, excluding the most recent month.
Short reversal (REV)	REV is the stock returns of the previous month.
Turnover ratio (TURN)	TURN denotes the number of shares traded over the total number of outstanding shares in the last month.
Illiquidity (ILLIQ)	ILLIQ is the absolute monthly stock return over monthly trading volume following Amihud (2002).
Idiosyncratic volatility (IVOL)	Following Ang et al. (2006b), IVOL is the standard deviation of the residual returns from the three-factor Fama-French (1993) model.
Systematic skewness (COSKEW) **Systematic kurtosis (COKURT)**	Following Ang et al. (2006a), COSKEW (COKURT) is the third (fourth) standardized central moment between the individual stock return and market return.
Lottery-like factors (MAX)	Following Bali et al. (2011), MAX equals the maximum daily returns during the last month.
Industry return reversal (Ret_Ind)	Following Hameed and Mian (2014), Ret_Ind denotes the part which stock return beyond industry return.
Inter-industry reversal (Ret_Mar)	Following Hameed and Mian (2014), Ret_Mar denotes the part which stock return beyond market return.

Table 2. Summary statistics

	Mean	Std	Min	25%	Median	75%	MAX
# shared analysts	13	12.98	1	3	8	18	102
# connected firms	149	126.99	1	50	117	211	1005
# stock number	1492	635.53	294	928	1696	2039	2508
% of total number of stocks covered	0.64	0.14	0.28	0.55	0.65	0.78	0.83
% of total market capitalization covered	0.79	0.12	0.51	0.78	0.83	0.86	0.92

Panel B: Descriptive statistic for the Main Variables

	CF	NPM	LNMV	BETA	LNBM	REV	MOM	ILLIQ	TURN	IVOL	COSKE	COKUR	MAX	Ret_Ind	Ret_Mar
Mean	0.014	0.310	15.721	1.114	-0.345	0.014	0.291	0.115	31.574	0.022	-0.015	0.012	0.104	0.000	0.008
Std	0.040	0.243	1.016	0.249	0.760	0.124	0.604	0.901	26.608	0.011	0.010	0.003	0.147	0.106	0.116

Min	-0.128	-1.126	13.798	0.049	-3.584	-0.342	-0.596	0.001	0.492	0.006	-0.046	-0.002	0.035	-0.373	-0.340
1st Quartile	-0.010	0.166	14.996	0.960	-0.841	-0.056	-0.050	0.028	14.747	0.016	-0.021	0.010	0.090	-0.059	-0.060
Median	0.011	0.297	15.540	1.120	-0.375	-0.003	0.165	0.056	24.671	0.021	-0.016	0.012	0.099	-0.010	-0.007
3rd Quartile	0.034	0.441	16.260	1.277	0.128	0.064	0.477	0.104	39.918	0.027	-0.010	0.014	0.102	0.045	0.059
Max	0.251	1.915	20.953	1.997	2.551	1.413	8.762	23.580	265.889	0.156	0.030	0.021	4.458	1.115	1.207

Panel C: Correlation coefficients for the Main Variables

	RET	CF	NPM	LNMV	BETA	LNBM	REV	MOM	ILLIQ	TURN	IVOL	COSKE	COKUR	MAX	Ret_Ind	Ret_Mar
RET		0.016	0.030	-0.037	-0.012	0.000	-0.037	0.005	0.039	-0.053	-0.030	-0.013	-0.003	-0.011	-0.042	-0.037
CF	0.013		-0.090	0.009	-0.018	-0.010	0.246	0.014	-0.012	0.072	0.089	0.014	-0.040	0.006	0.054	0.244
NPM	0.037	-0.087		-0.012	0.081	-0.084	-0.554	0.202	-0.036	-0.027	-0.118	0.033	-0.069	0.001	-0.481	-0.514
LNMV	-0.042	0.014	-0.007		-0.160	0.096	0.068	0.173	-0.346	-0.258	-0.098	0.248	0.069	-0.062	0.053	0.055
BETA	-0.027	-0.022	0.085	-0.124		-0.056	-0.040	-0.039	-0.044	0.256	0.132	-0.178	0.292	0.154	-0.021	-0.024
LNBM	0.004	-0.017	-0.099	0.039	-0.050		-0.007	-0.160	-0.024	-0.052	-0.174	-0.078	0.254	-0.102	0.002	-0.006
REV	-0.052	0.276	-0.520	0.070	-0.058	-0.003		-0.005	0.008	0.184	0.367	0.038	-0.066	0.048	0.845	0.925
MOM	0.001	0.024	0.254	0.183	-0.061	-0.163	-0.012		-0.097	0.112	0.207	0.152	-0.302	0.274	-0.004	0.003
ILLIQ	0.062	-0.021	-0.037	-0.747	-0.037	-0.056	-0.048	-0.199		-0.136	0.024	-0.089	-0.049	0.020	0.011	0.009
TURN	-0.060	0.066	0.021	-0.325	0.350	-0.069	0.118	0.113	-0.202		0.503	-0.018	-0.151	0.120	0.187	0.211
IVOL	-0.062	0.092	-0.051	-0.078	0.157	-0.208	0.270	0.223	-0.019	0.500		0.067	-0.325	0.239	0.330	0.362
COSKE	-0.018	0.013	0.044	0.237	-0.152	-0.112	0.021	0.168	-0.210	-0.028	0.077		-0.390	0.093	0.022	0.026
COKUR	0.011	-0.042	-0.088	0.057	0.235	0.276	-0.038	-0.302	-0.032	-0.164	-0.360	-0.380		-0.230	-0.046	-0.061
MAX	-0.029	0.002	0.018	-0.177	0.333	0.008	0.006	0.104	0.057	0.302	0.274	0.032	-0.180		0.048	0.052
Ret_Ind	-0.058	0.044	-0.446	0.062	-0.037	0.011	0.793	-0.011	-0.038	0.109	0.231	0.009	-0.018	0.015		0.913
Ret_Mar	-0.053	0.268	-0.482	0.056	-0.040	-0.001	0.915	-0.003	-0.040	0.142	0.273	0.011	-0.037	0.020	0.867	

Note. This table reports summary statistics. The sample includes firms linked by common analysts. Panel A report the timeseries averages of monthly cross-sectional simple descriptive statistics for sample firms. # shared analysts denotes the number of common-analyst for focal firm. # connected firms denotes the number of common-analyst peer firms for focal firm. # stock number denotes the number of monthly sample firms. % of total number of stocks covered denote the ratio of monthly sample firms to the total number of A-shares. % of total market capitalization covered denote the ratio of the total market value of the sample firm to the total market value of A-shares per month. Panel B report descriptive statistic for the main variables: the mean, standard deviation, min, the 1st quartile, median, the 3rd quartile and max. Panel C reports average cross-sectional pair-wise correlation coefficients. The values above (below) the diagonal are Pearson's product-momentum (Spearman's rank-based) coefficients. The sample contains 4275 stocks, and the study period runs from January 2004 to December 2022.

3. Baseline Empirical Findings

3.1. Univariate Sorts

We begin our empirical tests by conducting univariate portfolio-level analyses. Each month, we sort all stocks into quintile portfolios based on their NPM. We also construct long-short portfolios that buy (sell) stocks in the highest (lowest) NPM quintile. For all the portfolios, we compute the average returns and alphas produced from five models: the CAPM model, the three-factor model (Fama and French, 1993), the four-factor model (Carhart, 1997), the five-factor model (Fama and French, 2015), and the six-factor model (Fama and French, 2018). We obtain the relevant factor returns are directly from CSMAR database.

Table 3 presents the results of the univariate sorts. The first column in Panel A shows a monotonic increase in average excess return (R) from 0.94% (the lowest NPM quintile) to 2.22% (the highest NPM quintile) for equal-weighted portfolios. As shown in the last low in Panel A, the long-short portfolio generates a sizable return of 1.28% per month with a t-statistic of 5.20. Turning to the risk-adjusted returns, all alphas for the long-short portfolio are positive and statistically significant, indicating that abnormal returns cannot be explained by classical pricing factors. Panel B of Table 3 reports similar findings for value-weighted portfolios. In sum, these results suggest a significant positive relation between NPM and the cross-section of future stock returns.

3.2. Bivariate Sorts

To ensure that NPM, rather than firm characteristics or industry reversals, is driving the differences in the cross-sectional stock returns that we find, we next conduct bivariate portfolio sorts while controlling for well-known risk factors. In particular, at the end of month t, we sort stocks into quintile portfolios based on one of the control variables and further sort them into quintiles based on their NPM to generate 25 (5x5) portfolios. We then compute the equal-weighted and value-weighted portfolio returns and rebalance the portfolios in month t + 1. Within each quintile of portfolios sorted by the control variable, we also implement a long-short strategy by taking long positions in the highest NPM quintile and selling short stocks in the lowest NPM quintile. This enables us to evaluate whether the positive relation between NPM and future stock returns is influenced by the control variable.

We tabulate the results of bivariate sorts in Table 4, with Panel A for equal-weighted returns and Panel B for value-weighted returns. The last two rows display the average returns and the risk-adjusted returns (alphas) produced from the six-factor models for long-short portfolios. The results indicate that even after controlling for each of the control variables, the NPM effect continues to be statistically significant and economically meaningful. Panel A shows that across all specifications, the long-short portfolios yield positive and statistically significant monthly returns ranging from 0.52% to 1.20%, while the six-factor model alpha exhibits a similar pattern, ranging from 0.61% to 1.29%. Notably, the results in the last two columns indicate our measure cannot be explained by the industry return reversal (Ret_Ind) and inter-industry reversal (Ret_Mar) as in Hameed and Mian (2014). In Panel B, we obtain similar results for value-weighted portfolios. Overall, the return spreads among the control quintiles are predominantly large and statistically significant, suggesting that the NPM effect is robust to controlling for other well-known risk factors.

Table 3. Univariate Portfolio Sorts

	Panel A: Equal-weighted portfolios						**Panel B: Value-weighted portfolios**					
Quintile	**R**	**α1**	**α3**	**α4**	**α5**	**α6**	**R**	**α1**	**α3**	**α4**	**α5**	**α6**
1 (Low)	0.94	0.80	0.91	0.94	1.04	1.03	0.92	0.78	0.90	0.92	1.02	1.02
	(1.26)	(1.29)	(1.53)	(1.55)	(1.78)	(1.72)	(1.24)	(1.27)	(1.51)	(1.52)	(1.75)	(1.69)
2	1.46	1.32	1.40	1.44	1.53	1.54	1.44	1.30	1.38	1.42	1.51	1.51
	(2.03)	(2.25)	(2.48)	(2.51)	(2.80)	(2.72)	(2.00)	(2.22)	(2.45)	(2.48)	(2.77)	(2.69)
3	1.81	1.68	1.75	1.82	1.89	1.92	1.79	1.65	1.72	1.79	1.86	1.89
	(2.43)	(2.70)	(2.92)	(2.99)	(3.25)	(3.20)	(2.39)	(2.66)	(2.89)	(2.95)	(3.21)	(3.16)
4	1.93	1.81	1.92	1.97	2.07	2.08	1.90	1.78	1.89	1.94	2.04	2.05
	(2.64)	(2.95)	(3.23)	(3.28)	(3.61)	(3.53)	(2.61)	(2.91)	(3.19)	(3.23)	(3.57)	(3.48)
5 (High)	2.22	2.12	2.29	2.34	2.45	2.46	2.19	2.09	2.26	2.31	2.42	2.43
	(3.02)	(3.32)	(3.63)	(3.73)	(4.01)	(3.96)	(2.99)	(3.29)	(3.60)	(3.69)	(3.97)	(3.92)
High-Low	1.28	1.32	1.37	1.40	1.41	1.43	1.26	1.31	1.36	1.39	1.40	1.42
	(5.20)	(5.44)	(5.80)	(6.20)	(6.23)	(6.43)	(5.10)	(5.34)	(5.68)	(6.08)	(6.10)	(6.31)

Note. The table reports the performance of portfolios from univariate sorts on NPM. Low (High) indicates the quintiles with the lowest (highest) NPM, and High-Low denotes the zero-investment strategy that long (short) the High (Low) NPM portfolios. The strategies are equal-weighted (Panel A) or value-weighted (Panel B) and rebalanced monthly. R is the mean monthly excess return, while α1, α3, α4, α5, and α6 are alphas from the CAPM, Fama-French (1993) three-factor model, Carhart's (1997) four-factor model, Fama-French (2015) five-factor model, and Fama-French (2018) six-factor model respectively. The returns and alphas are displayed in percentage terms. The numbers in parentheses are t-statistics adjusted using bootstrap and Newey and West's (1987) method for mean returns and alphas, respectively. The sample covers 4275 stocks, and the sample period ranges from January 2004 to December 2022.

Table 4. Bivariate Portfolio Sorts

	Panel A: Equal-weighted Portfolios for *NPM*												
Quintile	LNMV	BETA	LNBM	REV	MOM	ILLIQ	TURN	IVOL	COSKEW	COKURT	MAX	Ret_Ind	Ret_Mar
1 (Low control)	1.29	0.42	1.35	0.5	1.34	0.83	0.61	0.64	1.24	0.94	0.66	1.25	1.04
	(5.37)	(1.18)	(4.50)	(1.70)	(4.34)	(2.46)	(1.79)	(2.54)	(5.41)	(2.99)	(2.47)	(5.26)	(4.93)
2	1.32	0.88	1.31	0.41	1.02	1.06	0.93	0.99	1.0	1.07	0.62	0.17	0.24
	(4.94)	(3.42)	(4.82)	(1.69)	(3.11)	(3.40)	(3.29)	(3.51)	(3.86)	(3.32)	(2.37)	(0.95)	(3.08)
3	1.41	0.89	1.1	0.62	0.89	1.35	0.63	0.71	1.17	0.97	1.03	0.24	0.12
	(5.26)	(3.11)	(4.62)	(2.18)	(3.32)	(4.31)	(2.28)	(2.46)	(3.93)	(3.55)	(3.38)	(1.33)	(1.87)
4	1.23	1.14	0.63	0.4	1.09	1.5	0.92	0.98	0.91	1.16	1.32	0.2	0.12
	(4.05)	(4.00)	(2.13)	(1.18)	(3.67)	(5.70)	(3.61)	(2.98)	(2.82)	(4.60)	(4.80)	(0.91)	(2.06)

5 (High control)	0.28	1.65	0.91	0.63	0.59	1.19	1.46	1.21	0.73	1.08	1.19	-0.29	-0.17
	(0.77)	(5.45)	(3.04)	(1.58)	(1.91)	(4.00)	(4.28)	(3.66)	(2.09)	(4.46)	(3.76)	(-1.00)	(-0.85)
# Sign. pos	4	4	5	4	5	5	5	5	5	5	5	1	4
# Sign. neg	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean H-L ret	1.11	0.99	1.06	0.51	0.99	1.19	0.91	0.91	1.01	1.04	0.96	0.32	0.27
	(4.85)	(4.21)	(4.90)	(2.02)	(4.30)	(4.90)	(3.72)	(3.67)	(4.26)	(4.57)	(4.15)	(1.74)	(3.62)
Mean H-L α_6	1.21	1.11	1.2	0.6	1.09	1.28	1.04	1.07	1.15	1.18	1.11	0.39	0.32
	(5.23)	(4.61)	(5.38)	(2.27)	(4.62)	(5.28)	(4.23)	(4.19)	(4.71)	(5.09)	(4.69)	(2.10)	(4.11)
Panel B: Value-weighted Portfolios for *NPM*													
Quintile	LNMV	BETA	LNBM	REV	MOM	ILLIQ	TURN	IVOL	COSKEW	COKURT	MAX	Ret_Ind	Ret_Mar
1 (Low control)	1.29	0.4	1.32	0.51	1.34	0.81	0.6	0.64	1.24	0.92	0.65	1.25	1.03
	(5.37)	(1.12)	(4.35)	(1.72)	(4.31)	(2.39)	(1.75)	(2.51)	(5.40)	(2.93)	(2.39)	(5.23)	(4.87)
2	1.32	0.86	1.32	0.43	0.99	1.05	0.93	0.99	0.99	1.04	0.59	0.16	0.23
	(4.94)	(3.27)	(4.76)	(1.74)	(3.01)	(3.36)	(3.29)	(3.46)	(3.84)	(3.21)	(2.23)	(0.88)	(2.96)
3	1.41	0.87	1.08	0.61	0.87	1.35	0.6	0.69	1.16	0.94	1.01	0.23	0.12
	(5.26)	(2.99)	(4.50)	(2.12)	(3.19)	(4.30)	(2.12)	(2.35)	(3.87)	(3.42)	(3.31)	(1.26)	(1.86)
4	1.23	1.14	0.61	0.39	1.08	1.5	0.9	0.97	0.91	1.16	1.31	0.2	0.12
	(4.05)	(3.93)	(2.05)	(1.14)	(3.62)	(5.68)	(3.48)	(2.91)	(2.79)	(4.53)	(4.74)	(0.87)	(2.05)
5 (High control)	0.28	1.63	0.88	0.61	0.6	1.17	1.44	1.18	0.7	1.06	1.18	-0.32	-0.17
	(0.77)	(5.37)	(2.88)	(1.51)	(1.92)	(3.87)	(4.23)	(3.54)	(1.98)	(4.37)	(3.67)	(-1.08)	(-0.86)
# Sign. pos	4	4	5	3	5	5	5	5	5	5	5	1	4
# Sign. neg	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean H-L ret	1.11	0.98	1.04	0.51	0.97	1.18	0.89	0.89	1.0	1.03	0.95	0.3	0.26
	(4.85)	(4.08)	(4.76)	(1.99)	(4.21)	(4.84)	(3.62)	(3.56)	(4.19)	(4.44)	(4.01)	(1.65)	(3.55)
Mean H-L α_6	1.21	1.09	1.18	0.6	1.08	1.27	1.03	1.06	1.14	1.17	1.09	0.38	0.32
	(5.23)	(4.48)	(5.25)	(2.24)	(4.53)	(5.22)	(4.12)	(4.08)	(4.63)	(4.96)	(4.55)	(2.01)	(4.07)

Note. This table represents monthly high-low NPM return spreads for portfolios constructed by the bivariate sorts on control variables and NPM. The Online Appendix provides a detailed definition for each variable. First, stocks are sorted into quintiles based on one of the control variables. Next, within each quintile, stocks are further sorted into quintiles based on NPM, producing 25 double-sorted portfolios. We report the average spread in monthly returns between the high- and low-NPM sub-quintiles across different quintiles of control variables. Portfolio 1 (5) indicates the quintile portfolio consisting of the stocks with the lowest (highest) control variable values. Panel A and B report results for equal- and value-weighted portfolios that are rebalanced each month respectively. The bottom rows report the number of quintiles of the control variable for which the high-low NPM return spread is positive or negative at the 10% significance level and the average of the return and alpha spreads across all quintiles. $\alpha 6$ is the alpha from the Fama and French (2018) six-factor model. The returns and alphas are reported in percentages. The numbers in parentheses are t-statistics adjusted using bootstrap and Newey and West's (1987) method for mean returns and alphas, respectively. The sample covers 4275 stocks, and the study period ranges from January 2004 to December 2022.

3.3. Cross-Sectional Regressions

To jointly control for multiple factors that may affect the relation between NPM and the cross-section of future stock returns at the stock level, we now turn to conduct Fama-MacBeth (1973) regressions. Specifically, we run the following cross-sectional regressions,

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{CFMSR,t} CFMSR_{i,t} + \sum_{j=1}^{K} \lambda_{j,t} Control_{j,i,t} + \varepsilon_{i,t+1} \ , \quad (3)$$

where $R_{i,t+1}$ is the excess return of stock i in month $t+1$, and $Control_{\mathrm{j,i,t}}$ denotes a set of lagged control variables as described in Section 2.3. $\lambda_{CFMSR,t}$ is the key estimated coefficient of interest.

Table 5 reports the results. The time-series average slope coefficients of NPM for all various specifications are positive and statistically significant at the 1% level. For instance, in column 1, the average slope $\lambda_{CF,t}$ from the monthly regression of excess returns on NPM alone is 0.020 with a Newey-West (1987) adjusted t-statistic of 4.36. Even when all control variables are included in the regression, as shown in the last column in Table 5, the average slope remains significantly positive. Thus, the Fama-MacBeth regression further confirms that NPM is positively priced in the cross-sectional Chinese stock returns.

3.4. Robustness Checks

To further assure the validity of our findings, we perform several robustness checks. Specifically, we reconstruct the long-short NPM portfolios from Section 3.1 with various methodological modifications. First, we examine the performance in subperiods, i.e., the first half, the second half, and the exclusion of January from the sample. Second, we explore the effect under different market states, such as volatile and stable markets, high and low dispersion markets, bull and bear markets, high- and low-interest rate markets. Third, we try different schemes to sort stocks and form portfolios, including the inverse volatility weight, quartile-, sextile-, and decile-based sorts. Fourth, we remove the largest (smallest) 10% market value of stocks to avoid the impact of extreme values. Fifth, we estimate NPM using window sizes of 1, 3, 6, and 9 months for periods of analyst coverage. For brevity, we report these results in Table 6. Our findings in all the robustness checks remain qualitatively unchanged.

4. NPM versus CF

As mentioned in Section 2.2, NPM is extended from CF in Ali & Hirshleifer (2020), which captures almost all existing cross-asset momentum factors. A natural question is how NPM is related to CF and whether NPM has incremental predictability for returns after controlling for the CF factor. To this end, we compare the pricing effect between NPM and CF by performing alternating bivariate analyses, cross-sectional regressions, and spanning tests of them. Table 7 reports these results.

Panel A in Table 7 displays the performance of portfolios sorted by NPM after first sorting by CF, and Panel B reports the vice versa. As shown in the last two columns, the average return and alpha differences for long-short portfolios are all positive and statistically significant at a 1% level, suggesting the pricing effect of NPM and CF cannot subsume each other. Panel C reports the average slope coefficients from monthly regressions of stock returns on either NPM or CF alone or together. The positive and significant slope coefficients of NPM and CF in the three specifications further confirm that both NPM and CF have positive predictability for cross-sectional stock returns in China and they cannot be explained by each other. Furthermore, we construct the NPM factor and CF factor following Ali and Hirshleifer (2020) to perform spanning tests and report the results in Panel D of Table 7, Consistent with the findings in the former three Panels, CF (NPM) cannot explain the returns on the NPM (CF) momentum factor, as their alpha remains economically large and statistically significant at a 1% level in the regressions.

Table 5. Fama-MacBeth Cross-Sectional Regressions

Fama-MacBeth Cross-Sectional Regressions for *NPM*													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
NPM	0.020	0.021	0.012	0.020	0.023	0.019	0.018	0.022	0.022	0.021	0.012	0.014	0.012
	(4.36)	(5.95)	(2.60)	(5.79)	(6.26)	(5.38)	(5.11)	(6.05)	(6.26)	(5.89)	(2.98)	(3.05)	(2.99)
BETA		-0.004	-0.005	-0.004	-0.004	0.003	-0.004	-0.005	-0.006	-0.004	-0.004	-0.005	0.001
		(-1.10)	(-1.37)	(-1.05)	(-0.88)	(0.74)	(-1.06)	(-1.31)	(-1.42)	(-0.89)	(-1.15)	(-1.24)	(0.20)
LNBM		0.000	0.000	0.001	0.000	0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	0.001
		(0.17)	(0.30)	(0.59)	(0.17)	(0.17)	(-0.17)	(-0.13)	(-0.06)	(0.13)	(0.15)	(0.32)	(1.31)
LNMV		-0.005	-0.004	-0.005	-0.004	-0.006	-0.005	-0.004	-0.004	-0.005	-0.004	-0.004	-0.006
		(-3.15)	(-3.07)	(-3.43)	(-2.52)	(-3.98)	(-3.19)	(-3.10)	(-3.09)	(-3.14)	(-3.07)	(-3.00)	(-4.68)
REV			-0.015										0.001
			(-1.65)										(0.05)
MOM				0.004									0.007
				(1.76)									(3.03)
ILLIQ					0.030								0.000
					(2.80)								(0.04)
TURN						-0.000							-0.000
						(-7.21)							(-7.29)
IVOL							-0.316						-0.141
							(-3.49)						(-1.94)
COSKEW								-0.073					0.043
								(-1.01)					(0.50)
COKURT									0.444				-0.201
									(1.19)				(-0.42)
MAX										-0.025			-0.002
										(-1.62)			(-0.16)
Ret_Ind											-0.026		-0.076
											(-3.73)		(-5.24)
Ret_Mar												-0.015	0.064
												(-1.91)	(2.91)
#Obs	337,723	337,723	337,723	337,723	337,723	337,723	337,723	337,723	337,723	337,723	337,723	337,723	337,723
$\overline{R}^2$	0.015	0.079	0.091	0.089	0.089	0.092	0.089	0.083	0.086	0.081	0.088	0.091	0.141

Note. The table reports the average slope coefficients from monthly regressions of stock returns on NPM and control variables: market beta (BETA), the log market value (LNMV), the log book-to-market ratio (LNBM), short-term reversal (REV), momentum (MOM), Amihud's illiquidity ratio (ILLIQ), turnover ratio (TURN), idiosyncratic risk (IVOL), co-skewness (SKEW), co-kurtosis (KURT), lottery-like factor (MAX), industry return reversal (Ret_Ind) and inter-industry reversal (Ret_Mar). The numbers in parentheses are t-statistics adjusted using Newey and West's (1987) method. $\overline{R^2}$ is the average cross-sectional R2 coefficient and #Obs is the total number of monthly observations in each specification. The sample covers 4275 stocks, and the study period is January 2004 to December 2022.

Table 6. Robustness Checks

	Equal-weighted portfolios						Value-weighted portfolios					
	R		$\alpha 3$		$\alpha 6$		R		$\alpha 3$		$\alpha 6$	
Panel A: subperiods												
First half	1.31	(4.20)	1.50	(4.97)	1.60	(5.79)	1.29	(4.14)	1.48	(4.91)	1.59	(5.72)
Second half	1.25	(3.25)	1.20	(3.37)	1.24	(3.72)	1.24	(3.18)	1.18	(3.28)	1.23	(3.63)
January excluded	1.21	(4.48)	1.31	(4.93)	1.35	(5.51)	1.20	(4.38)	1.29	(4.82)	1.34	(5.38)
Panel B: market states												
Volatile markets	1.04	(2.42)	1.04	(2.58)	1.04	(2.62)	1.02	(2.35)	1.02	(2.51)	1.02	(2.55)
Stable markets	0.96	(3.05)	1.00	(3.13)	1.13	(3.37)	0.95	(2.95)	0.98	(3.02)	1.12	(3.26)
High dispersion	1.39	(2.62)	1.64	(3.17)	1.73	(3.15)	1.37	(2.55)	1.62	(3.11)	1.71	(3.09)
Low dispersion	0.61	(2.84)	0.71	(3.14)	0.71	(2.78)	0.60	(2.74)	0.70	(3.03)	0.70	(2.71)
Bull markets	0.52	(1.62)	0.03	(0.06)	0.13	(0.28)	0.50	(1.54)	-0.01	(-0.02)	0.09	(0.20)
Bear markets	1.62	(3.63)	1.88	(2.88)	1.97	(2.81)	1.60	(3.59)	1.87	(2.85)	1.97	(2.79)
High interest rates	1.02	(1.82)	1.25	(2.16)	1.25	(2.17)	1.00	(1.76)	1.23	(2.09)	1.23	(2.10)
Low interest rates	0.99	(4.44)	0.98	(4.45)	1.05	(4.22)	0.98	(4.33)	0.97	(4.32)	1.03	(4.11)
Panel C Alternative portfolio implementation												
Quartile portfolios	0.91	(3.91)	1.00	(4.28)	1.04	(4.41)	0.90	(3.80)	0.98	(4.16)	1.03	(4.30)
Sixth portfolios	1.09	(3.95)	1.21	(4.42)	1.25	(4.55)	1.07	(3.86)	1.19	(4.32)	1.23	(4.45)
Decile portfolios	1.37	(4.13)	1.48	(4.58)	1.51	(4.66)	1.35	(4.05)	1.46	(4.49)	1.50	(4.57)
Inverse volatility weight	1.28	(5.20)	1.37	(5.80)	1.43	(6.43)	0.95	(3.70)	1.05	(4.14)	1.09	(4.25)
Panel D Sample modifications												
10% of smallest excluded	0.98	(3.81)	1.07	(4.18)	1.11	(4.24)	0.96	(3.72)	1.06	(4.09)	1.10	(4.16)
10% of biggest excluded	1.12	(4.78)	1.21	(5.07)	1.25	(5.25)	1.11	(4.72)	1.20	(5.00)	1.24	(5.19)
Panel E Different estimation periods												
1 month	0.94	(4.05)	0.93	(4.20)	0.97	(4.49)	0.94	(4.01)	0.93	(4.17)	0.97	(4.43)
3 months	1.21	(5.37)	1.26	(5.76)	1.32	(6.41)	1.21	(5.28)	1.25	(5.66)	1.32	(6.29)
6 months	1.16	(4.80)	1.31	(6.00)	1.24	(5.34)	1.15	(4.71)	1.23	(5.23)	1.30	(5.89)
9 months	1.21	(4.98)	1.29	(5.46)	1.35	(6.07)	1.20	(4.89)	1.28	(5.36)	1.34	(5.97)

Note. The table reports the performance of portfolios formed on NPM under different methodological modifications for robustness checks of the baseline result. R is the mean excess return. $\alpha 3$ and $\alpha 6$ are alphas from three-factor (market, size, and book-to-market) and six-factor (market, size, book-to-market, investment, profitability, and momentum) models, respectively. The returns and alphas are presented in percentage terms. The numbers in parentheses are Newey-West's (1987) adjusted t-statistics. Panel A reports the performance for different subperiods. Panel B displays the results under different market states. Panel C concerns the alternative breakpoints used to form the portfolios. Panel D has made changes to the sample. Panel E regards extended holding periods for the portfolios. Panel F documents different estimation periods of NPM. The sample covers 4275 stocks, and the study period is from January 2004 to December 2022.

However, the alpha (1.29%) for regression using the NPM factor as the dependent variable is larger than that for the CF factor (0.97%), indicating that NPM has a stronger pricing effect than CF. The reason is that our proposed NPM not only contains the information of peer firms covered by common analysts but also measures the extent to which investors underreact.

Table 7. NPM Versus CF

	Low	2	3	4	High	H-L R	H-L $\alpha6$
Panel A. Sorted by NPM controlling for CF							
Equal-Weighted	0.69	0.75	0.94	0.53	1.27	0.84	0.89
	(2.23)	(2.72)	(3.39)	(1.90)	(3.54)	(3.79)	(4.01)
Value-Weighted	0.69	0.75	0.93	0.53	1.28	0.83	0.88
	(2.17)	(2.68)	(3.33)	(1.85)	(3.53)	(3.73)	(3.94)
Panel B. Sorted by CF controlling for NPM							
Equal-Weighted	0.76	0.95	1.18	1.32	1.19	1.08	1.23
	(2.90)	(3.42)	(4.50)	(3.87)	(3.13)	(4.91)	(5.63)
Value-Weighted	0.77	0.92	1.18	1.30	1.18	1.07	1.22
	(2.88)	(3.28)	(4.44)	(3.78)	(3.08)	(4.83)	(5.54)
Panel C: Cross-sectional regressions							
		(1)		(2)		(3)	
NPM		0.020				0.021	
		(4.36)				(4.72)	
CF				0.078		0.102	
				(3.06)		(4.09)	
$\overline{R^2}$		0.015		0.014		0.027	
#Obs		337,723		337,723		337,723	
Panel D: Spanning tests							
		Dependent Variable: NPM factor				Dependent Variable: CF factor	
α		1.29				0.97	
		(5.32)				(3.52)	
NPM						-0.217	
						(-1.63)	
CF		-0.214					
		(-1.58)					
Six-factors		controlled				controlled	

Note. The table reports the results for comparing the return predictability of the net peer momentum (NPM) versus the connected-firm momentum (CF). Panel A reports average spreads in monthly returns between the high- and low-CF sub-quintiles while controlling for NPM, and Panel B displays the vice versa. Portfolio Low to High refer to the quintiles of stocks with different levels of control variables. Panel C shows the average slope coefficients from monthly Fama-Macbeth (1973) regressions of stock returns on NPM, CF, or both. Panel D presents the results for spanning tests and α is the intercept term. The sample covers 4275 stocks, and the study period is January 2004 to December 2022.

5. Conclusion

This study constructs a novel predictor of stock returns, the net peer momentum (NPM), calculated as the difference between returns on connected firms (Ali & Hirshleifer, 2020) and the return on the focal firm. Portfolio-level analyses and firm-level cross-sectional regressions indicate a positive and significant relation between the past NPM and expected stock returns. The stocks in the highest NPM quintile generate 1.28% average monthly higher returns than stocks in the lowest NPM quintile. This effect is robust to many considerations. Furthermore, we compare the predictability of NPM with

CF using a variety of test methods. We find that both NPM and CF exhibit significant predictability for cross-sectional stock returns and they cannot subsume each other, but the NPM's effect prevails. Our results could be directly implemented to form profitable investment strategies. Finally, exploring potential explanations for the pricing effect of NPM and its role in other markets or asset classes may be valuable directions for future research.

Supplementary Materials: The Online Appendix is available upon request.

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