Diamond Cuts Diamond: News Co-mention Momentum Spillover Prevails in China

Shuyi Ge *, Shaoran Li †, Hanyu Zheng ‡

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Abstract

We conduct a comprehensive study on momentum spillovers in the Chinese stock market using various types of economic linkages. By developing a flexible and innovative algorithm to identify linkages among listed firms using millions of Chinese business news articles, we find that the news co-mention momentum spillover is significantly stronger compared to other forms of momentum spillovers. Using spanning tests and Fama-MacBeth regressions, we further show that the news co-mention momentum spillover unifies all different forms of momentum spillover effects in the Chinese stock market. Notably, the analyst co-coverage momentum spillover effect, which is the dominant species in the US stock market, is subsumed by the news co-mention momentum spillover effect in the Chinese stock market. We further explore the differences in the information content of links implied by news co-mentioning and other proxies. We suggest that the dominance of news co-mention momentum spillover over others can be attributed to two primary factors: comprehensive information and prompt updates.

Keywords: Economic Linkage, Big Textual Data, Momentum Spillover, News co-mention, Limited attention

JEL Classification: G11, G12, G14

*The School of Finance, Nankai University. Email: sg751_shuyige@outlook.com

†The School of Economics, Peking University. Email: lishaoran@pku.edu.cn

‡Faculty of Business and Economics, The University of Hong Kong. Email: nickzhy@outlook.com

1 Introduction

In the past decade, a new momentum-like anomaly known as "momentum spillovers" or "cross-firm momentum" has raised a lot of attention in the US stock market. A focal firm's stock price responds sluggishly to new information about economically linked firms, and as a result, the past returns of linked firms predict the future return of the focal firm. The literature documents the existence of such momentum spillover effect via various types of economic linkages, including industry links (Moskowitz and Grinblatt, 1999; Hou, 2007), customer-supply links (Cohen and Frazzini, 2008), geographic links (Parsons et al., 2020; Jin and Li, 2020), technology links (Lee et al., 2019; Duan et al., 2022), news-implied links (Scherbina and Schlusche, 2013), concept links (Du et al. (2022)), and analyst co-coverage links (Ali and Hirshleifer, 2020), etc.

In the US market, the cross-firm momentum via analyst co-coverage unifies the "zoo" of other momentum spillover effects (Ali and Hirshleifer, 2020). Unlike developed markets, the Chinese stock market is relatively young, and it possesses several distinctive features that make it particularly intriguing for research. The first prominent feature of the Chinese stock market is the dominance of retail investors who are less sophisticated (Bailey et al., 2009). It's generally more costly for them to collect and process information, and they are more likely to be inattentive to new information about linked firms while making investing decisions. Consequently, we might expect a stronger lead-lag effect among linked firms in the Chinese stock market. The second prominent feature of the A market is that investors trade in response to news quickly (Pan et al., 2016), which leads to its high turnover rate. Given these special features, two natural questions arise: whether various forms of momentum spillover effects exist in the Chinese stock market and whether there exists a dominant species that unifies the "zoo" of all momentum spillover effects.

In this paper, we conduct a comprehensive study on momentum spillovers in the Chinese stock market using various types of economic linkages. We find that the momentum spillover effect among firms linked through news co-mentioning (referred to as the news co-mention momentum spillover) is significantly stronger than others. Using spanning tests and Fama and MacBeth (1973) regressions, we show that all different forms of cross-firm momentum effects can be unified by the news co-mention momentum spillover in the Chinese stock market. Notably, the analyst co-coverage momentum spillover effect, which is the dominant species in the US stock market, is subsumed by the news co-mention momentum spillover effect in the Chinese stock market. We further explore the differences in the information content of links implied by news co-mentioning and other proxies. And we suggest that the dominance of news co-mention momentum spillover over others can be attributed to two primary factors: comprehensive information and prompt updates.

To be specific, to construct the news co-mention linkages, we adopt two strategies. The first one follows Scherbina and Schlusche (2013) and Ge et al. (2022), which define two firms as linked if they are co-mentioned in the same piece of news article during a pre-specified identification window. This identification strategy is referred to as *same_article*. One potential issue with this identification strategy is that two firms that happen to appear in the same article may appear in different sentences and are actually unrelated to each other. Given this concern, the second identification strategy we adopt is called *same_sentence*, which defines two firms as linked if they are co-mentioned in the same sentence of the piece of news article during a pre-specified identification window.[1]

With the news-implied linkages, we proceed to test the existence of the news co-mention momentum spillover

[1]A similar link identification strategy is adopted in Schwenkler and Zheng (2019) and Schwenkler and Zheng (2021).

effect. Duan et al. (2022) document that the momentum spillover effects in the A market are more prominent for the weekly returns as the turnover rate is extremely high in the Chinese stock market. In addition, He et al. (2021) argue that Chinese investors may pay more attention to the past week's returns rather than the past month's returns. Given the above reasons, we mainly focus on momentum spillovers at the weekly frequency. At the end of each week, we construct a signal for each stock based on the weighted average returns of its linked stocks. We sort stocks into quintiles, and a long-short strategy could be constructed, which involves the purchase of stocks from the top quintile while shorting stocks from the bottom quintile. We construct eight such long-short trading strategies using combinations of the two identification strategies and four identification windows (window lengths including 3-, 6-, 9-, and 12-month),[2] and these trading strategies that are based on news co-mention momentum spillover all generate significant and positive abnormal returns. For instance, adopting *same_sentence* identification strategy and a 3-month identification window, the long-short return is 1.94% (t-statistic=5.33), and the corresponding Liu et al. (2019) four-factor (CH-4 for short later) adjusted alpha is 1.86% (t-statistic=5.23).[3] Moreover, we find that the *same_sentence* strategy works better than the *same_article* strategy as the former yields larger abnormal returns with the same identification window. This finding aligns with our expectation that the *same_sentence* strategy is more effective in identifying genuine links among firms. Another interesting finding is that the strength of news co-mention momentum spillover decreases steadily as the length of the identification window increases. This can be attributed to the fast updating of news, rendering stale information less useful in identifying relevant linkages.

We then compare the strength of news co-mention momentum spillover with various other momentum spillover effects studied in the existing literature. The seven other cross-firm momentum effects we examine include shared-analyst momentum, industry momentum, geographic momentum at the province and city levels, customer-supplier momentum, technology momentum, statistical momentum, and concept momentum. Similar to the previous case, for each linkage type, we construct signals for each stock based on the weighted average returns of its linked stocks and sort all stocks into quintiles. The long-short strategies exploiting most of those cross-firm momentum effects also yield positive and statistically significant abnormal returns. However, these returns are noticeably smaller in both economic and statistical magnitudes compared to those obtained using news co-mentioning.

Given that the news co-mention momentum spillover effect is significantly stronger than others, we follow Ali and Hirshleifer (2020) to use spanning tests and Fama and MacBeth (1973) regressions to investigate whether the news co-mention momentum spillover encompasses and unifies the various other momentum spillover effects observed in the Chinese stock market.

To conduct the spanning tests, we construct the long-short factor returns based on news co-mentioning and the other six types of linkages discussed earlier.[4] Considering the superior performance of the *same_sentence* identification strategy, we focus on this strategy for the construction of the news co-mention momentum spillover factor. We construct four factors using identification windows of 3, 6, 9, and 12 months. For instance, we denote Sentence_3 as the news co-mention momentum spillover factor based on identifying linkages using a 3-month window with the *same_sentence* strategy. Strikingly, the alphas of all other momentum spillover factors become

[2] The identification window cannot be too short as it would result in only a small number of firms with news-links.

[3] These returns are monthly returns converted from weekly ones.

[4] Due to the low quality of disclosed data regarding top customers in China, we do not consider the customer-supplier momentum spillover factor, which is often used as the representative cross-firm momentum in the US (e.g., Huang et al. (2021) and Huang et al. (2022)).

insignificant, and some even turn negative when we add the news co-mention momentum spillover factor to the CH-4 factor model. For instance, the long-short strategy based on statistical momentum generates a CH-4 alpha of 1.34% (t-statistic=3.35), and its economic magnitude ranks second among all competitors. However, when we add the Sentence_3 factor, its CH-4+Sentence_3 model adjusted alpha decreases drastically to 0.17% (t-statistic=0.43). In contrast, none of the other six momentum factors can explain any of the four news co-mention momentum spillover factors (i.e., Sentence_3, Sentence_6, Sentence_9, Sentence_12). Additionally, among the four news co-mention momentum spillover factors, the factor constructed with a shorter identification window can explain the factors with longer identification windows, but not vice versa. The factor-spanning tests show that all different forms of cross-firm momentum effects can be unified by the news co-mention momentum spillover in the Chinese stock market. The conclusion remains to be robust when we change the factor model, industry classification, and news co-mention type. Fama-MacBeth regressions further support this conclusion. Based on both union and intersection samples, after adding the news co-mention peer firm returns as an explanatory variable, the variables based on other cross-firm momentum effects all become insignificant.

We then explore the differences in the information content of links implied by news co-mentioning and other proxies. Scherbina and Schlusche (2013), Schwenkler and Zheng (2019) find that news co-mentioning reveals a wide range of economic linkages among companies, including same industry, business alliances, partnerships, banking and financing, customer-supplier, production similarity, etc. To examine whether the news co-mention momentum spillover is stronger than others because news-implied linkages are more comprehensive, we conduct an exercise to analyze the within- and cross-industry momentum spillovers separately for each type of linkage. Firstly, we find that, for the news co-mention linkage, the degree of overlap with industry information is relatively low compared to other types of linkages. On the other hand, the shared-analyst linkage shows the highest degree of overlap with the industry linkage. Next, for each linkage type, we decompose linked firms into industry peers and cross-industry peers, and we examine the two corresponding momentum spillover effects separately. We find that for news co-mentioning, the long-short portfolio based on within-industry and cross-industry momentum spillovers generate very similar returns and CH-4 adjusted alphas. In contrast, for other linkage types, the within-industry momentum spillover is noticeably stronger. For example, in the case of geographic and technology linkages, we find that only the long-short portfolio based on the within-industry momentum spillover effect generates a positive and statistically significant alpha. The cross-industry momentum spillover effect does not yield significant abnormal returns. In the case of analyst co-coverage links, we find that although its cross-industry momentum generates a positive alpha, it is marginally significant and only half the size of that obtained from the within-industry momentum. This exercise provides evidence that news co-mentioning reveals a wider range of economic links, and news-implied linkages are more comprehensive compared to other types of linkage proxies. Specifically, news co-mentioning incorporates both industry information and valuable non-industry linkage information, which contributes to its strong predictive power for future returns.

In addition to containing comprehensive information, another advantage of news is its prompt update, which helps us to identify changes in linkages among firms in time. We keep track of the percentage change in different linkage networks over time, and we find that the news-implied network updates faster than other networks. Every week, some links are added to the new network, and some stale links are removed. Due to the fast update, it is more challenging for investors to gather and process this information, which might explain why news co-mention momentum spillover is stronger. In contrast, other networks are more persistent, making it relatively easier for investors to take this information into account when making decisions.

After confirming that news co-mention momentum spillover unifies various momentum spillover effects and highlighting the advantages of news in identifying linkages, we further investigate the mechanism behind this news-based momentum spillover. We find that the news co-mention momentum is weaker among firms with higher analyst coverage, more analyst reports, larger float values, higher institutional holder proportions, less opacity, and less linkage complexity. These findings provide support for the limited attention explanation of news co-mention momentum.[5] Recent work by Huang et al. (2021) proposes a new behavioral explanation for the cross-firm momentum anomaly, suggesting that investors are slow to react to good news when the stock price is near its 52-week high and slow to react to bad news when the stock price is far from its 52-week high due to the anchoring effect. However, our empirical analysis does not support this explanation, possibly because the 52-week high effect itself is not empirically supported in the Chinese stock market (Zhang et al., 2019; Hou et al., 2023).

We conduct some additional heterogeneity analysis and robustness checks. In China, state-owned enterprises (SOEs) play a critical role in shaping the market dynamics and contributing to the overall economy. We conduct separate portfolio analyses for SOEs and non-SOEs, and interestingly, we find that the news co-mention momentum spillover is stronger for non-SOEs than SOEs. It is possible that the observed difference is due to media bias. Given that SOEs in China are politically related, it is plausible that the news co-mentioning about SOEs may be less precise in capturing peer firm relationships compared to non-SOEs. In the robustness part, we take transaction cost and shell effect into consideration. Following Fan et al. (2021), we consider a transaction cost of 16 bps for each trade (buying and selling combined). The long-short portfolio constructed based on news co-mention momentum generates a mean return of 1.29% (t-statistic=3.56), and the CH-4 adjusted alpha is 1.21% (t-statistic=3.42). In contrast, after taking transaction cost into consideration, trading strategies based on other cross-firm momentum effects all have insignificant alphas. This suggests that the news co-mention momentum strategy remains robust and profitable even when considering real-world transaction costs while others are not. To eliminate the potential shell effect in the Chinese stock market, we follow Liu et al. (2019) to drop firms with sizes at the bottom 30% of the market. Our key results remain unchanged.

This paper contributes to two strands of literature. Firstly, it provides new evidence on cross-firm momentum. Previous literature focus on testing the cross-firm momentum driven by different linkages in the US stock market (e.g., industry connection (Moskowitz and Grinblatt, 1999; Hou, 2007), supply chain (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Gençay et al., 2015), conglomerate-standalone linkage (Cohen and Lou, 2012), alliance partnership (Cao et al., 2016), annual report similarity (Hoberg and Phillips, 2018), technology similarity (Lee et al., 2019), geographic proximity (Parsons et al., 2020; Jin and Li, 2020), analyst co-coverage (Ali and Hirshleifer, 2020), competition relationship (Eisdorfer et al., 2022), etc.). In this paper, we conduct a comprehensive study on momentum spillovers in the Chinese stock market using various types of economic linkages. It sheds light on the interplay between different linkages and their effects on stock returns, providing valuable insights for investors and researchers interested in cross-momentum strategies in emerging markets. Broadly speaking, this paper also contributes to the expanding literature on empirical asset pricing and anomalies in the Chinese stock market (see Jiang et al. (2018), Leippold et al. (2022), Jansen et al. (2021), Hou et al.

[5] Most previous studies attribute the momentum spillover effect to investors' limited attention to news from peer firms. See Burt and Hrdlicka (2021) for a detailed list of these studies. If this limited attention theory explains the news co-mention momentum in China, we would expect to see a weaker momentum spillover effect when information from peer firms is more transparent and easier to get.

(2023), and others).

The paper relates to the literature that extracts soft information from textual data. In recent years, there has been an explosion of empirical research in economics and finance that utilizes text as data. To mention a few examples, Ke et al. (2019) utilize information from news articles for predicting asset returns, Hu et al. (2021) extract information from Reddit to study the impact of social media on market dynamics, and Cong et al. (2019) develop a framework to generate 'textual factors' from large text datasets. News data has received significant attention among various alternative data sources, and there is a growing interest in using news coverage to identify linkages among firms. Studies such as Scherbina and Schlusche (2013) have demonstrated the usefulness of firm linkages identified through news co-mentioning in predicting stock returns. Additionally, Schwenkler and Zheng (2019) have developed a machine-learning method to construct a news-implied network of firms, and they also applied the same identification strategy to establish crypto peers (Schwenkler and Zheng (2021)). Guo et al. (2017) have explored the association between news co-mentioning and investor attention spillovers. This paper adopts two different identification strategies to infer firm linkages from news, and we show that sentence co-mentioning strategy is more effective in identifying genuine links among firms. Unlike the findings of Scherbina and Schlusche (2013), who use article co-mentioning to identify linkages and found that trading strategies based on the predictability of linked firms' past returns may not be profitable when considering transaction costs, we demonstrate that our strategy, based on sentence co-mentioning to infer links, remains robust and profitable even when accounting for real-world transaction costs. In addition, we show that due to the unique advantages of news information, all different forms of cross-firm momentum effects can be unified by the news co-mention momentum spillover in the Chinese stock market.

The rest of the paper is organized as follows. In Section 2, we introduce the data and the construction of different linkages. Section 3 conducts the portfolio analysis for each type of momentum spillover effect. In Section 4, we examine the unifying effect of the news co-mention momentum spillover and explore the differences in the information content of links implied by news co-mentioning and other proxies. Section 5 investigates the mechanism underlying the news co-mention momentum. In Section 6, we conduct some further analysis and robustness checks. Section 7 concludes. Additional materials are given in Appendix.

2 Data and summary statistics

The sample stocks used in this paper include all A-shares listed on the main boards of the Shanghai Stock Exchange (SSE), Shenzhen Stock Exchange (SZSE), and the Growth Enterprise Market (GEM). Special treatment (ST) shares are excluded.[6] In the robustness analysis, we also exclude firms that have the bottom 30% capitalization from the sample. This is done to prevent potential biases related to the shell effect in the Chinese stock market, as highlighted in the study by Liu et al. (2019). The full sample period for our analysis spans from 2006 to 2020. Due to data availability issues specific to each linkage type, the sample periods may vary and be shorter when conducting analysis for different types of linkages. Stock trading data, financial statements, and risk-free interest rates (one-year deposit rate) are from CSMAR. The CH-4 factor data is obtained from Robert

[6] Since April 22, 1998, the Shanghai and Shenzhen stock exchanges have implemented Special Treatment (ST) for the stock trading of listed firms with abnormal financial conditions. ST shares are prefixed with "ST" and are considered to have extremely high risk. Therefore, they are often excluded from research about the Chinese stock market.

F. Stambaugh's website.[7]

In later subsections, we provide details on the data sources and construction methodology for each type of economic linkage considered in the study, as well as the corresponding predictive signals derived from these linkages. We first discuss the news co-mention links, which are our main focus. Then, we provide brief descriptions of seven other proxies for inter-firm linkages commonly studied in the literature, including the analyst co-coverage (Ali and Hirshleifer, 2020), customer-supplier relationship (Cohen and Frazzini, 2008), industry classification(Hou, 2007), geographic proximity (Parsons et al., 2020), technology affinity (Lee et al., 2019), statistical similarity of firm features (He et al., 2021), and concept category (Du et al., 2022).

2.1 News Co-mention Linkages

We use millions of news articles from the Financial Text Intelligent Analysis Platform of RESSET and the Juyuan Database spanning from 2006 to 2020.[8] We filtered out 1,138,247 news articles that mentioned at least one listed firm in the A market. Table 14 from Appendix A presents a summary of the daily basic information of the news data since 2006. Prior to 2012, the news data is relatively sparse, with an average of fewer than 100 news pieces per day. The news data has become much more abundant since 2012. Given that, although the news data has been available since 2006, in the main body of the paper, we use the subset from 2012 to 2020 when the news data quality is high. For robustness check, we also consider different sample periods.

We adopt two strategies to construct the news co-mention linkages. The first identification strategy is referred to as *same_article*, which defines two firms as linked if they are co-mentioned in the same piece of news article during a pre-specified identification window. One potential issue with this identification strategy is that two firms that happen to appear in the same article may appear in different sentences and are actually unrelated to each other. Given this concern, the second identification strategy we adopt is called *same_sentence*, which defines two firms as linked if they are co-mentioned in the same sentence of the same piece of news article during a pre-specified identification window.

For both identification strategies, we consider identification windows of various lengths, including 3 months, 6 months, 9 months, and 12 months. The identification window cannot be too short or too long in order to strike a balance between capturing an adequate amount of news co-mentions and the inclusion of very stale information. Short windows (e.g., 1-month) result in a small number of stocks with news links, while long windows (e.g., over one year) include outdated news with limited predictability. At the end of each week, for a focal firm i, we calculate the news-based predictive signal as the average excess return of linked firms weighted by the number of co-mentions during the identification window. To be precise, we have eight news-based signals with different identification strategies and window lengths. For example, the signal constructed based on *same_sentence* and 3-month window is denoted as *Sentence_3_Rtn*, and the corresponding trading strategy is referred to as *Sentence_3*.

[7]The website provides monthly and daily CH-4 factor data. We construct weekly factors by using cumulative daily factor returns in one week (i.e., at the end of each trading week, the weekly CH-4 factor is the cumulative return of daily CH-4 factor returns from the first trading day to the last trading day of the week).

[8]We access the data from the Financial Engineering Laboratory of Peking University.

Table 1: Summary statistics

Link type	Variables	Count	Mean	Std.	Min.	Median	Max.
Sentence_3	# Stocks	464	1100	280	715	996	1840
	# Peer firms	510429	9	16	1	3	235
	Value	510429	22.45	71.08	0.27	7.19	2509.88
	Peer firm return	510429	0.0050	0.0697	-0.4101	0.0034	24.1232
Sentence_6	# Stocks	464	1515	231	1164	1462	2324
	# Peer firms	702802	12	21	1	4	311
	Value	702802	19.12	61.36	0.27	6.76	2509.88
	Peer firm return	702802	0.0044	0.0641	-0.4102	0.0036	24.1232
Sentence_9	# Stocks	464	1758	187	1316	1756	2502
	# Peer firms	815530	15	25	1	5	321
	Value	815530	17.73	57.27	0.27	6.56	2509.88
	Peer firm return	815530	0.0038	0.0555	-0.4101	0.0036	1.5622
Sentence_12	# Stocks	464	1925	199	1437	1915	2613
	# Peer firms	893012	17	28	1	6	355
	Value	893012	16.91	54.89	0.27	6.41	2509.88
	Peer firm return	893012	0.0034	0.0540	-0.4103	0.0035	1.0741
Article_3	# Stocks	464	1332	293	903	1234	2223
	# Peer firms	618272	16	32	1	5	454
	Value	618272	20.41	65.11	0.27	6.96	2509.88
	Peer firm return	618272	0.0047	0.0559	-0.4101	0.0043	3.3824
Article_6	# Stocks	464	1750	233	1355	1742	2704
	# Peer firms	812053	23	42	1	8	631
	Value	812053	17.79	57.39	0.27	6.58	2509.88
	Peer firm return	812053	0.0041	0.0526	-0.4101	0.0044	0.8516
Article_9	# Stocks	464	1976	229	1478	1952	2816
	# Peer firms	917064	29	51	1	10	757
	Value	917064	16.69	54.22	0.27	6.38	2509.88
	Peer firm return	917064	0.0036	0.0507	-0.4097	0.0042	1.0741
Article_12	# Stocks	464	2122	278	1569	2121	2891
	# Peer firms	984555	35	59	1	12	867
	Value	984555	16.06	52.43	0.27	6.24	2509.88
	Peer firm return	984555	0.0033	0.0493	-0.4103	0.0041	1.0741
Analyst	# Stocks	768	1326	348	476	1429	1872
	# Peer firms	1018102	98	84	1	75	609
	Value	1018102	15.45	57.09	0.18	6.60	6285.82
	Peer firm return	1018102	0.0032	0.0445	-0.4099	0.0049	0.9588
Customer	# Stocks	566	109	56	24	71	197
	# Peer firms	61428	1	0	1	1	5
	Value	61428	8.37	20.68	0.08	4.53	517.98
	Peer firm return	61428	0.0025	0.0580	-0.3662	0.0008	2.6103
Industry	# Stocks	768	2336	795	1048	2313	3893
	# Peer firms	1794095	130	83	2	110	364
	Value	1794095	13.85	59.28	0.11	4.88	6285.82
	Peer firm return	1794095	0.0039	0.0463	-0.2713	0.0058	0.5055
Geographic	# Stocks	768	2355	783	1088	2329	3892
	# Peer firms	1808617	201	162	3	157	651
	Value	1808617	13.84	59.05	0.09	4.88	6285.82
	Peer firm return	1808617	0.0040	0.0445	-0.2885	0.0063	1.0308
Technology	# Stocks	768	1020	513	318	954	2117
	# Peer firms	783093	680	501	1	599	2109
	Value	783093	17.99	82.98	0.08	5.27	6285.82
	Peer firm return	783093	0.0040	0.0437	-0.3096	0.0064	0.9269
Statistical	# Stocks	768	2015	704	988	2014	3548
	# Peer firms	1547320	263	79	115	240	390
	Value	1547320	14.19	56.96	0.09	5.03	2619.90
	Peer firm return	1547320	0.0032	0.0453	-0.2879	0.0052	0.2410
Concept	# Stocks	227	2970	497	2044	3028	3821
	# Peer firms	674244	433	504	1	260	2704
	Value	674244	17.14	60.78	0.48	6.21	2509.88
	Peer firm return	674244	0.0005	0.0340	-0.1711	0.0006	0.6113

This table reports summary statistics. The sample stocks include all listed stocks on the main board of the Shanghai Stock Exchange, Shenzhen Stock Exchange, and Growth Enterprise Market (GEM). ST shares are excluded. The news co-mention linkages are based on either *same_sentence* or *same_article* strategy, using identification windows of 3 months, 6 months, 9 months, and 12 months. The industry linkage is based on the Shenwan-1 classification. The geographic linkage is at the province level. The sample period of news co-mention momentum is 2012-2020. The sample period of customer-supplier momentum is 2010-2020. The sample period of concept momentum is Aug. 2016-2020. The sample periods for other momentums are 2006-2020.

2.2 Other Linkages

Next, we will describe the construction of other types of linkages in order to conduct a comprehensive study on momentum spillovers in the Chinese stock market.

2.2.1 Analyst Co-coverage Linkages

The analyst reports data used in our study are from the Chinese Research Data Services Platform (CNRDS). This platform functions similarly to Wharton Research Data Services (WRDS) and provides access to a wide range of Chinese research data in the fields of finance and economics. The sample period for our study is from January 2005 to December 2020, which covers the earliest available analyst prediction data on the CNRDS platform. There is a total of 1,478,413 pieces of analyst predictions over the sample period. After removing data with null values and eliminating duplicates based on analyst codes, report dates, and stock codes, we are left with 530,696 unique pieces of analyst prediction data for the identification of shared-analyst linkage.

We adopt the approach outlined by Ali and Hirshleifer (2020) to identify shared-analyst linkages and compute the shared-analyst peer firm return, denoted as $Analyst\_Rtn$. At the end of each trading week, two firms are defined as the shared-analyst peer firms if they are co-covered by the same analyst teams in the past 12 months.[9] At the end of each week, for a focal firm i, the shared-analyst peer firm return, $Analyst\_Rtn_{it}$, is the average excess return of analyst peer firms, weighted by the number of shared analyst teams. Since a one-year identification window is required to identify the shared-analyst linkages, the predictive signals can be computed from the beginning of 2006.

2.2.2 Industry Linkages

There are three frequently used industry classification systems in China, namely CSRC, CITIC, and Shenwan.[10] The historical information about the industry classifications used in the study is obtained from the RESSET database, where we collect yearly data for each classification level of CSRC, CITIC, and Shenwan. We mainly focus on the primary classification of Shenwan as it is the most popular classification system in the Chinese financial sector. At the end of each week, for a focal firm i, the industry peer firm return, denoted as $Industry\_Rtn_{it}$, is calculated as the equal-weighted average excess return of all other stocks from the same industry.

2.2.3 Customer-supplier Linakges

We follow Cohen and Frazzini (2008) and extract the information about the top-5 customers for all listed firms from their annual reports. However, for Chinese listed firms, the disclosure of the real names of their top customers is not mandated by China Securities Regulatory Commission (CSRC). Due to the voluntary nature of the disclosure, many firms choose to use digits, English letters, or Chinese numbers to represent their customers

[9] In the Chinese stock market, analyst reports are often produced by a team of analysts rather than individual analysts. In our study, we consider all analysts within a team as a cohesive unit and do not distinguish them as individual analysts. In other words, two stocks are defined as shared-analyst peer firms only if they are covered by the same analyst team. This approach acknowledges that analyst reports are collaborative efforts that incorporate the ideas and insights of the entire team.

[10] In 2020, for the CSRC system, there are 19 primary industries and 81 secondary industries in the sample. For the CITIC system, there are 29 primary industries, 83 secondary industries, and 188 tertiary industries in the sample. For the Shenwan system, there are 28 primary industries, 104 secondary industries, and 227 tertiary industries in the sample.

instead of providing their real names or stock codes. This makes it challenging to identify firms' customers using the dataset. Moreover, some disclosed customers are not listed firms (they can be local governments, schools, and individuals). As a result, the number of customer-supplier linkages identified is much smaller than other linkages. Summary statistics from Table 1 show that for each trading week, on average, there are only 109 sample stocks whose customers can be clearly identified. To ensure an adequate number of sample firms have customer-supplier linkages, we limit the sample period from January 2010 to December 2020. To avoid any potential look-ahead bias, we set a lag of six months between the fiscal ending date and the portfolio formation date.[11] At the end of each week, for a focal firm i, the customer peer firm return $Customer\_Rtn_{it}$ is computed as the weighted average value of its customers' excess returns.

2.2.4 Geographic Linkages

According to the findings of Parsons et al. (2020), the stock returns of a firm can be predicted by the returns of its peer firms that are headquartered in the same geographic location. In our study, we define geographic peer firms at both the province level and the city level in China. The historical data about headquarters locations are obtained from CSMAR.[12] There are 32 provincial districts (including four municipalities, five provincial autonomous regions, and 23 provinces) and 399 cities (including four municipalities). In our analysis, we consider all firms located within the same province or city as geographic peers (i.e., two types of geographic linkages). At the end of each week, for a focal firm i, the geographic peer firm return $Geographic\_Rtn_{it}$ is calculated as the equal-weighted excess return of all of its geographic neighbor firms.

2.2.5 Technology Linkages

We follow the methodology in Lee et al. (2019) and define the technology peer firms based on technology similarity. The patent data is from the CCER database which provides detailed patent information for listed firms, including the International Patent Classification (IPC) patent class and the patent grant date. Technology similarity between firm i and j at time t is computed as

$$TECH_{ijt} = \frac{\left(T_{it}T'_{jt}\right)}{\left(T_{it}T'_{it}\right)^{1/2}\left(T_{jt}T'_{jt}\right)^{1/2}}.$$

$T_{it} = (T_{it1}, T_{it2}, \cdots, T_{itm})$ is the proportion vector of patents among each class in IPC in the five years preceding time t for firm i, where m is the number of all classifications. At the end of each week, for a focal firm i, the technology peer firm return, $Technology\_Rtn_{it}$, is the average return of its technology peer firms weighted by their technology similarity. To avoid the look-ahead bias, we set a lag of at least six months between the fiscal-year end and the portfolio formation date.

2.2.6 Statistical Linkages

He et al. (2021) find that a firm's return can be predicted by the past return of firms that are similar to it on some particular characteristics. In line with their work, we define statistical peer firms as stocks that have the

[11] For example, for July to December 2020, we use the customer information disclosed in the annual report of 2019, while for January to June 2020, we use the customer information disclosed in the annual report of 2018.

[12] In the context of China, firms are typically associated with two geographical locations: the location of their headquarters and the place of registration. In most cases, these two locations are the same. However, if there is a difference between the two, we prioritize the location of the headquarters. If the information regarding the headquarters location is not available but the registration address is, we use the registration address as a substitute.

closest Euclidean distance on five firm-level characteristics: closed stock price (P), firm size ($SIZE$), book-to-market ratio (BM), ROE (ROE), and assets growth (AG).[13] The distance between firm i and firm j is be computed as:

$$d_{ij} = \sqrt{(P_i - P_j)^2 + (SIZE_i - SIZE_j)^2 + (BM_i - BM_j)^2 + (ROE_i - ROE_j^2) + (AG_i - AG_j)^2}.$$

At the end of each week, for a focal firm i, we calculate the distances of all other firms with it, and the top 10% of firms with the smallest distances are considered as the statistical peers of firm i.[14] The statistical peer firm return $Statistical\_Rtn_{it}$ is then calculated as the equal-weighted excess return of its statistical peer firms.

2.2.7 Concept Linakges

In the stock market, one "concept" refers to a group of stocks that share a specific trend or topic, such as new energy or e-commerce. Following Du et al. (2022), two firms are considered concept peers if they belong to the same concept. The historical records of concepts and constituent stocks used in our study are obtained from the publicly accessible RESSET database.[15] Due to data availability, the sample period for concept momentum analysis in our study spans from August 2016 to December 2020. During this period, we identify a total of 336 concepts. Table 1 shows that for each week during the sample period, there are 2,970 sample stocks with concept linkages on average. At the end of each week, for a focal firm i, the concept peer firm return $Concept\_Rtn_{it}$ is the weighted average returns of its concept peers, where the weight is the number of common concepts.

2.3 Summary Statistics

Table 1 shows the summary statistics for different linkage types. Under *Sentence_3*, each focal firm has nine peer firms on average, fewer than 16 peers from *Article_3*. This aligns with our expectations as the *same_sentence* strategy removes the potential noise links from the *same_article* strategy, resulting in fewer links identified. Furthermore, the number of peer firms identified increases with the length of the identification window. For other linkage types (except customer-supplier), we generally observe a higher number of links, and each sample stock tends to have more peers on average.

[13] To avoid the look-ahead bias, we use accounting variables (BM, ROE, and AG) that are lagged by at least one year. For example, from January to June, the variables are based on the fiscal report two years ago, while from July to December, they are based on the fiscal report one year ago. For $SIZE$, the total market value at the end of June last year is used for the first half of the year, while the total market value at the end of June this year is used for the second half of the year. P is the weekly closed price at the end of the trading week. Each of the five variables is standardized by its cross-sectional mean and standard deviation.

[14] Different from He et al. (2021), where 50 smallest distances are used to define similar stocks in the US market, it may be more appropriate to use a percentage rather than a fixed number to define similar stocks in the Chinese market. This is because the number of A-shares in China has significantly increased over the past decades. By using a percentage of the sample size, we can maintain a consistent criterion for defining similar stocks regardless of changes in the overall market size.

[15] We acknowledge that there may be differences in the data sources and quality between our study and Du et al. (2022). They spent a lot of effort scraping the concept data from the Joinquant database. Since concept momentum is not our main focus, we rely on publicly available data, which may have limitations in terms of coverage and quality.

3 Portfolio Analysis

In this section, we examine the relationship between past peer firm return signals computed using various types of linkages and future stock returns. At the end of each trading week, all sample stocks are sorted into quintiles according to peer firm return signals computed using various linkages. Stocks are equal-weighted within each quintile group. The long-short portfolio involves buying the highest group and selling the lowest group. All portfolios are held for one week and are rebalanced weekly. In addition to reporting the average return over the risk-free rate, we also calculate the alpha using the CH-4-factor model. The weekly returns and alphas are then converted to a monthly frequency for better comparability with existing literature.

3.1 News Co-mention Momentum Spillover

We first report the main results for news co-mention momentum spillovers. Table 2 presents the results of eight trading strategies based on different identification strategies (*same_sentence* and *same_article*) and window lengths (3 months, 6 months, 9 months, and 12 months). Panel A and Panel B show the excess returns, and CH-4 adjusted alphas of each portfolio, respectively.

Overall, the eight long-short portfolios that exploit news co-mention momentum spillovers exhibit statistically and economically significant positive excess returns, which can not be explained by the CH-4 factors, including the market, size, value, and abnormal turnover rate. Among the eight strategies, *Sentence_3* performs the best and yields a monthly return of 1.94% (t-statistic=5.33), and even the worst performing one (*Article_12*) yields a monthly return of 1.36% (t-statistic=4.49). The Spearman correlation coefficients between the rank of news-based peer firm returns and the long-only portfolio returns are equal to one or close to one. This indicates a positive and monotonic relationship between the two variables, suggesting that higher news-based peer firm returns are associated with higher long-only portfolio returns.

When comparing the eight news-based trading strategies that employ different identification strategies and identification window lengths, we observe that while the overall news co-mention momentum spillover effect is strong, there are substantial differences among the eight combinations. First, give the same identification window length, *same_sentence* strategy always performs better than *same_article* strategy. Taking the 3-month windows as an example, *Sentence_3* strategy generates a long-short return and alpha of 1.94% (t-statistics=5.33) and 1.86% (t-statistic=5.23) respectively, higher than 1.63% (t-statistic=1.63) and 1.58% (t-statistic=5.16) for that of *Article_3*. The results are similar for other identification windows, indicating that *same_sentence* might be more effective in identifying genuine links among firms. This is because when two firms appear in the same article but in different sentences, there are chances that they are unrelated to each other.

Table 2: The news co-mention momentum spillover: portfolio sorting results

Panel A: Excess returns								
	same_sentence				*same_article*			
Identification windows	3-month	6-month	9-month	12-month	3-month	6-month	9-month	12-month
1 (Low)	0.74	0.81	0.85	0.84	0.89	0.88	0.85	0.84
	(0.88)	(0.96)	(1.02)	(1.00)	(1.07)	(1.06)	(1.02)	(1.01)
2	1.06	1.06	1.01	0.94	1.08	1.06	1.01	1.00
	(1.32)	(1.31)	(1.23)	(1.15)	(1.32)	(1.29)	(1.23)	(1.21)
3	1.11	1.16	1.09	1.15	1.20	1.15	1.12	1.09
	(1.38)	(1.42)	(1.34)	(1.38)	(1.49)	(1.40)	(1.35)	(1.31)
4	1.38	1.44	1.38	1.37	1.33	1.40	1.39	1.41
	(1.65)	(1.71)	(1.65)	(1.63)	(1.60)	(1.67)	(1.68)	(1.68)
5 (High)	2.68	2.38	2.30	2.22	2.54	2.34	2.26	2.21
	(2.96)	(2.66)	(2.57)	(2.48)	(2.84)	(2.66)	(2.52)	(2.49)
5-1	**1.94**	**1.55**	**1.44**	**1.37**	**1.63**	**1.45**	**1.40**	**1.36**
	(5.33)	**(4.97)**	**(4.68)**	**(4.49)**	**(5.30)**	**(5.14)**	**(4.62)**	**(4.49)**
SpearmanR	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B: CH-4 adjusted alphas								
	same_sentence				*same_article*			
Identification windows	3-month	6-month	9-month	12-month	3-month	6-month	9-month	12-month
1 (Low)	0.41	0.48	0.51	0.49	0.55	0.53	0.51	0.50
	(0.49)	(0.56)	(0.61)	(0.59)	(0.66)	(0.63)	(0.61)	(0.60)
2	0.78	0.74	0.69	0.61	0.77	0.74	0.67	0.66
	(0.98)	(0.92)	(0.84)	(0.75)	(0.95)	(0.91)	(0.82)	(0.80)
3	0.77	0.81	0.71	0.76	0.89	0.81	0.77	0.73
	(0.98)	(1.01)	(0.88)	(0.94)	(1.11)	(1.00)	(0.94)	(0.88)
4	1.06	1.10	1.06	1.04	0.99	1.06	1.04	1.07
	(1.29)	(1.35)	(1.30)	(1.27)	(1.21)	(1.30)	(1.28)	(1.29)
5 (High)	2.27	2.00	1.92	1.84	2.14	1.95	1.87	1.83
	(2.66)	(2.38)	(2.26)	(2.17)	(2.52)	(2.34)	(2.21)	(2.16)
5-1	**1.86**	**1.51**	**1.41**	**1.35**	**1.58**	**1.42**	**1.35**	**1.32**
	(5.23)	**(4.89)**	**(4.59)**	**(4.38)**	**(5.16)**	**(4.98)**	**(4.45)**	**(4.35)**
SpearmanR	0.90	1.00	1.00	1.00	1.00	1.00	1.00	1.00
P-value	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00

This table reports the portfolio sorting results of the news co-mention momentum spillover effect of the *same_sentence* type and *same_article* type under the four identification windows, respectively. *Same_sentence* strategy considers firms appearing in the same sentence of the same news article during a given identification window as news co-mention peers, while the *same_article* strategy considers firms appearing in the same article during a given identification window as news co-mention peers. The identification windows include 3-month, 6-month, 9-month, and 12-month. The news co-mention peer firm return of a focal firm is computed as the average excess return of news co-mention peer firms of the focal firm during the identification window, weighted by the number of co-mentions. At the end of each trading week, all sample stocks are sorted quintiles based on the news co-mention peer firm returns. Within each quintile group, the stocks are equally weighted. The long-short portfolio involves buying the highest group and selling the lowest group. All portfolios are held for one week and are rebalanced weekly. The sample period is 2012-2020. Panel A reports the excess returns of portfolios, and Panel B reports the intercepts (alphas) of the regression of the returns on CH-4 factors (market, size, value, abnormal turnover rate) (Liu et al., 2019). All weekly returns and alphas are converted into monthly percentages using compound interest. SpearmanR reports the Spearman correlation coefficient between the portfolio return and the serial number for each sorting. Newey and West (1987) adjusted t-statistics are shown in parentheses. Long-short returns/alphas with t-statistics higher than 2.00 are highlighted in bold.

In addition, given the link identification strategy, the returns of the long-short portfolio decrease as the length of the identification window increases. Unlike other linkages such as industry links and technology links, which tend to be more stable and persistent in the long term, news is highly time-sensitive and reflects recent information from the market. News-based linkages capture the immediate market sentiment, investor behaviors, and breaking news events, which can quickly change over time. As a result, the news linkages are less persistent compared to other linkages and can exhibit rapid shifts as new information becomes available. The use of a long identification window may include outdated news that is no longer relevant. This might explain the observed results. However, a shorter identification window results in a smaller number of sample stocks with news-implied linkages. For instance, if we adopt *same_sentence* strategy and use a 1-month window to identify the links, there are only 500 sample stocks on average each week that have news-implied links. To strike a balance between the performance and the sample size, the shortest identification window is 3 months. Since *Sentence_3* strategy generates the largest returns among the eight candidates, for later comparison with other momentum spillover effects, we use the *Sentence_3* strategy.

3.2 Other Momentum Spillovers

Table 3 reports the portfolio sorting results for other types of linkages, including the analyst co-coverage, industry, geographic proximity, customer-supplier, technology, statistical similarity, and concept. For better comparison, the result of *Sentence_3* is included as the first column. Panel A shows the mean excess return, and the CH-4 adjusted alpha of each portfolio is reported in Panel B.

Most of these cross-momentum anomalies observed in the US market also exist in the Chinese stock market. In particular, the momentum spillover via statistical linkages yields a monthly long-short average excess return and alpha of 1.36% (t-statistic=3.93) and 1.34% (t-statistic=3.35), respectively, which is the second-highest among all strategies, following the *Sentence_3* strategy. The analyst co-coverage momentum spillover was found to unify all momentum spillover effects in the US market. In the Chinese stock market, a long-short portfolio based on that yields an average return of 0.86% (t-statistic=3.33) and CH-4 alpha of 0.85% (t-statistic=2.97). Long-short average return and alpha based on industry momentum using Shenwan-1 industry classification are 0.77% (t-statistic=3.25) and CH-4 alpha of 0.76% (t-statistic=3.00), respectively. The technology momentum generates a slightly lower average return and alpha of 0.58% (t-statistic=2.73) and 0.60% (t-statistic=2.64). Although we have a short sample for concept momentum, it produces a mean return of 0.81% (t-statistic=2.25) per month.[16]

Among all the cross-momentum strategies examined, only the customer momentum strategy does not yield positive returns or CH-4 alpha. We attribute the poor performance of the customer momentum strategy to the low quality and limited availability of disclosed customer data for listed firms in China. As previously mentioned, only a small number of firms choose to disclose the real names of their customers, and the majority of disclosed customers are not listed firms. Consequently, the sample that we can use to do portfolio analysis is small. To avoid potential bias resulting from this small sample size, we exclude the customer momentum in later analysis.

[16]Unlike the results reported by Du et al. (2022), our concept momentum strategy generates insignificant alpha after adjusting for the CH-4 factor. We believe that the discrepancy in results can be attributed to the difference in data sources related to concepts. They have utilized web-crawling technology to obtain additional and longer historical records about concepts, which may have contributed to their significant findings.

Table 3: Other momentum spillovers: portfolio sorting results

Panel A: Excess returns									
	News co-mention	Analyst	Industry	Province	City	Customer	Technology	Statistical	Concept
1 (Low)	0.74	1.18	1.35	1.51	1.61	0.92	1.54	0.91	-0.45
	(0.88)	(1.59)	(1.82)	(2.06)	(2.15)	(1.19)	(2.05)	(1.22)	(-0.50)
2	1.06	1.28	1.52	1.64	1.67	0.22	1.66	1.35	-0.15
	(1.32)	(1.80)	(2.05)	(2.21)	(2.25)	(0.27)	(2.21)	(1.75)	(-0.17)
3	1.11	1.61	1.74	1.77	1.78	0.17	1.94	1.71	0.10
	(1.38)	(2.24)	(2.28)	(2.37)	(2.41)	(0.22)	(2.56)	(2.25)	(0.11)
4	1.38	2.03	1.90	1.84	1.81	0.95	1.92	2.09	0.21
	(1.65)	(2.81)	(2.49)	(2.44)	(2.40)	(1.20)	(2.52)	(2.79)	(0.25)
5 (High)	2.68	2.04	2.12	1.86	1.79	0.38	2.12	2.28	0.36
	(2.96)	(2.74)	(2.74)	(2.42)	(2.35)	(0.48)	(2.72)	(3.03)	(0.44)
5-1	**1.94**	**0.86**	**0.77**	**0.35**	**0.18**	-0.53	**0.58**	**1.36**	**0.81**
	(5.33)	**(3.33)**	**(3.25)**	**(2.77)**	**(2.05)**	(-1.46)	**(2.73)**	**(3.93)**	**(2.25)**
SpearmanR	1.00	1.00	1.00	1.00	0.90	0.10	0.90	1.00	1.00
P value	0.00	0.00	0.00	0.00	0.04	0.87	0.04	0.00	0.00

Panel B: CH-4 adjusted alphas									
	News co-mention	Analyst	Industry	Province	City	Customer	Technology	Statistical	Concept
1 (Low)	0.41	0.82	0.98	1.13	1.23	0.72	1.11	0.58	-0.40
	(0.49)	(1.09)	(1.29)	(1.52)	(1.61)	(0.94)	(1.45)	(0.75)	(-0.44)
2	0.78	0.92	1.12	1.24	1.31	0.16	1.26	0.95	-0.11
	(0.98)	(1.26)	(1.48)	(1.64)	(1.74)	(0.21)	(1.65)	(1.22)	(-0.13)
3	0.77	1.29	1.32	1.39	1.37	0.15	1.61	1.29	0.10
	(0.98)	(1.75)	(1.70)	(1.82)	(1.80)	(0.19)	(2.10)	(1.67)	(0.11)
4	1.06	1.72	1.48	1.42	1.43	0.67	1.54	1.65	0.19
	(1.29)	(2.38)	(1.94)	(1.84)	(1.87)	(0.87)	(1.97)	(2.17)	(0.21)
5 (High)	2.27	1.68	1.74	1.48	1.36	0.12	1.71	1.93	0.33
	(2.66)	(2.21)	(2.20)	(1.89)	(1.75)	(0.16)	(2.14)	(2.51)	(0.39)
5-1	**1.86**	**0.85**	**0.76**	**0.34**	0.13	-0.60	**0.60**	**1.34**	0.74
	(5.23)	**(2.97)**	**(3.00)**	**(2.56)**	(1.37)	(-1.43)	**(2.64)**	**(3.35)**	(1.89)
SpearmanR	0.90	0.90	1.00	1.00	0.70	-0.70	0.90	1.00	1.00
P value	0.04	0.04	0.00	0.00	0.19	0.19	0.04	0.00	0.00

This table reports the portfolio sorting performance of the shared-analyst momentum, industry momentum, geographic momentum, customer momentum, technology momentum, statistical momentum, and concept momentum. For comparison, the result for the news co-mention momentum of *same_sentence* type under the 3-month identification window (*Sentence_3*) is shown in the first column. The industry momentum spillover is based on the first level of Shenwan classification (Shenwan-1), and the results are shown in column 2. The geographic momentum spillover is constructed at both the province and city levels, and the results are shown in columns 3 and 4, respectively. Columns 5-8 present the results for customer momentum, technology momentum, statistical momentum, and concept momentum, respectively. Due to data quality, the sample period of news co-mention momentum is 2012-2020, the sample period of customer momentum is 2010-2020, the sample period of concept momentum is Aug. 2016-2020, and the sample periods for other momentums are 2006-2020. For each linkage type, at the end of each trading week, we first calculate the peer returns of all focal firms and then sort all stocks into quintiles based on the peer firm return. Within each quintile group, the stocks are equally weighted. The long-short portfolio involves buying the highest group and selling the lowest group. All portfolios are held for one week and are rebalanced weekly. Panel A gives the excess returns of portfolios, and Panel B presents the intercepts of the regression of the returns on CH-4 factors (Liu et al., 2019) (market, size, value, abnormal turnover rate). All weekly returns and alphas are converted into monthly percentages using compound interest. SpearmanR reports the Spearman correlation coefficient between the portfolio return and the serial number for each sorting. Newey and West (1987) adjusted t-statistics are shown in parentheses. Long-short returns/alphas with t-statistics higher than 2.00 are highlighted in bold.

In the Chinese stock market, the geographic momentum is not strong. Province-level momentum is statistically significant but the long-short strategy based on that yields only a small average return of 0.35% per month. City-level momentum is even weaker and is not significance after controlling for the CH-4 factors.

Overall, the news co-mention momentum spillover effect is stronger than other types of momentum spillovers in the Chinese stock market. A natural question then arises: whether the news co-mention momentum spillover encompasses and unifies the various other momentum spillover effects.

4 The Unifying Effect

In this section, we examine whether the news co-mention momentum spillover effect encompasses and unifies the various other momentum spillover effects observed in the Chinese stock market. To do so, we follow Ali and Hirshleifer (2020) to use spanning tests and Fama and MacBeth (1973) regressions. In addition, we investigate the information content differences between news co-mentioning and other proxies to gain further insights into the features of news-implied linkages.

4.1 Factor Spanning Tests

To test whether the anomaly returns of different types of momentum spillovers can be explained by each other, we construct an augmented CH-4 model as follows:

$$R_t = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{PMO}PMO_t + \beta_{MS}MS_t,$$

where R_t is the anomaly return of one momentum spillover factor to be explained, and the MS(momentum spillover) factor on the right-hand side is another momentum spillover factor used as an additional explanatory variable. We use "CH-4+a specific MS factor" to indicate the set of explanatory variables used to explain the target momentum spillover factor R_t. For example, CH-4+Sentence_3 means the set of explanatory variables includes CH-4 factors plus a news co-mention momentum factor of the *Sentence_3* type. If the news co-mention momentum factor does explain the momentum spillover factor R_t, then we should observe the alpha of the model becoming smaller and potentially insignificant after controlling for the news co-mention momentum factor. Additionally, the β_{MS} should be significantly positive.

Panel A of Table 4 shows the alpha of regressing the time series of the target momentum spillover factor R_t on the CH-4 factors plus a specific MS factor. The column name corresponds to the name of the target factor R_t, and the row name indicates the set of variables in the augmented CH-4 model. All news co-mention momentum factors are constructed using the *same_sentence* identification strategy, which has shown superior performance. We also present results obtained using the *same_article* method in Table 20 in the robusteness part, which yields similar outcomes. We find that most of the news co-mention momentum spillover factors, particularly those using a short identification window to establish links, are capable of explaining other momentum spillover factors. For instance, after controlling for the Sentence_3 factor, the alphas of all other momentum spillover factors become small and insignificant. While the CH-4 alpha of the statistical momentum factor is as large as 1.34% (t-statistic=3.35), its CH-4+Sentence_3 alpha becomes only 0.17% (t-statistic=0.43). In the case of the analyst, industry, technology, and concept momentum, alphas even turn negative after the addition of the Sentence_3 factor.

The results are similar for the Sentence_6, Sentence_9, and Sentence_12 factors, which all have strong explanatory power for other factors. One special case is the geographic momentum factor. Although it has insignificant alpha in the CH-4+Sentence_3 model, the factor still has positive and significant alpha if one controls any of the three longer-term news co-mention factors. This is in line with our previous findings that the strength of news co-mention momentum decreases as the length of the identification window increases. Actually, the Sentence_3 momentum factor can explain the news co-mention momentum factor with longer identification windows, but not vice versa.

Panel B of Table 4 reports the factor loadings of other momentum spillover factors on the CH-4+Sentence_3 model. All the loading coefficients of the Sentence_3 factor are significantly positive, and much bigger than the loadings on CH-4, indicating that all other cross-asset momentum anomalies are explained by their loadings on the Sentence_3 news co-mention momentum factor.

As a comparison, we also attempt to explain the news co-mention momentum spillover factors with other cross-momentum factors including the factors based on analyst co-coverage momentum, industry momentum, geographic momentum, technology momentum, statistical momentum, and concept momentum. We find that none of the four news co-mention momentum spillover factors can be explained by those other momentum spillover factors as the alphas all remain large and significant. For example, the momentum spillover via statistical linkages yields a high monthly long-short return and CH-4 alpha, which is the second-highest among all trading strategies. However, the Sentence_3 momentum factor still generates an alpha of 1.16% (t-statistic=4.17) per month under the CH-4+Statistical model. Moreover, even the weakest news co-mention momentum spillover factor (i.e., the Sentence_12 factor) yields a CH-4+Statistical alpha of 0.51% (t-statistic=2.57) per month. The analyst co-coverage momentum factor, which was found to explain all other cross-momentum factors in the US market, cannot explain either the news co-mention momentum spillover factors or the statistical momentum factor. In the last row of panel A, we include all the six momentum spillover factors that are not related to news as additional explanatory variables. We find that the CH-4+Non_news model is unable to explain the news co-mention momentum spillover factors. This suggests that even when we include all other non-news related momentum spillover factors as additional explanatory variables, they cannot explain the abnormal returns associated with the news co-mention momentum anomaly.[17]

We conduct several robustness checks, and the detailed results can be found in subsubsection 6.3.3. Firstly, we run regressions with the Sentence_3 factor as the sole explanatory variable (CH-4 factors are excluded), which is shown in Table 17. Besides, we construct industry momentum factors based on other industry classifications, and the results are shown in Table 18. Furthermore, we perform spanning tests for different sub-sample periods, including the periods 2006-2020 and 2012-2020. The results are summarized in Table 19. Finally, in Table 20, we convert the co-mention momentum from *same_sentence* type to *same_article* type under the four identification windows. Overall, our main findings remain robust to these changes that we made.

[17] In the CH-4+Non_news model, we include all six non-news factors as explanatory variables. However, we recognize the concern that the small sample size of concept momentum could potentially impact our results. To address this concern, we perform a robustness check by excluding the concept momentum variable from the model. Our results are robust to the exclusion of the concept momentum variable.

Table 4: Factor spanning test

Panel A: Alphas of factor spanning tests										
	Sentence_3	Sentence_6	Sentence_9	Sentence_12	Analyst	Industry	Geographic	Technology	Statistical	Concept
CH-4+Sentence_3		-0.15	-0.22	-0.30	-0.44	-0.53	0.25	-0.26	0.17	-0.51
		(-1.51)	(-1.76)	(-2.15)	(-1.76)	(-2.10)	(1.92)	(-1.11)	(0.43)	(-1.59)
CH-4+Sentence_6	**0.37**		-0.08	-0.16	-0.34	-0.45	**0.27**	-0.21	0.26	-0.41
	(3.48)		(-1.17)	(-1.80)	(-1.47)	(-1.93)	**(2.11)**	(-0.95)	(0.71)	(-1.37)
CH-4+Sentence_9	**0.54**	**0.16**		-0.08	-0.25	-0.38	**0.26**	-0.17	0.30	-0.31
	(3.95)	**(2.16)**		(-1.62)	(-1.13)	(-1.76)	**(2.08)**	(-0.79)	(0.91)	(-1.10)
CH-4+Sentence_12	**0.65**	**0.27**	**0.11**		-0.17	-0.32	0.27	-0.13	0.36	-0.26
	(4.27)	**(2.88)**	**(2.30)**		(-0.81)	(-1.53)	(2.15)	(-0.60)	(1.13)	(-0.94)
CH-4+Analyst	**1.18**	**0.80**	**0.67**	**0.58**		0.11	0.24	0.17	**0.70**	0.06
	(4.97)	**(4.25)**	**(3.79)**	**(3.47)**		(0.76)	(1.83)	(0.99)	**(2.18)**	(0.28)
CH-4+Industry	**1.35**	**0.98**	**0.84**	**0.76**	0.15		0.25	0.14	**0.78**	0.33
	(5.08)	**(4.49)**	**(4.30)**	**(4.03)**	(0.96)		(1.92)	(0.87)	**(2.25)**	(1.67)
CH-4+Geographic	**1.62**	**1.28**	**1.13**	**1.06**	**0.59**	**0.55**		**0.44**	**1.05**	0.34
	(4.94)	**(4.38)**	**(3.94)**	**(3.72)**	**(2.21)**	**(2.26)**		**(2.07)**	**(2.61)**	(0.92)
CH-4+Technology	**1.49**	**1.12**	**0.99**	**0.91**	0.34	0.27	**0.27**		**0.93**	0.25
	(4.63)	**(4.07)**	**(3.86)**	**(3.63)**	(1.59)	(1.41)	**(2.05)**		**(2.50)**	(0.98)
CH-4+Statistical	**1.16**	**0.77**	**0.61**	**0.51**	0.20	0.23	0.23	0.25		0.04
	(4.17)	**(3.28)**	**(2.90)**	**(2.57)**	(0.90)	(0.97)	(1.69)	(1.24)		(0.14)
CH-4+Concept	**1.33**	**0.89**	**0.71**	**0.60**	0.29	-0.16	**0.35**	0.04	**0.92**	
	(4.06)	**(3.65)**	**(3.08)**	**(2.81)**	(1.30)	(-0.89)	**(2.19)**	(0.18)	**(2.61)**	
CH-4+Non_news	**1.15**	**0.72**	**0.52**	0.40						
	(3.59)	**(3.00)**	**(2.22)**	(1.92)						

Panel B: CH-4+Sentence_3 factor loading										
	Sentence_3	Sentence_6	Sentence_9	Sentence_12	Anayst	Industry	Geographic	Technology	Statistical	Concept
Sentence_3		**0.896**	**0.878**	**0.886**	**0.835**	**0.748**	**0.086**	**0.518**	**0.862**	**0.747**
		(28.82)	**(23.66)**	**(21.14)**	**(11.93)**	**(10.92)**	**(4.09)**	**(7.12)**	**(8.50)**	**(6.68)**
mktrf		-0.012	-0.014	-0.028	-0.085	-0.069	0.011	-0.034	-0.078	-0.012
		(-1.10)	(-0.82)	(-1.54)	(-3.55)	(-2.60)	(0.84)	(-1.42)	(-1.73)	(-0.30)
VMG		-0.008	-0.008	-0.007	-0.001	-0.018	-0.027	-0.051	0.019	0.004
		(-0.36)	(-0.25)	(-0.21)	(-0.02)	(-0.26)	(-1.00)	(-0.73)	(0.17)	(0.04)
SMB		0.010	0.006	0.016	0.044	0.054	-0.001	-0.026	0.068	0.025
		(0.46)	(0.19)	(0.42)	(0.75)	(0.85)	(-0.05)	(-0.46)	(0.61)	(0.26)
PMO		-0.032	-0.037	-0.057	-0.082	-0.036	-0.018	-0.059	-0.203	0.087
		(-2.03)	(-1.97)	(-2.05)	(-2.06)	(-0.79)	(-1.16)	(-1.49)	(-2.33)	(0.97)
Adj. R2		0.881	0.824	0.797	0.525	0.460	0.063	0.275	0.355	0.351
# Obs.		464	464	464	464	464	464	464	464	227

Panel A reports the intercept (or alpha) of regressing the time series of different long-short momentum returns on the CH-4 factors (MKT, SMB, HML, PMO) (Liu et al., 2019) plus each MS cross-firm momentum factor. The construction of the MS factor is given in subsection 4.1. The column name indicates the type of long-short momentum return (i.e., the dependent variable), while the row name means the augmented CH-4 model (i.e., the original CH-4 model plus a specific MS factor). For example, the alphas of the row CH-4+Sentence_3 indicate the alphas from the time-series regressions of long-short portfolio returns of other momentums on MKT, SMB, HML, PMO and the Sentence_3 factor. In the last row of panel A, we include all the six momentum spillover factors that are not related to news as additional explanatory variables. All news co-mention momentum factors are based on *same_sentence* type under identification windows including 3-month, 6-month, 9-month, and 12-month. The industry momentum is based on the Shenwan-1 classification, while the geographic momentum is based on the province level. We do not consider the customer momentum due to the low data quality. The sample period of news co-mention momentum is 2012-2020. The sample period of concept momentum is Aug. 2016-2020. The sample periods for other momentums are 2006-2020. Newey and West (1987) adjusted t-statistics are shown in parentheses. Alphas with t-statistics higher than 2.00 are highlighted in bold. Panel B reports the factor loadings of other momentum spillover long-short returns on the CH-4+Sentence_3 model. Coefficients with t-statistics higher than 2.00 are highlighted in bold.

4.2 Fama-Macbeth Regression Tests

Our spanning tests reveal that all other cross-asset momentum anomalies can be explained by the news co-mention momentum spillover factor. To provide additional evidence, we employ Fama-MacBeth regressions to examine the relationship between the stock excess return in the next week and the weighted average peer firm returns constructed using different linkage proxies.[18] Our control variables include the size (taking logarithms), book-to-market ratio, and stock return in the past week. All independent variables are standardized by their cross-sectional means and standard deviations.

We estimate two sets of regressions based on two different samples. The first one takes the union of all samples of average peer firm returns constructed using different linkage proxies,[19] and the second sample takes the intersection set of all peer return samples. Table 5 presents the results of the two sets of Fama-MacBeth regressions. Panel A and Panel B present the results for the union sample and intersection sample, respectively. Columns 1-7 use each peer firm return alone as the dependent variable respectively. The past-one-week news co-mention peer firm return, *Sentence_3_Rtn*, exhibits the strongest predictability power for future returns, both statistically and economically. A one standard deviation increase in the past-one-week *Sentence_3_Rtn* is associated with an increase of 27.1 bps in the future return, with a t-statistic of 5.53. For the analyst and statistical momentum, which follow the news co-mention momentum according to portfolio analysis, their predictive powers are much smaller, with just 7.1 bps (t-statistic=4.32) and 3.9 bps (t-statistic=2.57) per standard deviation change of the peer firm return, respectively. The geographic peer firm return does not exhibit a significant predictive power of the future return based on either the union sample or the intersection sample. This result is consistent with the portfolio sorting and spanning tests.

In column 8 of Panel A, both *Sentence_3_Rtn* and *Analyst_Rtn* are included in the regression. The coefficient and t-statistic of *Sentence_3_Rtn* hardly change with the inclusion of *Analyst_Rtn*. However, the coefficient of *Analyst_Rtn* decreases substantially by 56% from 0.071 to 0.031. A one standard deviation increase in *Sentence_3_Rtn* predicts an increase of 26.5 bps in the future return, while a one standard deviation increase in *Analyst_Rtn* predicts an increase of just 3.1 bps in the future return. Telling from Panel B column 2, we reach a similar result if we use the intersection sample. These results indicate that the analyst momentum, which is found to unify all momentum spillover effects in the US (Ali and Hirshleifer, 2020), does not possess the same predictive power in the Chinese market. Instead, its role is taken by the news co-mention momentum. When we include *Sentence_3_Rtn* and any other peer firm return in the regression analysis, we reach similar conclusions. The predictive powers of all other lagged peer firm returns decrease significantly once the *Sentence_3_Rtn* is controlled. From column 9, including *Sentence_3_Rtn* largely weakens *Industry_Rtn*, whose effect becomes insignificant. As shown in column 5, the technology peer firm return alone is a strong predictor of future returns. However, the coefficient of *Technology_Rtn* becomes insignificant once *Sentence_3_Rtn* is added. From columns 6 and 12, we find that the coefficient of the statistical peer return decreases by more than 50% after the inclusion of *Sentence_3_Rtn*. The geographic and concept momentum effects exhibit similar results.

[18]The news co-mention peer firm return is based on *Sentence_3* strategy; the industry peer firm return is based on the Shenwan-1 classification; and the geographic peer firm return is based on peers at the province level.

[19]We fill peer firm returns of null values with 0.

Table 5: Fama-MacBeth regressions

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Panel A: FM regressions based on union samples														
Sentence_3_Rtn	0.271							0.265	0.264	0.270	0.267	0.267	0.120	0.257
	(5.53)							(5.41)	(5.38)	(5.51)	(5.45)	(5.52)	(3.16)	(5.29)
Analyst_Rtn		0.071						0.031						0.020
		(4.32)						(1.57)						(1.31)
Industry_Rtn			0.040						0.019					0.007
			(2.34)						(0.86)					(0.39)
Geographic_Rtn				0.015						0.016				0.013
				(1.59)						(1.68)				(1.49)
Technology_Rtn					0.039						0.028			0.019
					(2.57)						(1.44)			(1.24)
Statistical_Rtn						0.039						0.022		0.016
						(1.64)						(0.75)		(0.56)
Concept_Rtn							0.036						0.035	
							(1.59)						(1.55)	
Control	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Avg. R Square	0.060	0.061	0.064	0.059	0.059	0.062	0.046	0.064	0.067	0.062	0.062	0.065	0.048	0.076
Total Obs.	1709464	1709464	1709464	1709464	1709464	1709464	653094	1709464	1709464	1709464	1709464	1709464	653094	1709464
Avg. Obs.	2226	2226	2226	2226	2226	2226	2877	2226	2226	2226	2226	2226	2877	2226
Panel B: FM regressions based on intersection samples														
Sentence_3_Rtn	0.234							0.159	0.230	0.233	0.229	0.048	0.112	0.059
	(5.69)							(5.13)	(5.57)	(5.69)	(5.11)	(3.77)	(3.51)	(2.10)
Analyst_Rtn		0.081						0.026						0.022
		(4.96)						(1.07)						(0.65)
Industry_Rtn			0.041						-0.009					0.039
			(2.36)						(-0.38)					(1.25)
Geographic_Rtn				0.015						-0.001				0.030
				(1.58)						(-0.11)				(1.91)
Technology_Rtn					0.037						0.021			0.041
					(2.43)						(0.83)			(1.94)
Statistical_Rtn						0.079						0.100		0.017
						(3.39)						(3.27)		(0.49)
Concept_Rtn							0.036						0.022	
							(1.59)						(0.74)	
Control	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Avg. R Square	0.088	0.064	0.064	0.059	0.079	0.058	0.046	0.086	0.096	0.090	0.125	0.070	0.067	0.131
Total Obs.	503829	988653	1694481	1707853	750982	1456040	653094	305452	501611	503511	232484	441002	205109	106708
Avg. Obs.	1086	1287	2206	2224	978	1896	2877	658	1081	1085	501	950	904	230

This table presents the results of the Fama and MacBeth (1973) regressions. The dependent variable is the excess stock return in the next week, while the independent variable is the peer firm return for each type of economic linkage constructed in subsection 2.2. The control variables include the firm size (taking logarithms), book-to-market ratio, and stock return in the past week. All independent variables are standardized with their cross-sectional means and standard deviations. The news co-mention momentum is based on *same_sentence* type under the 3-month identification window. The industry momentum is based on the Shenwan-1 classification. The geographic momentum is conducted on the province level. We do not consider the customer momentum due to the low data quality. The sample period of news co-mention momentum is 2012-2020. The sample period of concept momentum is Aug. 2016-2020. The sample periods for other momentums are 2006-2020. We estimate the regressions based on two samples. Panel A uses the union set of samples, and peer firm returns of null values are filled with 0 (concept momentum samples are excluded from taking the union due to its very short time series). Panel B uses the intersection set of all samples of different peer firm returns. Columns 1-7 use each peer firm return alone as the dependent variable respectively. In columns 8-13, *Sentence_3_Rtn* is added to the regressions. In column 14, all peer firm returns except for *Concept_Rtn* (due to the very short time series) are added to the regression. Newey and West (1987) adjusted t-statistics are shown in parentheses. For brevity, all coefficients are multiplied by 100.

As indicated in columns 4, 10, and 7, 13 of Panel A and Panel B, the coefficients of *Geographic_Rtn* and *Concept_Rtn* are not significant, whether or not we control for news co-mention momentum variable in the regression. Particularly, in the case of the intersection sample, the coefficient of *Geographic_Rtn* even becomes negative after controlling for *Sentence_3_Rtn*. After all, according to the previous portfolio sorting analysis, the geographic and concept momentum effects lack both statistical and economic significance.

Finally, in column 14 of Table 5, we show the FM regression results with all peer firm returns included.[20] *Sentence_3_Rtn* remains to be a strong predictor of the future stock return after controlling for all of the previously documented cross-firm momentums simultaneously. Based on the union sample, Panel A reveals that *Sentence_3_Rtn* exhibits the strongest predictive power among all past peer firm returns. A one standard deviation increment in *Sentence_3_Rtn* is associated with an increase of 25.7 bps in future returns (with a t-statistic of 5.29). In contrast, all other peer firm returns lose predictive power in this big regression.

Overall, the results of the Fama-MacBeth regressions are consistent with the previous portfolio sorting analysis and factor-spanning test, providing further evidence that the past news co-mention peer firm return exhibits a strong and robust predictive power for future stock returns. Moreover, the predictive power of news co-mention peer firm return largely subsumes the predictability of other types of momentum spillover effects. This holds true for both the union sample and the intersection sample.

4.3 Further Analysis

The factor-spanning test and Fama-MacBeth regressions show that all different forms of cross-firm momentum effects can be unified by the news co-mention momentum spillover in the Chinese stock market. In this subsection, we delve deeper into the differences in the information content of links implied by news co-mentioning and other proxies, aiming to gain a better understanding of the unique characteristics and effectiveness of news co-mentioning as a linkage identification strategy compared to alternative methods.

As argued by Scherbina and Schlusche (2013) and Schwenkler and Zheng (2019), one of the advantages of news-implied economic linkages is their ability to reveal a broader range of economic linkages. To examine whether news co-mention momentum spillover is stronger than others because news-implied linkages are more comprehensive, we conduct an exercise to analyze the within- and cross-industry momentum spillovers separately for each type of momentum spillover in subsubsection 4.3.1. Another advantage of news is its prompt update, which helps us to identify changes in linkages among firms in time. We also conduct a small exercise in subsubsection 4.3.2 to investigate that aspect.

4.3.1 Cross- and Within-Industry Momentum Spillovers

Unlike the US market, where the shared-analyst momentum serves as the unifying momentum spillover effect, our findings in the Chinese stock market suggest that the momentum driven by news-co-mention linkages, rather than shared-analyst linkages, can encompass the predictability of other momentum spillover effects. This discrepancy could be attributed to the differences in the information content of these linkages. One characteristic of Chinese analysts is that each of them tends to cover firms in one industry. This might lead to a high degree of

[20] Concept peer firm returns are excluded from the analysis due to its very short time series (from Aug. 2016 to 2020). Including concept returns would significantly shorten the sample time series.

information overlapping between the shared-analyst linkage and industry linkage.[21] News, on the other hand, might reveal a broader range of economic linkages (i.e., a lower degree of overlapping with industry links).

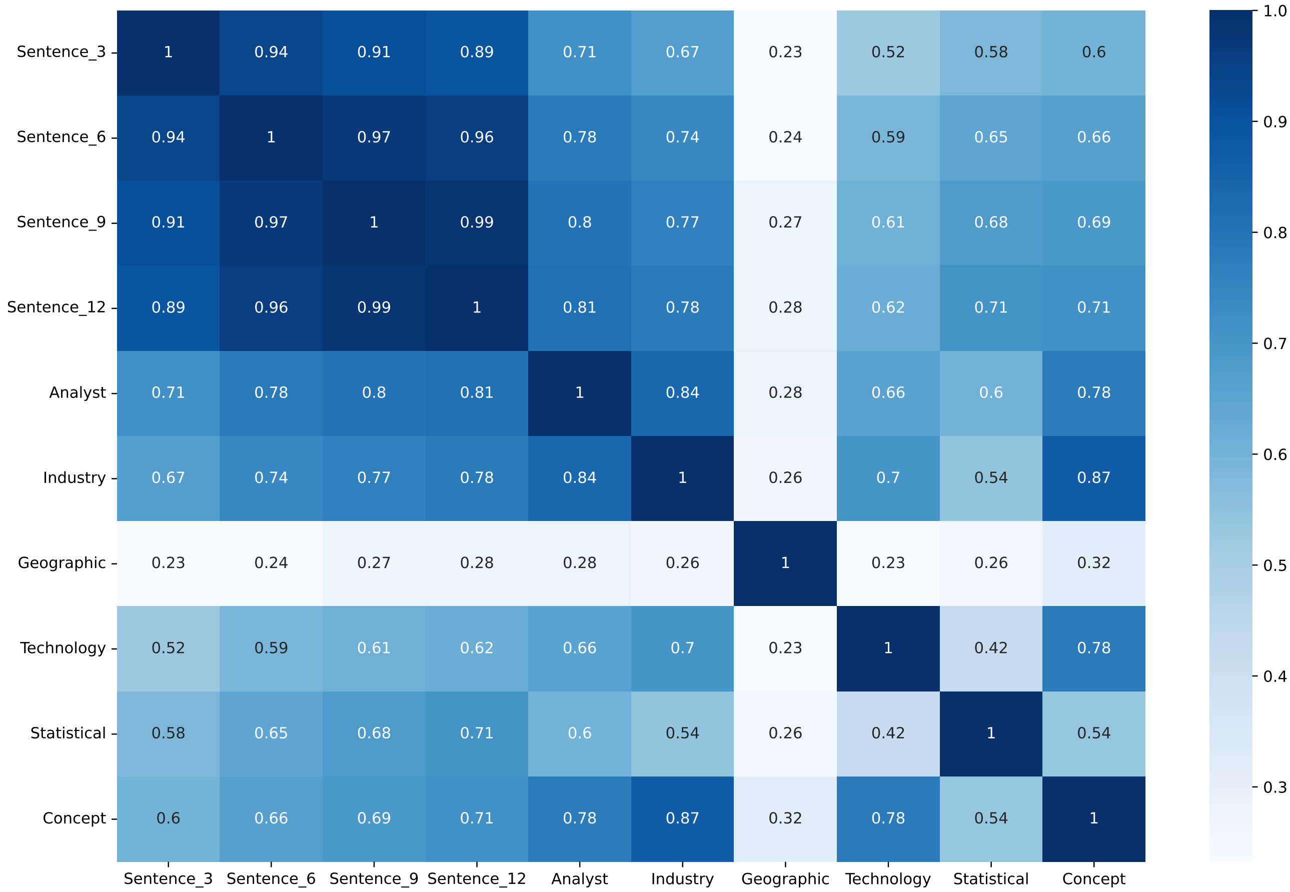

Figure 1: Correlation of momentum spillover factors

This figure is the heatmap of the correlation coefficients between various momentum spillover factors MS. The ten momentum spillover factors are *same_sentence* type co-mention momentums under identification windows of 3-, 6-, 9-, 12-month, shared-analyst momentum, industry momentum (Shenwan-1), geographic momentum (province level), technology momentum, statistical momentum, and concept momentum. The construction of the MS factor is given in subsection 4.1. We do not consider the customer momentum due to the low data quality. The sample period of co-mention momentum is 2012-2020. The sample period of concept momentum is Aug. 2016-2020. The sample periods for other momentums are 2006-2020.

Table 6 reports the time series median of the percentage of within-industry links for each linkage type. The higher the percentage, the greater the proportion of linked firms that belong to the same industry. We consider two levels of CSRC classifications, three levels of CITIC classifications, and three levels of Shewan classifications to analyze the industry composition of these linkages.

To investigate the information overlapping, we plot the correlation heatmap among different momentum factors used in the spanning tests, which is shown in Figure 1. As expected, the analyst momentum factor is highly correlated with the industry momentum factor (the correlation coefficient is 0.84), indicating a degree of overlapping information between these two factors. The concept momentum factor also exhibits a high correlation with the industry momentum factor (the correlation coefficient is 0.87), which can be attributed

[21] In China, analysts are often referred to as industry researchers, highlighting their specialization in specific industry classifications. In Appendix B, we show the industry research directions of the Research Division of China Securities Co., Ltd. (CSC) according to its recruitment advertisement for fresh graduates. The advertisement reveals that analysts within CSC are already organized and assigned based on industry classifications.

to the fact that many stock concepts are derived from industry classifications. In comparison, the correlation between Sentence_3 and the industry factor is moderate at 0.67, indicating that the short-term news factor incorporates a significant amount of non-industry information. The geographical momentum factor has the lowest correlation with all other factors, which are all below 0.3.

Table 6: Percentages of within-industry linkages

	CSRC-1	CSRC-2	CITIC-1	CITIC-2	CITIC-3	Shenwan-1	Shenwan-2	Shenwan-3
News co-mention	52.44	3.45	7.67	1.65	0.31	8.53	1.83	0.50
Analyst	72.61	20.37	40.30	15.81	7.06	42.51	14.40	5.77
Geographic	47.15	1.92	4.18	0.65	0.06	4.14	0.53	0.00
Technology	82.18	7.75	9.52	3.55	1.72	9.79	3.15	1.33
Statistical	57.89	3.73	5.24	2.23	1.07	5.40	1.87	0.83
Concept	55.73	9.70	14.10	7.14	4.27	14.94	7.02	3.83

This table reports the time series median of the percentage of within-industry links for each linkage type under different industry classifications. The higher the percentage, the higher the overlap between that linkage and the industry linkage. We report the results of six types of linkages, including the news co-mention linkage, shared-analyst linkage, geographic linkage, technology linkage, statistical linkage, and concept linkage under two levels of CSRC classifications (CSRC-1, -2), three levels of CITIC classifications (CITIC-1, -2, -3), and three levels of Shewan classifications (Shenwan-1, -2, -3). The news co-mention linkage is based on *same_sentence* type under the 3-month identification window. The geographic linkage is at the province level. The sample period of news co-mention linkage is 2012-2020. The sample period of concept linkage is Aug. 2016-2020. The sample periods for other linkages are 2006-2020.

Overall, the analyst linkages show the highest degree of overlap with the industry linkages. The median percentages of analyst peer firms from the same industry are the highest under seven out of eight classification methods. For instance, under the CITIC-1 classification, the percentage of analyst linkage from the same industry is 40.30%, which is the highest among all linkage types. The concept linkage comes in second with a percentage of 14.10%. In comparison, the overlap percentage of the news co-mention linkage is 7.67%, indicating a lower degree of overlap compared to the analyst linkage. The result confirms that Chinese analysts tend to cover firms from the same industry, indicating that the shared-analyst linkage captures information that largely overlaps with the industry linkage.

For the news co-mention linkage, the degree of overlap with industry information is relatively low compared to other types of linkages. Specifically, it is the second lowest (only after the geographic linkage) in the CSRC-1, -2, CITIC-2, -3, Shenwan-2, -3 classifications, and the third lowest (only after the geographic linkage and statistical linkage) in the CITIC-1 and Shenwan-1 classifications. This again confirms that the news factor incorporates a significant amount of non-industry information.

Next, for each linkage type, we decompose linked firms into cross-industry peers and within-industry peers, and we examine the two corresponding momentum spillover effects separately. Specifically, when analyzing the cross-industry effect, we consider only the peer firms from different industries compared to the focal firm. Conversely, when examining the within-industry effect, we focus only on the peer firms from the same industry as the focal firm. For each type of linkage, we conduct portfolio sorting analysis separately based on the cross-industry and within-industry peer firm returns. This exercise is meaningful because most of the previous studies primarily focus on within-industry information transfer and momentum spillover. For example, Liu et al. (2022) specifically studied the information transfer between peer firms, with the peer firms referring to intra-industry peers only. By exploring both within-industry and cross-industry effects, this paper provides a more comprehensive understanding of how information propagates among firms in the Chinese stock market.

Table 7 reports the long-short portfolio excess returns and CH-4 alphas of the news co-mention, analyst, geographic, technology, statistical, and concept momentum, separately considering cross-industry and within-industry links. For the news co-mention linkage, there is not much difference in the predictive power of cross-industry peer returns and within-industry peer returns. The cross-industry news co-mention momentum yields an average excess return of 1.73% (t-statistic=4.95), while the within-industry news co-mention momentum yields 1.76% (t-statistic=3.92). From Panel B, the cross-industry and within-industry news co-mention momentum generates the same CH-4 adjusted alphas at 1.65% (t-statistics = 5.06 and 3.74, respectively) per month.

Table 7: Cross- and within-industry momentum spillovers: portfolio analysis

Panel A: Excess return						
	News co-mention	Analyst	Geographic	Technology	Statistical	Concept
Cross Industry	1.73	0.45	0.10	0.13	0.89	0.22
	(4.95)	(2.44)	(0.95)	(0.83)	(2.92)	(0.71)
Within Industry	1.76	0.78	0.43	0.75	0.94	0.54
	(3.92)	(3.20)	(2.52)	(3.19)	(3.32)	(1.61)
Panel A: CH-4 adjusted alphas						
	News co-mention	Analyst	Geographic	Technology	Statistical	Concept
Cross Industry	1.65	0.45	0.07	0.12	0.80	0.16
	(5.06)	(2.34)	(0.59)	(0.73)	(2.26)	(0.48)
Within Industry	1.65	0.75	0.42	0.79	0.89	0.43
	(3.74)	(2.82)	(2.33)	(3.08)	(2.79)	(1.19)

This table reports the long-short portfolio based on cross- and within-industry momentum spillovers for each linkage type. We consider five momentum spillover effects, including the news co-mention momentum, analyst momentum, geographic momentum, technology momentum, statistical momentum, and concept momentum. The news co-mention momentum is based on *same_sentence* type under the 3-month identification window. The geographic momentum is at the province level. The industry classification we adopt is the CSRC-1 classification. For the cross-industry effect, when calculating the peer firm return, only peer firms from different industries from the focal firm are considered. On the contrary, for the within-industry effect, when calculating the peer firm return, only peer firms from the same industry as the focal firm are considered. At the end of each trading week, all sample stocks are sorted into quintiles according to their cross- and within-industry peer firm return, respectively. The long-short portfolio involves buying the highest group and selling the lowest group. The sample period of news co-mention momentum is 2012-2020. The sample period of concept momentum is Aug. 2016-2020. The sample periods for other momentums are 2006-2020. Panel A shows the excess returns of the long-short portfolios, while Panel B reports the CH-4 adjusted alphas. All returns alphas are converted to monthly using compound interest. Newey and West (1987) adjusted t-statistics are shown in parentheses.

In contrast, for any other type of linkage, the within-industry momentum effect is stronger. For instance, the within-industry analyst momentum generates a CH-4 alpha of 0.75% (t-statistic=2.34) per month, whereas the cross-industry analyst momentum produces a CH-4 alpha of 0.45% (t-statistic=2.34) per month. Comparing that with the alpha of the shared-analyst momentum (0.85%, with t-statistic=2.97), we find that the predictive power mostly stems from within-industry information. We observe similar patterns for statistical linkage and concept linkage, which both have a stronger within-industry momentum effect. For the geographic and technological linkages, only the within-industry effects are significant.

Overall, these results suggest that news co-mention linkages exhibit unique characteristics compared to other types of linkages. While other types of linkages show a higher degree of overlap with the industry linkage (except for the geographic linkage), news co-mention linkages capture a broader range of economic linkages. They incorporate both industry information and valuable non-industry linkage information, which contributes to their strong predictive power for future returns. This finding helps explain why news co-mention momentum spillover effects tend to dominate and unify other types of momentum spillovers in the Chinese stock market.

4.3.2 Speed of Update

As mentioned previously, the strong predictive power and unifying effect of the news co-mention momentum can be attributed to two advantages of the news co-mention linkage: comprehensive information and prompt updates. subsubsection 4.3.1 demonstrates that the news content is all-encompassing, and it incorporates both industry information and valuable non-industry linkage information. From the portfolio analysis, we have seen that the predictive power of the news co-mention momentum decreases as the identification window gets longer, which provides indirect evidence for the prompt updates. In this subsection, we present additional evidence by monitoring the percentage change in various linkage networks over time. This analysis allows us to assess the dynamics and updates of these networks, providing further support for the timeliness and prompt updates of the news co-mention linkage.

We calculate the change rate of a given network matrix at week t, denoted as $\%Change_t$, to measure the speed of the linkage change in the week. Specifically:

$$\%Change_t = \frac{\sum_j \sum_i \mid \mathbf{M_t}_{(i,j)} - \mathbf{M_{t-1}}_{(i,j)} \mid}{\sum_j \sum_i \mathbf{M_{t-1}}_{(i,j)}} \times 100\%,$$

where $\mathbf{M_t}$ is the network matrix at week t, and $\mathbf{M_t}_{(i,j)}$ is the element at row i and column j of the network matrix.

We then compute the weekly change rate time series for each linkage type. The summary statistics of the change rate of each linkage are reported in Table 8. The results show that the news co-mention matrix updates much faster than other types of linkages. Specifically, on average, there is a 16.07% change in co-mention linkages from one week to the next. This proportion is higher than the change rate of analyst linkages (3.61%), statistical linkages (10.53%), and concept linkages (1.27%), which are also updated on a weekly basis. Furthermore, the change rates of industry, geographic, and technology linkages are much lower since their network matrices update on a yearly basis. The mean ratios for these linkages are almost 0, indicating very little change from one week to the next.

These results provide direct evidence that the news co-mention linkage updates more quickly compared to other economic linkages. This faster update speed suggests that the co-mention linkage method is more effective at capturing and identifying changes in linkages among firms in a timely manner.

Table 8: Summary statistics of the linkage change rate

	Mean	Std	Min	Median	Max
News co-mention	16.07%	0.20	0.94%	13.61%	316.70%
Analyst	3.61%	0.03	0.11%	2.76%	42.92%
Industry	0.12%	0.01	0.00%	0.00%	21.85%
Geographic	0.10%	0.01	0.00%	0.00%	7.43%
Technology	0.64%	0.05	0.00%	0.00%	42.09%
Statistical	10.53%	0.12	1.69%	8.71%	110.17%
Concept	1.27%	0.08	0.00%	0.48%	116.23%

This table reports the summary statistics of the change rate of six economic linkages, including the news co-mention linkage, shared-analyst linkage, industry linkage, geographic linkage, technology linkage, statistical linkage, and concept linkage. The news co-mention linkage is based on *same_sentence* type under the 3-month identification window. The industry linkage is based on the Shenwan-1 classification. The geographic linkage is at the province level. The change rate of a certain linkage type in one week is computed as below: subtract the network matrix last week from the matrix this week, then take the absolute value of all the elements of the difference matrix and make a summation, divided by the sum of all elements of the network matrix last week. The sample period of news co-mention linkage is 2012-2020. The sample period of concept linkage is Aug. 2016-2020. The sample period for other linkages is 2006-2020.

5 Mechanism

In this section, we further investigate the mechanism behind this news-based momentum spillover. There are two main theories that attempt to explain the cross-firm momentum anomaly. The first one is the investors' limited attention theory, which has gained widespread acceptance as an explanation for various types of cross-firm predictability.[22] According to the theory, gathering information about peer firms requires additional effort and attention from investors. As a result, investors may overlook or underestimate the importance of such information, leading to a lead-lag effect between the stock returns of peer firms and the focal firm. In recent years, a new behavioral-based psychological barrier theory has been proposed by Huang et al. (2021) as an alternative explanation of the momentum spillover effect. This theory argues that, due to the cognitive bias of anchoring, investors tend to react slowly to positive news from peer firms when the focal stock price is close to its 52-week high. This is because they believe that the stock price has already reached its peak and is unlikely to increase further. Similarly, investors also tend to respond slowly to negative news from peer firms when the focal stock price is far from its 52-week high. [23]This behavior creates a lead-lag effect between the returns of peer firms and the focal firm. We will examine the two explanations respectively.

5.1 Limitied Attention

Since it is difficult to quantify investors' attention precisely, the literature often relies on indirect metrics to evaluate limited attention. In particular, if the lead-lag effect in stock returns is a result of investors' inattention to peer firms' information, we would expect to observe a stronger predictive power of the news co-mention

[22]In fact, most previous studies attribute the momentum spillover effect to investors' limited attention to news from peer firms. See Burt and Hrdlicka (2021) for a detailed list of these studies.

[23]In a different context, Hung et al. (2022) linked the aggregate 52-week high to limited attention. They argued that a higher market level 52-week high is associated with a large amount of good firm-specific information in the market, which, in turn, may lead to overwhelmed investors and subsequent underreactions.

momentum when it is more challenging for investors to access information about peer firms.

There are several methods to measure investors' attention. Typically, firms with greater analyst coverage, larger market capitalization, and higher institutional holdings are expected to attract more attention from investors (Du et al., 2022), and information about these firms is more readily available and accessible to investors. In this case, investors are less likely to overlook important information. As a result, the stock price of the focal firm will respond more promptly to relevant information, thereby weakening the lead-lag effects between peer firms. Moreover, in the case of less opaque firms, the speed of information diffusion tends to be faster. This means that investors can obtain information about these firms more easily, which in turn reduces the cross-firm momentum effect among less opaque firms. Furthermore, the complexity of the network can also serve as a measure to assess investors' attention. According to research by Zhu (2019), the predictability of cross-firm momentum diminishes among firms with more intricate linkage networks. This is because it becomes more challenging for investors to understand and identify the peers of firms within a complicated network. The fact that a complex environment may lead agents to fail to account for the informational content is also discussed in theoretical studies, such as Mondria et al. (2022).

To obtain a more robust conclusion, we utilize all the aforementioned indirect proxies to measure investor attention. We employ the total number of analysts covering the firm ($\#Analysts$), and the total number of analyst reports about the firm ($\#Reports$) in the year to capture analyst attention. Additionally, we use the log float value of the firm to measure its size. The institutional holding ratio ($\%Institution$) is computed as the proportion of shares held by institutional investors to the total shares of the listed firm. The opacity indicator of one firm, denoted as $OPACITY$, is computed as the past-three-year sum of the absolute value of annual discretionary accruals (DISACC) (Hutton et al., 2009). For the network complexity, we follow Ali and Hirshleifer (2020) and use the degree centrality (i.e., the number of peer firms, denoted as $\#Peers$) as the proxy variable.

At the end of each trading week, we create dummy variables for each of the six proxy variables. Each of the dummy variables takes a value of one if the corresponding variable value for a focal firm is higher than the median value of the sample, and zero otherwise. For example, the dummy variable based on the number of analysts $Dummy\#Analysts$ equals one if the number of analysts of one firm is higher than the sample median, and 0 otherwise. For each of the dummy variables, we add an interaction term between it and the news co-mention peer firm return $Sentence\_3\_Rtn$ to the Fama-MacBeth regression specified in subsection 4.2.

Table 9 presents the results of the Fama-MacBeth regressions with the interaction terms. Columns 1-4 show that the coefficient of the interaction terms $Dummy\#Analysts \times Sentence\_3\_Rtn$, $Dummy\#Reports \times Sentence\_3\_Rtn$, $DummyValues \times Sentence\_3\_Rtn$, and $Dummy\%Institution \times Sentence\_3\_Rtn$ are all significantly negative. This suggests that the predictive power of the news co-mention momentum is weaker among firms with higher analyst coverage, more analyst reports, larger float values, and higher institutional holder proportions. From columns 5-6, the interaction terms $DummyOPACITY \times Sentence\_3\_Rtn$ and $Dummy\#Peers \times Sentence\_3\_Rtn$ are both positive and significant. This suggests that the news co-mention momentum is stronger among firms that are more opaque (whose information is less transparent) and firms with a higher network degree.

Table 9: Limited attention and FM regressions

	1	2	3	4	5	6
Sentence_3_Rtn	0.040	0.042	0.054	0.041	0.004	0.022
	(6.19)	(6.05)	(6.17)	(6.14)	(1.11)	(5.04)
Dummy#Analysts × Sentence_3_Rtn	-0.014					
	(-2.13)					
Dummy#Reports × Sentence_3_Rtn		-0.024				
		(-3.17)				
DummyValues × Sentence_3_Rtn			-0.052			
			(-4.97)			
Dummy%Institution × Sentence_3_Rtn				-0.013		
				(-2.25)		
DummyOPACITY × Sentence_3_Rtn					0.041	
					(4.75)	
Dummy#Peers × Sentence_3_Rtn						0.033
						(3.87)
Intercept	-0.032	-0.032	0.007	-0.008	-0.007	-0.009
	(-9.69)	(-9.35)	(1.94)	(-2.99)	(-1.91)	(-4.04)
Control	YES	YES	YES	YES	YES	YES
Avg. R Square	0.096	0.097	0.094	0.093	0.093	0.094
Total Obs.	507665	507665	507665	507665	507665	507665
Avg. Obs.	1094	1094	1094	1094	1094	1094

This table reports the results of Fama-MacBeth regressions, where interaction terms between the news co-mention peer firm return and different limited attention dummy proxies are included. The news co-mention momentum is based on *same_sentence* type under the 3-month identification window. The dependent variable is the stock excess return in the next week. The independent variables include the interaction term between the news co-mention peer firm return *Sentence_3_Rtn* and the six dummy variables. The six proxy variables for limited attention are the number of analysts (*#Analysts*), the number of reports (*#Reports*), the float value (*Values*), the proportion of institutional holders (*%Institution*), the opacity indicator (*OPACITY*) (Hutton et al., 2009), and the network complexity (*#Peers*). We then define corresponding dummy variables for these six proxy variables at the end of each trading week. For each dummy, we let it be one if the corresponding variable value of a focal firm is higher than the sample median, and zero otherwise. For example, *Dummy#Analysts* equals one if the number of analysts of one firm is higher than the cross-sectional sample median, else zero. The sample period is 2012-2020. The control variables include the firm size (taking logarithms), book-to-market ratio, and stock return in the past week. All independent variables are standardized with their cross-sectional means and standard deviations. Newey and West (1987) adjusted t-statistics are shown in parentheses.

We also perform a portfolio analysis by dividing all sample stocks into two groups (high group for dummy=1 and low group for dummy=0) based on each of the six dummy variables created earlier. Subsequently, we sort all stocks within each of the two groups into quintiles based on their values of *Sentence_3_Rtn*. For each of the two groups, we construct a long-short portfolio by purchasing stocks from the highest quintile and selling stocks from the lowest quintile.

Table 10 reports the portfolio grouping sorting results. From columns 1-4, the long-short portfolio exhibits a higher mean excess return and alpha for the group with fewer analysts, fewer reports, smaller size, and lower institutional holder proportions. These differences are statistically significant, except for the institutional holding one. From columns 5-6, the long-short portfolio exhibits a higher mean excess return and alpha for the group with a higher degree of opacity and a higher network degree.

Overall, both the Fama-MacBeth regressions and the portfolio analysis support the limited attention theory.

Table 10: Limited attention and portfolio sorting

Panel A: Excess returns						
	# Analysts	# Reports	Float values	% Institutional	OPACITY	# Peer firms
Higher group	1.37	1.25	0.70	1.64	3.16	2.56
	(4.54)	(4.21)	(2.49)	(5.15)	(5.34)	(4.10)
Lower group	2.44	2.60	3.00	2.06	0.57	1.29
	(5.33)	(5.51)	(5.58)	(4.82)	(2.50)	(5.06)
Higher-Lower	**-0.95**	**-1.14**	**-2.86**	-0.48	**2.42**	**0.94**
	(-2.85)	**(-3.22)**	**(-4.34)**	(-1.34)	**(4.61)**	**(2.07)**
Panel B: CH-4 alphas						
	# Analysts	# Reports	Float values	% Institutional	OPACITY	# Peer firms
Higher group	1.31	1.23	0.70	1.53	3.01	2.41
	(4.20)	(4.05)	(2.32)	(4.84)	(5.55)	(4.04)
Lower group	2.36	2.50	2.82	2.02	0.58	1.28
	(5.41)	(5.50)	(5.63)	(4.74)	(2.36)	(5.02)
Higher-Lower	**-0.90**	**-1.04**	**-2.51**	-0.47	**2.27**	0.89
	(-2.96)	**(-3.26)**	**(-4.27)**	(-1.25)	**(4.70)**	(1.92)

This table reports the portfolio sorting results for different attention groups. The news co-mention momentum is based on *same_sentence* type under the 3-month identification window. At the end of each trading week, we group all sample stock into two groups according to the six proxy variables for limited attention. The six proxy variables for limited attention are the number of analysts (*#Analysts*), the number of reports (*#Reports*), the float value ($Values$), the proportion of institutional holders (*%Institution*), the opacity indicator ($OPACITY$) (Hutton et al., 2009), and the network complexity (*#Peers*). For each proxy variable, the group with variables larger than the median value is the higher group, while the group with variables smaller than the median is the lower group. We then conduct the portfolio sorting analysis according to *Sentence_3_Rtn* for the two groups respectively. The long-short portfolio of the higher group involves buying the highest quintile and selling the lowest quintile. The sample period is 2012-2020. Panel A shows the excess returns of the long-short portfolios, while Panel B reports the CH-4 adjusted alphas. All returns alphas are converted to monthly using compound interest. Newey and West (1987) adjusted t-statistics are shown in parentheses. Returns/alphas of Higher-Lower portfolios with t-statistics higher/lower than 2.00/-2.00 are highlighted in bold.

5.2 Psychological Barrier

To examine the psychological barrier theory, we adopt the method used in Huang et al. (2021) and define the nearness to the 52-week high as the ratio of the closing price at the end of the trading week to the maximum daily closing price observed over the past 12 months.

Table 11: Psychologial barrier and news co-mention momentum

Panel A: Excess mean returns					
	CR1	CR2	CR3	CR4	CR5
PRC1	0.43	1.11	0.99	1.20	0.53
	(0.40)	(1.08)	(1.03)	(1.23)	(0.55)
PRC2	0.55	0.83	1.09	0.49	0.92
	(0.55)	(0.94)	(1.17)	(0.55)	(1.07)
PRC3	0.39	0.74	0.74	0.97	0.49
	(0.46)	(0.81)	(0.80)	(1.12)	(0.59)
PRC4	0.24	1.36	1.03	0.39	0.38
	(0.24)	(1.50)	(1.18)	(0.44)	(0.47)
PRC5	0.72	1.04	0.82	-0.08	1.91
	(0.61)	(0.93)	(0.80)	(-0.09)	(1.73)
PRC5- PRC1	0.25	-0.07	-0.16	-1.27	1.38
	(0.29)	(-0.07)	(-0.20)	(-1.68)	(1.39)
Port.55-Port.11				1.48	
				(1.57)	
Panel B: CH-4 adjusted alphas					
	CR1	CR2	CR3	CR4	CR5
PRC1	-0.08	0.57	0.39	0.80	0.00
	(-0.08)	(0.54)	(0.41)	(0.79)	(0.00)
PRC2	-0.05	0.17	0.68	0.03	0.38
	(-0.05)	(0.18)	(0.75)	(0.04)	(0.44)
PRC3	0.23	0.30	0.47	0.75	0.31
	(0.27)	(0.34)	(0.51)	(0.87)	(0.39)
PRC4	0.10	1.05	0.57	0.38	0.16
	(0.11)	(1.16)	(0.69)	(0.43)	(0.19)
PRC5	1.01	1.06	0.64	-0.13	1.75
	(0.91)	(0.98)	(0.62)	(-0.14)	(1.70)
PRC5- PRC1	1.05	0.49	0.25	-0.92	1.74
	(1.21)	(0.48)	(0.32)	(-1.17)	(1.98)
Port.55-Port.11				**1.83**	
				(2.04)	

This table reports the double sorting performance according to the nearness to the 52-week high (*PRC*) and the news co-mention peer firm return (denoted as *CR* in the table). The news co-mention momentum is based on *same_sentence* type under the 3-month identification window. Following Huang et al. (2021), at the end of each trading week, all sample stocks are independently sorted into 5 × 5 portfolios based on *CR* and *PRC*. The portfolios are held for one week and rebalanced weekly. Stocks are equal-weighted within each group. We also present the differences in returns between the corner portfolios. For example, Port.55 denotes the portfolio within the CR5 and PRC5 group, and Port.11 denotes the portfolio within the CR1 and PRC1 group. The sample period is 2012-2020. Panel A shows the excess returns of the long-short portfolios, while Panel B reports the CH-4 adjusted alphas. All returns alphas are converted to monthly through compound interest. Newey and West (1987) adjusted t-statistics are shown in parentheses. Returns/alphas of long-short portfolios with t-statistics higher than 2.00 are highlighted in bold.

Then, we construct 5 × 5 double-sorting equal-weighted portfolios independently based on the nearness to the 52-week high (denoted as *PRC* later) and the news co-mention peer firm return (*Sentence_3_Rtn*, denoted as *CR* in Table 11). If the psychological barrier theory holds, we would expect to observe increasing portfolio returns as we move up the ranks of *PRC*, and the long-short portfolio should exhibit highly significant positive returns.

Table 11 reports the mean excess returns and CH-4 adjusted alphas of the double-sorting portfolios. In contrast to the findings of Huang et al. (2021), who examined the US stock market, we do not observe an increasing trend in portfolio alpha with the ranks of PRC within each CR quintile. This result indicates that the psychological barrier theory cannot explain the momentum spillover effect in the Chinese stock market. The reason could be that the 52-week high effect itself is not empirically supported in the Chinese stock market. As documented in Hou et al. (2023), the 52-week high effect in China only leads to a modest adjusted alpha of 0.32%, which is not statistically significant. Moreover, the study conducted by Zhang et al. (2019) in the Chinese stock market found evidence of a 52-week low effect (i.e., stocks with prices near their 52-week lows tend to exhibit higher future returns), which is the opposite of the traditional 52-week high effect documented by George and Hwang (2004).

6 Futher Analysis and Robustness Checks

6.1 Longer Inverstment Horizons

In the previous portfolio sorting analysis, we hold the portfolio for one week and perform weekly rebalancing. In this subsection, we extend the analysis to examine the predictive power of the news co-mention momentum over longer investment horizons, including holding periods of 2, 3, 4, 8, 12, 24, and 36 weeks. To address the issue of inconsistent rebalancing frequency (which remains weekly) and holding period, we adopt the overlapping portfolio method, as described in Jegadeesh and Titman (1993) and Eisdorfer et al. (2022). We calculate the equal-weighted average of these overlapping portfolios. For instance, with a 2-week holding period, at the end of each trading week, we allocate only half of the total position to construct the portfolio based on the strategy for that week. The portfolio is then held for 2 weeks. In the following week, we use the other half of the total position to construct the portfolio for the next week.

Table 12 shows the performance of long-short portfolios with longer holding periods for different momentum spillover effects. Generally, the predictive power of each cross-firm momentum decreases as the holding period increases. For the news co-mention momentum, as the holding period increases from 1-week to 2-week and then to 3-week, the long-short mean excess return decreases from 1.94% (t-statistic=5.33) to 1.56% (t-statistic=4.95) and 1.18% (t-statistic=4.36) respectively. The noticeable decrease in the strength of the news co-mention momentum under longer investment horizons can be attributed to the fast update of the news co-mention linkage. Peer firms identified through news co-mention are time-sensitive, and their relationships could be valid only in the short term. Therefore, investment strategies based on news co-mention momentum should be executed within a short-term timeframe. However, linkages such as the shared-analyst, industry, and concept linkages typically remain relevant and effective over the longer term, leading to a more gradual decrease in the strength of the corresponding momentum spillover effects. Despite this, the news co-mention momentum strategy continues to outperform other momentum spillover effects in most investment horizons, except for the 4-week and 8-week holding periods. However, it should be noted that the dominance of the news co-mention momentum diminishes as the investment horizon lengthens, which is due to the fast update nature of the news co-mention linkage.

Table 12: Momentum performances over longer investment horizons

Panel A: Excess returns of long-short portfolios							
	2-week	3-week	4-week	8-week	12-week	24-week	36-week
News co-mention	1.55	1.18	0.87	0.42	0.27	0.19	0.18
	(5.24)	(4.74)	(4.78)	(4.20)	(3.20)	(3.29)	(3.63)
Analyst	1.03	0.86	0.80	0.43	0.26	0.16	0.18
	(5.63)	(5.47)	(5.93)	(4.42)	(3.22)	(2.58)	(3.13)
Industry	0.73	0.62	0.54	0.34	0.22	0.13	0.11
	(4.16)	(4.40)	(4.28)	(3.59)	(2.69)	(2.23)	(1.88)
Geographic	0.41	0.30	0.26	0.12	0.08	0.05	0.07
	(5.05)	(4.43)	(4.31)	(2.96)	(2.05)	(1.80)	(2.59)
Technology	0.50	0.34	0.27	0.20	0.14	0.13	0.12
	(3.08)	(2.47)	(2.30)	(2.22)	(1.84)	(2.37)	(2.30)
Statistical	1.32	1.10	0.90	0.51	0.25	0.03	0.14
	(5.22)	(4.83)	(4.48)	(3.24)	(1.91)	(0.27)	(1.79)
Concept	0.65	0.68	0.54	0.32	0.19	0.17	0.19
	(2.56)	(3.36)	(2.66)	(2.30)	(1.73)	(2.22)	(3.13)
Panel B: CH-4 adjusted alphas long-short portfolios							
	2-week	3-week	4-week	8-week	12-week	24-week	36-week
News co-mention	1.56	1.18	0.90	0.42	0.27	0.18	0.19
	(4.95)	(4.36)	(4.36)	(4.19)	(3.21)	(3.35)	(3.69)
Analyst	1.05	0.86	0.81	0.42	0.22	0.10	0.14
	(5.29)	(5.09)	(5.76)	(4.02)	(2.65)	(1.73)	(2.47)
Industry	0.76	0.65	0.58	0.32	0.19	0.08	0.07
	(4.00)	(4.26)	(4.36)	(3.20)	(2.33)	(1.42)	(1.26)
Geographic	0.42	0.30	0.27	0.12	0.07	0.04	0.05
	(4.95)	(4.27)	(4.29)	(2.74)	(1.72)	(1.35)	(1.93)
Technology	0.53	0.34	0.28	0.17	0.12	0.09	0.08
	(3.05)	(2.36)	(2.25)	(1.89)	(1.49)	(1.66)	(1.61)
Statistical	1.36	1.14	0.97	0.53	0.27	0.00	0.10
	(4.73)	(4.39)	(4.37)	(3.09)	(2.06)	(0.00)	(1.36)
Concept	0.58	0.66	0.55	0.34	0.19	0.15	0.17
	(2.20)	(2.98)	(2.48)	(2.30)	(1.70)	(1.87)	(2.96)

This table reports the long-short returns and alphas of the news co-mention momentum, analyst momentum, industry momentum, geographic momentum, technology momentum, statistical momentum, and concept momentum over longer investment horizons. The news co-mention momentum is based on *same_sentence* type under the 3-month identification window. The industry momentum is based on the Shenwan-1 classification. The geographic momentum is at the province level. We convert the holding period from 1-week to 2-, 3-, 4-, 8-, 12-, 24-, and 36-week. We follow the method in Jegadeesh and Titman (1993) and Eisdorfer et al. (2022) to have overlapping portfolios. The sample period of news co-mention momentum is 2012-2020. The sample period of concept momentum is Aug. 2016-2020. The sample periods for other momentums are 2006-2020. We report the equal-weighted average of these overlapping portfolios. Panel A shows the excess returns of portfolios, while Panel B shows the intercepts of the regression of the returns on CH-4 factors (Liu et al., 2019) (market, size, value, abnormal turnover rate). All returns and alphas are converted into monthly. Newey and West (1987) adjusted t-statistics are shown in parentheses.

6.2 Heterogeneity of Momentum Spillover Effects for SOEs and Non-SOEs

In this subsection, we examine the heterogeneity of momentum spillover effects based on ownership differences. State-owned enterprises (SOEs) play a critical role in shaping the market dynamics and contributing to the overall economy. SOEs differ from non-state-owned enterprises (non-SOEs) due to their considerations of not only corporate economic performance but also political objectives (Jiang and Kim, 2020; Leippold et al., 2022).

These additional factors often influence the stock prices of SOEs. We conduct separate portfolio analyses for SOEs and non-SOEs.

At the end of each trading week, we divide the sample stocks into two groups: state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). For each linkage type, we then perform separate portfolio sorting analyses for SOEs and non-SOEs.

Table 13: Heterogeneity of momentum spillover effects for SOEs and Non-SOEs

Panel A: Excess returns of long-short portfolios							
	News co-mention	Analyst	Industry	Geographic	Technology	Statistical	Concept
non-SOE	2.48	0.82	0.59	0.34	0.28	1.29	0.60
	(5.90)	(3.45)	(2.56)	(2.82)	(1.17)	(4.29)	(1.68)
SOE	0.73	0.81	0.83	0.30	0.66	1.20	0.94
	(2.81)	(3.01)	(3.57)	(2.03)	(3.10)	(3.36)	(2.87)
non-SOE - SOE	**1.73**	0.01	-0.24	0.04	-0.38	0.09	-0.34
	(5.23)	(0.05)	(-1.31)	(0.27)	(-1.56)	(0.39)	(-1.17)
Panel B: CH-4 adjusted alphas of long-short portfolios							
	News co-mention	Analyst	Industry	Geographic	Technology	Statistical	Concept
non-SOE	2.38	0.84	0.65	0.36	0.31	1.23	0.50
	(5.69)	(3.24)	(2.67)	(3.08)	(1.27)	(3.51)	(1.32)
SOE	0.71	0.77	0.75	0.29	0.65	1.17	0.93
	(2.48)	(2.53)	(3.02)	(1.72)	(2.92)	(2.84)	(2.63)
non-SOE - SOE	**1.66**	0.07	-0.11	0.07	-0.33	0.06	-0.43
	(4.67)	(0.35)	(-0.58)	(0.45)	(-1.37)	(0.26)	(-1.44)

This table reports the differences in momentum spillover effects between SOEs and non-SOEs. The news co-mention momentum is based on *same_sentence* type under the 3-month identification window. The industry momentum is based on the Shenwan-1 classification. The geographic momentum is at the province level. At the end of each trading week, we divide the sample stocks into SOEs and non-SOEs. Then within each sample group, we sort all stocks into quintiles according to the peer firm returns based on each linkage type. The long-short portfolio is buying the highest quintile and selling the lowest quintile. Non-SOE - SOE indicates the taking the difference of the time series long-short returns and alphas between the non-SOE group and SOE group. Within each quintile group, the stocks are equally weighted. All portfolios are held for one week and are rebalanced weekly. The sample period of news co-mention momentum is 2012-2020. The sample period of concept momentum is Aug. 2016-2020. The sample periods for other momentums are 2006-2020. Panel A shows the excess returns of portfolios, while Panel B shows the intercepts of the regression of the returns on CH-4 factors (market, size, value, abnormal turnover rate). All returns and alphas are converted into monthly. Newey and West (1987) adjusted t-statistics are shown in parentheses. Spreads between non-SOEs and SOEs with t-statistics greater than 2.00 are highlighted in bold.

Table 13 reports the differences in momentum spillover effects between SOEs and non-SOEs. Interestingly, among the various momentum spillover effects examined, only the news co-mention momentum demonstrates a notable discrepancy based on the ownership difference. Specifically, among non-SOEs, the news co-mention momentum generates a significant long-short return and alpha of 2.48% (t-statistic=5.90) and 2.38% (t-statistic=5.69) per month. In contrast, among SOEs, it produces a relatively lower long-short return and alpha of 0.73% (t-statistic=2.81) and 0.71% (t-statistic=2.48) per month. The difference in long-short returns from the news co-mention momentum between non-SOEs and SOEs is 1.73% (t-statistic=5.23), which is both statistically and economically significant. This disparity suggests that the impact of news co-mentions on stock returns differs significantly between SOEs and non-SOEs. In contrast to the news co-mention momentum, the differences in returns due to the ownership between non-SOEs and SOEs are not statistically significant for other momentum spillovers. It is possible that the observed results are due to media bias. Given that SOEs in China are politically related and often have political objectives (Jiang and Kim (2020) and Schweizer et al. (2020)), it is plausible that the news co-mentioning about SOEs may be less precise in capturing peer firm relationships compared to non-SOEs.[24]

6.3 Robustness Checks

In this subsection, we conduct several robustness tests to examine the robustness of our findings. Specifically, we consider the impact of transaction costs and the shell effect on our results. In addition, we conduct a series of robustness checks for the unifying effect of the news co-mention momentum.

6.3.1 Transaction Cost

The portfolio sorting analysis is conducted on a weekly basis in this study. Compared to monthly rebalancing, the weekly approach involves more frequent trading activities, making it important to consider transaction costs in real-world investment. To address this concern, follow Fan et al. (2021) to set the transaction cost at 16 bps per trade (buying and selling combined).[25]

Table 15 in Appendix C presents the portfolio sorting results of each type of cross-firm momentum, taking into account the 16 bps transaction cost. The trading strategy based on the news co-mention momentum remains significantly profitable after taking the transaction costs into account. The long-short portfolio generates an average excess return of 1.29% (t-statistic=3.56) and a CH-4 adjusted alpha of 1.21% (t-statisitc=3.42) per month.

However, other momentum spillover effects do not generate profitable trading strategies after taking the transaction costs into account. The analyst momentum strategy yields a long-short mean excess return of 0.21% and an alpha of 0.20%, both of which are statistically insignificant. Similarly, the industry momentum effect does not generate profitable trading strategies once we consider the transaction cost. The statistical momentum strategy, which initially showed strong performance without considering transaction costs, experiences a significant decline both economically and statistically when transaction costs are taken into account. The magnitude of the excess mean return decreases considerably, and the CH-4 adjusted alpha becomes statistically insignificant at 0.69% with a t-statistic of 1.74. Furthermore, when considering the 16 bps transaction cost, the trading strategies based on geographic momentum, technology momentum, and concept momentum exhibit negative long-short returns and CH-4 adjusted alphas.

[24]In China, SOEs often have closer ties to the government and are subject to more government oversight compared to non-state-owned enterprises (non-SOEs). The government may strategically use media outlets for economic and political purposes, leading to potential biases in news coverage.

[25]In the context of stock trading in China, transaction costs typically consist of three components. Firstly, there is a stamp duty, which is levied on the total transaction amount at a rate of 10 bps. It is important to note that the stamp duty is only imposed on sellers. The second component is the transfer fee, which amounts to 1 bps for both buying and selling transactions in the Shanghai Stock Exchange. This fee is applicable to stocks with a price of 20 CNY per share. Lastly, there is the trading commission, which is the fee paid by investors to brokers for executing their trades. The trading commission is subject to a maximum limit of 3 bps of the transaction amount. However, the typical rates for trading commissions are around 2.5 bps. It is worth mentioning that institutional investors with higher trading volumes often enjoy lower commission rates compared to individual investors. Setting the transaction cost at 16 bps implicitly assumes a conservative approach by considering a turnover ratio of 100% for each rebalancing period.

6.3.2 Dropping Shell Firms

According to Liu et al. (2019), back-door listings through reverse mergers are common in China due to the strict and costly IPO process. This can lead to the presence of shell firms with inflated market values and biased stock returns that are disconnected from their underlying fundamentals. To address this potential issue and ensure the robustness of our analysis, we exclude shell firms from the dataset and re-evaluate the portfolio sorting analysis for each cross-firm momentum.

At the end of each trading week, we sort all sample stocks except for the ST shares and stocks with the bottom 30% capitalization based on their peer firm returns. The stocks are then divided into quintiles, and within each quintile, they are equally weighted. The long-short portfolio strategy involves buying the stocks in the highest quintile and selling the stocks in the lowest quintile. These portfolios are held for one week and rebalanced weekly.

Table 16 in Appendix C reports the excess reuturns and CH-4 adjusted alphas after droppping the shell firms. Our main results are robust to the exclusion of shell firms. Despite a small decrease in the predictive power, the news co-mention momentum continues to dominate other momentum spillover effects. To be specific, the news co-mention momentum strategy generates a statistically significant long-short average return and CH-4 adjusted alpha of 1.00% (t-statistic=3.87) and 0.95% (t-statistic=3.63), respectively. The analyst, industry, geographic, and statistical momentum also exhibit a slight decrease in their predictive power but remain statistically significant. However, the technology and concept momentum lose their predictability after excluding shell firms from the analysis.

6.3.3 Robustness of the Unifying Effect

In this section, we perform a series of robustness checks to further validate the unifying effect of the news co-mention momentum.

Firstly, we conduct the spanning tests without CH-4 factors. In this way, we can exclude the influence of the CH-4 factors and better examine the explanatory power of each momentums spillover factor. Table 17 in Appendix C shows that the news co-mention factor alone is sufficient to explain all other momentum spillover effects. However, none of the other six factors demonstrate the same level of explanatory power as the news co-mention factor across the four identification windows.

In the main body of the paper, we primarily focus on the industry linkage based on the Shenwan-1 classification. Next, we test the unifying effect of the news co-mention momentum over the industry momentum based on alternative industry classifications, including the three levels of Shenwan classification (Shenwan-1, -2, -3), two levels of CSRC classification, (CSRC-1, -2), and three levels of CITIC classification (CITIC-1, -2, -3). For brevity, for the news co-mention factors, we only use the Sentence_3 factor. Table 18 in Appendix C reports the alphas of the news co-mention momentum factor from the CH-4+Industry model and the alphas of the eight industry factors from the CH-4+Sentence_3 model. The news co-mention momentum factor always has a significantly positive alpha given all the candidate industry factors. On the contrary, all the eight industry momentum factors are explained by the news co-mention momentum factor, and their alphas are negative when the Sentence_3 factor is included.

The full sample period analyzed is from 2012 to 2020 in the main body of the paper. This is primarily due to the limited availability of news data in the earlier years. In contrast, most of the other momentum factors were analyzed from 2006 to 2020. As a robustness check, we consider an alternative sample period from 2006-2020,[26] and the results are reported in Table 19 from Appendix C. The news co-mention momentum factor cannot be explained by any of the other factors, and it always has a significantly positive alpha in all specifications. In contrast, all the other factors can be explained by the news co-mention momentum factor, as their alphas are either insignificant or even exhibit a negative sign when the Sentence_3 factor is included.

Finally, we turn to *same_article* link identification strategy when conducting spanning tests. Specifically, we construct the news co-mention momentum factor based on *same_article* type under identification windows of 3, 6, 9, and 12 months. The spanning test results are shown in Table 20 from Appendix C. Our main results are robust to the choice of news linkage identification strategy.

7 Conclusions

In recent years, there has been a surging interest in the extraction and utilization of soft information contained within news articles. This paper utilizes a large dataset of millions of Chinese news articles and applies both article co-mentioning and sentence co-mentioning strategies to identify economic linkages among firms. Our work demonstrates the benefits of utilizing big alternative big data by showing that economic linkages identified from business news contain rich and valuable information. We find that the news co-mention momentum spillover unifies all different forms of momentum spillover effects that have been previously studied in the Chinese stock market. These include shared-analyst momentum, industry momentum, geographic momentum at the province and city levels, customer-supplier momentum, technology momentum, statistical momentum, and concept momentum. This result remains robust even when considering different choices of news-linkage identification strategy, alternative definitions for competitor links, and various sample periods.

To further explore the source of this unifying effect, we examine the differences in the information content of news-implied links and other linkages. We find that the news-implied linkages are more comprehensive compared to other types of linkage proxies. Specifically, news co-mentioning incorporates both industry information and valuable non-industry linkage information, which contributes to its strong predictive power for future returns. Furthermore, news exhibits the advantage of prompt updates, allowing us to timely identify changes in linkages among firms.

We also investigate the mechanism behind the news-based momentum spillover. We find that the news co-mention momentum is weaker among firms with higher analyst coverage, more analyst reports, larger float values, higher institutional holder proportions, less opacity, and less linkage complexity, supporting the limited attention explanation.

In the last, we wish to point out that the trading strategy based on news co-mention momentum spillover effect is profitable when considering real-world transaction costs. However, due to the quick update nature of news, investment strategies based on news co-mention momentum should be executed within a short-term timeframe.

[26] The news database starts from 2006.

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Appendix

Appendix A. Descriptive Statistics for the News Data

Table 14: Descriptive statistics for the news data

Year	Mean	Std.	Max	Min
2006	97.23	59.60	252	1
2007	88.04	61.19	337	1
2008	70.72	28.88	152	3
2009	57.83	27.19	137	12
2010	61.06	33.66	135	1
2011	72.23	41.87	194	1
2012	84.29	52.16	183	1
2013	243.08	185.71	657	1
2014	336.04	212.59	699	1
2015	236.23	158.75	589	1
2016	197.29	131.52	493	1
2017	126.35	89.32	359	1
2018	156.37	105.31	467	1
2019	136.68	94.55	464	1
2020	334.87	313.69	1685	1

This table summarizes the daily number of news items for each year from 2006 to 2020.

Appendix B. An Eexample of Analysts' Research Directions

Another name for analysts in China is industry researchers. This name can better reflect the fact that most Chinese analysts focus on one specific industry and are accordingly grouped in advance. Therefore, the analyst co-coverage linkage largely comes from the industry linkage.

In this part, we show an example of the research groups and directions of analysts from the Research Division of China Securities Co., Ltd., a representative and leading security company in China. The information is collected manually from its public recruitment advertisement for fresh graduates in 2023 summer.

- **Finance**

  Banking, Non-bank, FinTech

- **TMT** [27]

  Communication, Computer, Electronics, Media, Artificial intelligence

- **Consumption**

  Food and beverage, Clothing and textile, Education, Home appliances, Commerce, Agriculture, Social service

- **Pharmaceutical**

  Pharmacy, BioTech, Medical apparatus and instruments, Medicine

- **Manufacturing**

  Military, Electrical equipment (new energy), Machinery, Automobile (new energy), Lithium battery

- **Property and cycles**

  Real estate, Architecture, Chemical, Environment, Transportation, Metal and new metal materials, Coal, Small- and mid-cap stocks

The bolded names indicate the general research groups, while the names below indicate the specific research coverage directions (directions of macro, strategy, and financial engineering are not listed).

From the collected information, it is clear that the specific directions largely overlap with industry classifications. Therefore, the shared-analyst linkage has strong limitations in identifying peer firms from the market, which may account for the failure of the unifying effect of it in China.

[27] Abbreviation for telecommunications, media, and technology.

Appendix C. Tables of Robustness Checks

Table 15: Considering transaction costs

Panel A: Excess returns							
	News co-mention	Analyst	Industry	Geographic	Technology	Statistical	Concept
1 (Low)	0.09	0.53	0.70	0.87	0.89	0.27	-0.96
	(0.11)	(0.72)	(0.95)	(1.18)	(1.19)	(0.36)	(-1.03)
2	0.42	0.63	0.87	0.99	1.01	0.70	-0.88
	(0.52)	(0.89)	(1.18)	(1.34)	(1.35)	(0.91)	(-0.97)
3	0.46	0.96	1.09	1.13	1.29	1.07	-0.59
	(0.58)	(1.34)	(1.43)	(1.51)	(1.71)	(1.40)	(-0.66)
4	0.74	1.38	1.25	1.19	1.27	1.45	-0.43
	(0.88)	(1.92)	(1.64)	(1.59)	(1.67)	(1.93)	(-0.49)
5 (High)	2.03	1.39	1.47	1.22	1.47	1.63	-0.36
	(2.25)	(1.87)	(1.91)	(1.58)	(1.90)	(2.17)	(-0.42)
5-1	**1.29**	0.21	0.12	-0.29	-0.06	**0.71**	-0.04
	(3.56)	(0.83)	(0.53)	(-2.36)	(-0.31)	**(2.07)**	(-0.11)
SpearmanR	1.00	1.00	1.00	1.00	0.90	1.00	1.00
P value	0.00	0.00	0.00	0.00	0.04	0.00	0.00
Panel B: CH-4 adjusted alphas							
	News co-mention	Analyst	Industry	Geographic	Technology	Statistical	Concept
1 (Low)	-0.23	0.18	0.33	0.49	0.47	-0.06	-0.89
	(-0.28)	(0.24)	(0.44)	(0.66)	(0.61)	(-0.07)	(-0.92)
2	0.14	0.28	0.48	0.60	0.62	0.31	-0.85
	(0.17)	(0.38)	(0.63)	(0.79)	(0.81)	(0.39)	(-0.90)
3	0.13	0.64	0.68	0.75	0.97	0.64	-0.58
	(0.17)	(0.88)	(0.88)	(0.98)	(1.26)	(0.84)	(-0.63)
4	0.42	1.08	0.84	0.77	0.89	1.01	-0.46
	(0.51)	(1.49)	(1.10)	(1.01)	(1.15)	(1.33)	(-0.49)
5 (High)	1.62	1.03	1.10	0.83	1.07	1.28	-0.39
	(1.91)	(1.36)	(1.39)	(1.07)	(1.33)	(1.67)	(-0.44)
5-1	**1.21**	0.20	0.12	-0.30	-0.04	0.69	-0.14
	(3.42)	(0.72)	(0.47)	(-2.29)	(-0.18)	(1.74)	(-0.36)
SpearmanR	0.90	0.90	1.00	1.00	0.90	1.00	1.00
P value	0.04	0.04	0.00	0.00	0.04	0.00	0.00

This table reports the portfolio sorting performances of the news co-mention momentum, analyst momentum, industry momentum, geographic momentum, technology momentum, statistical momentum, and concept momentum considering a transaction cost of 16 bps (buy and sell combined). The sample stocks include all listed stocks on the main board of the Shanghai Stock Exchange, Shenzhen Stock Exchange, and Growth Enterprise Market (GEM). ST shares are excluded. The news co-mention momentum is based on *same_sentence* type under the 3-month identification window. The industry momentum is based on the Shenwan-1 classification. The geographic momentum is at the province level. The sample period of news co-mention momentum is 2012-2020. The sample period of concept momentum is Aug. 2016-2020. The sample periods for other momentums are 2006-2020. At the end of each trading week, all sample stocks are sorted into quintiles based on different peer firm returns respectively. Within each quintile group, the stocks are equally weighted. The long-short portfolio involves buying the highest group and selling the lowest group. All portfolios are held for one week and are rebalanced weekly. Panel A presents the excess returns of portfolios, and Panel B shows the intercepts of the regression of the returns on CH-4 factors (Liu et al., 2019) (market, size, value, abnormal turnover rate). All weekly returns and alphas are converted into monthly percentages using compound interest. SpearmanR reports the Spearman correlation coefficient between the portfolio return and the serial number for each sorting. Newey and West (1987) adjusted t-statistics are shown in parentheses. Long-short returns/alphas with t-statistics higher than 2.00 are highlighted in bold.

Table 16: Dropping shell firms

Panel A: Excess returns							
	News co-mention	Analyst	Industry	Geographic	Technology	Statistical	Concept
1	0.43	0.92	0.95	1.10	1.13	0.83	-0.52
	(0.53)	(1.25)	(1.30)	(1.53)	(1.55)	(1.12)	(-0.56)
2	0.78	1.04	1.09	1.19	1.15	1.05	-0.25
	(0.99)	(1.48)	(1.52)	(1.64)	(1.59)	(1.40)	(-0.27)
3	0.84	1.38	1.28	1.29	1.49	1.38	-0.03
	(1.09)	(1.95)	(1.72)	(1.77)	(2.03)	(1.85)	(-0.04)
4	1.04	1.79	1.37	1.39	1.47	1.60	-0.16
	(1.28)	(2.50)	(1.84)	(1.89)	(1.97)	(2.20)	(-0.19)
5	1.43	1.74	1.69	1.44	1.57	1.80	0.06
	(1.73)	(2.34)	(2.22)	(1.90)	(2.08)	(2.42)	(0.07)
5-1	**1.00**	**0.81**	**0.74**	**0.33**	0.44	**0.96**	0.58
	(3.87)	**(2.96)**	**(2.73)**	**(2.34)**	(1.84)	**(2.63)**	(1.52)
SpearmanR	1.00	0.90	1.00	1.00	0.90	1.00	0.90
P value	0.00	0.04	0.00	0.00	0.04	0.00	0.04
Panel B: CH-4 adjusted alphas							
	News co-mention	Analyst	Industry	Geographic	Technology	Statistical	Concept
1	0.17	0.60	0.62	0.79	0.75	0.53	-0.47
	(0.21)	(0.79)	(0.83)	(1.07)	(1.00)	(0.69)	(-0.50)
2	0.52	0.73	0.79	0.86	0.82	0.72	-0.23
	(0.67)	(1.01)	(1.07)	(1.16)	(1.09)	(0.95)	(-0.25)
3	0.56	1.10	0.96	0.97	1.21	1.02	-0.06
	(0.73)	(1.51)	(1.26)	(1.30)	(1.62)	(1.35)	(-0.06)
4	0.76	1.54	0.99	1.04	1.15	1.25	-0.24
	(0.95)	(2.14)	(1.32)	(1.39)	(1.51)	(1.69)	(-0.26)
5	1.12	1.40	1.37	1.10	1.21	1.48	-0.02
	(1.40)	(1.84)	(1.73)	(1.43)	(1.55)	(1.94)	(-0.02)
5-1	**0.95**	**0.80**	**0.74**	**0.32**	0.46	**0.95**	0.46
	(3.63)	**(2.62)**	**(2.55)**	**(2.05)**	(1.84)	**(2.25)**	(1.14)
SpearmanR	1.00	0.90	1.00	1.00	0.90	1.00	0.70
P value	0.00	0.04	0.00	0.00	0.04	0.00	0.19

This table reports the portfolio sorting performances of the news co-mention momentum, analyst momentum, industry momentum, geographic momentum, technology momentum, statistical momentum, and concept momentum after dropping all stocks with the bottom 30% capitalization on the main board of the Shanghai Stock Exchange, Shenzhen Stock Exchange, and Growth Enterprise Market (GEM). ST shares are also excluded. The news co-mention momentum is based on *same_sentence* type under the 3-month identification window. The industry momentum is based on the Shenwan-1 classification. The geographic momentum is at the province level. The sample period of news co-mention momentum is 2012-2020. The sample period of concept momentum is Aug. 2016-2020. The sample periods for other momentums are 2006-2020. At the end of each trading week, all sample stocks are sorted into quintiles based on different peer firm returns respectively. Within each quintile group, the stocks are equally weighted. The long-short portfolio involves buying the highest group and selling the lowest group. All portfolios are held for one week and are rebalanced weekly. Panel A is the excess returns of portfolios, and Panel B is the intercepts of the regression of the returns on CH-4 factors (Liu et al., 2019) (market, size, value, abnormal turnover rate). All weekly returns and alphas are converted into monthly percentages using compound interest. SpearmanR reports the Spearman correlation coefficient between the portfolio return and the serial number for each sorting. Newey and West (1987) adjusted t-statistics are shown in parentheses. Long-short returns/alphas with t-statistics higher than 2.00 are highlighted in bold.

Table 17: Spanning tests without CH-4 factors

Dependent factors Explainoary factors	Sentence_3	Sentence_6	Sentence_9	Sentence_12	Analyst	Industry	Geographic	Technology	Concept
Sentence_3		-0.18	-0.25	-0.34	-0.53	-0.62	0.22	-0.36	-0.54
		(-1.79)	(-1.96)	(-2.45)	(-2.04)	(-2.48)	(1.74)	(-1.54)	(-1.70)
Sentence_6	**0.41**		-0.09	-0.18	-0.40	-0.51	0.24	-0.30	-0.45
	(3.78)		(-1.26)	(-2.16)	(-1.73)	(-2.29)	(1.97)	(-1.37)	(-1.49)
Sentence_9	**0.58**	**0.17**		-0.09	-0.31	-0.44	0.24	-0.25	-0.34
	(4.23)	**(2.34)**		(-2.01)	(-1.39)	(-2.10)	(1.95)	(-1.20)	(-1.17)
Sentence_12	**0.71**	**0.29**	**0.13**		-0.22	-0.36	**0.25**	-0.20	-0.27
	(4.66)	**(3.39)**	**(2.72)**		(-1.02)	(-1.77)	**(2.05)**	(-0.96)	(-0.98)
Analyst	**1.27**	**0.86**	**0.72**	**0.62**		0.11	**0.25**	0.14	0.07
	(5.07)	**(4.30)**	**(3.80)**	**(3.43)**		(0.82)	**(2.01)**	(0.90)	(0.32)
Industry	**1.43**	**1.02**	**0.89**	**0.79**	0.15		**0.26**	0.12	0.37
	(5.15)	**(4.59)**	**(4.33)**	**(3.98)**	(1.08)		**(2.09)**	(0.77)	(1.88)
Geographic	**1.69**	**1.32**	**1.17**	**1.08**	**0.60**	**0.55**		**0.42**	0.46
	(5.19)	**(4.61)**	**(4.17)**	**(3.90)**	**(2.42)**	**(2.40)**		**(2.05)**	(1.38)
Technology	**1.59**	**1.19**	**1.06**	**0.97**	0.37	0.29	**0.28**		0.35
	(4.72)	**(4.19)**	**(3.96)**	**(3.71)**	(1.89)	(1.63)	**(2.23)**		(1.32)
Statistical	**1.25**	**0.83**	**0.67**	**0.55**	0.20	0.22	0.24	0.22	0.12
	(4.50)	**(3.64)**	**(3.19)**	**(2.75)**	(0.94)	(1.04)	(1.84)	(1.15)	(0.39)
Concept	**1.41**	**0.97**	**0.77**	**0.63**	0.31	-0.19	**0.31**	-0.03	
	(4.28)	**(3.95)**	**(3.31)**	**(3.04)**	(1.38)	(-1.02)	**(2.03)**	(-0.14)	
Non_news	**1.23**	**0.81**	**0.58**	**0.45**					
	(3.93)	**(3.36)**	**(2.49)**	**(2.20)**					

This table reports the intercept (or alpha) of regressing the time series of different long-short momentum returns on the MS momentum spillover factor alone. The construction of the MS factor is given in subsection 4.1. The column name indicates the type of long-short momentum return, i.e., the dependent variable, while the index name means the MS factor, i.e., the explanatory variable. For example, the alphas of the row Sentence_3 indicate the alphas from the time-series regressions of long-short portfolio returns of other momentums on the Sentence_3 factor alone. In the last row, we include all the six momentum spillover factors that are not related to news as additional explanatory variables. The news co-mention momentum factors are based on *same_sentence* type under identification windows including 3-month, 6-month, 9-month, and 12-month. The industry momentum is based on the Shenwan-1 classification, while the geographic momentum is conducted on the province level. We do not consider the customer momentum due to the low data quality. The sample stocks include all listed stocks on the main board of the Shanghai Stock Exchange, Shenzhen Stock Exchange, and Growth Enterprise Market (GEM). ST shares are excluded. The sample period of news co-mention momentum is 2012-2020. The sample period of concept momentum is Aug. 2016-2020. The sample periods for other momentums are 2006-2020. Newey and West (1987) adjusted t-statistics are shown in parentheses. Alphas with t-statistics higher than 2.00 are highlighted in bold.

Table 18: Robustness checks based on alternative industry classifications

1		2	
	Alphas of Sentence_3		CH-4+Sentence_3
CH-4+Shenwan-1	**1.35**	Alpha of Shenwan-1	-0.53
	(5.08)		(-2.10)
CH-4+Shenwan-2	**1.34**	Alpha of Shenwan-2	-0.54
	(5.02)		(-2.08)
CH-4+Shenwan-3	**1.30**	Alpha of Shenwan-3	-0.48
	(5.17)		(-2.11)
CH-4+CSRC-1	**1.55**	Alpha of CSRC-1	-0.11
	(4.94)		(-0.45)
CH-4+CSRC-2	**1.44**	Alpha of CSRC-2	-0.64
	(5.38)		(-2.38)
CH-4+CITIC-1	**1.48**	Alpha of CITIC-1	-0.71
	(5.54)		(-2.66)
CH-4+CITIC-2	**1.27**	Alpha of CITIC-2	-0.52
	(4.97)		(-2.01)
CH-4+CITIC-3	**1.33**	Alpha of CITIC-3	-0.59
	(5.48)		(-2.57)

This table reports the factor-spanning test results of the industry momentum under different classification systems. We adopt three levels of Shenwan classification (Shenwan-1, -2, -3), two levels of CSRC classification, (CSRC-1, -2), and three levels of CITIC classification (CITIC-1, -2, -3) to construct the industry momentum factor. The Sentence_3 news co-mention factor is based on *same_sentence* type under the 3-month identification window. Column 1 indicates CH-4+Industry adjusted alphas of the Sentence_3 long-short return based on the eight classification methods, respectively, and the row name indicates the specific type of each CH-4+Industry model. Column 2 represents the CH-4+Sentence_3 adjusted alphas of the industry momentum based on the eight classification methods. The CH-4 factors (MKT, SMB, HML, PMO) are from Liu et al. (2019). The sample stocks include all listed stocks on the main board of the Shanghai Stock Exchange, Shenzhen Stock Exchange, and Growth Enterprise Market (GEM). ST shares are excluded. The sample period is 2012-2020. Newey and West (1987) adjusted t-statistics are shown in parentheses. Alphas with t-statistics higher than 2.00 are highlighted in bold.

Table 19: Spanning tests of different sample periods

Panel A: Period: 2006-2020						
	Sentence_3	Analyst	Industry	Geographic	Technology	Statistical
CH-4+Sentence_3		-0.09	-0.06	0.23	0.05	0.44
		(-0.45)	(-0.27)	(1.67)	(0.22)	(1.21)
CH-4+Analyst	**0.71**		0.11	0.24	0.17	**0.70**
	(3.61)		(0.76)	(1.83)	(0.99)	**(2.18)**
CH-4+Industry	**0.74**	0.15		0.25	0.14	**0.78**
	(3.54)	(0.96)		(1.92)	(0.87)	**(2.25)**
CH-4+Geographic	**1.01**	**0.59**	**0.55**		**0.44**	**1.05**
	(3.95)	**(2.21)**	**(2.26)**		**(2.07)**	**(2.61)**
CH-4+Technology	**0.85**	0.34	0.27	**0.27**		**0.93**
	(3.42)	(1.59)	(1.41)	**(2.05)**		**(2.50)**
CH-4+Statistical	**0.72**	0.20	0.23	0.23	0.25	
	(2.96)	(0.90)	(0.97)	(1.69)	(1.24)	
CH-4+Non_news	**0.61**	0.32	0.22	0.12		
	(2.99)	(1.94)	(1.42)	(0.87)		
Panel B: Period: 2012-2020						
	Sentence_3	Analyst	Industry	Geographic	Technology	Statistical
CH-4+Sentence_3		-0.44	-0.53	0.25	-0.26	0.17
		(-1.76)	(-2.10)	(1.92)	(-1.11)	(0.43)
CH-4+Analyst	**1.18**		-0.07	**0.31**	0.04	**0.87**
	(4.97)		(-0.43)	**(2.55)**	(0.22)	**(2.54)**
CH-4+Industry	**1.35**	**0.34**		**0.31**	0.10	**1.06**
	(5.08)	**(2.01)**		**(2.59)**	(0.60)	**(3.01)**
CH-4+Geographic	**1.62**	**0.77**	0.46		0.40	**1.34**
	(4.94)	**(2.38)**	(1.56)		(1.52)	**(3.02)**
CH-4+Technology	**1.49**	**0.53**	0.22	**0.33**		**1.28**
	(4.63)	**(2.05)**	(1.09)	**(2.90)**		**(3.08)**
CH-4+Statistical	**1.16**	0.21	0.00	**0.28**	0.15	
	(4.17)	(0.81)	(0.01)	**(2.24)**	(0.63)	
CH-4+Non_news	**1.07**	**0.70**	**0.52**	**0.42**		
	(4.57)	**(3.66)**	**(3.05)**	**(2.64)**		

This table reports the intercept (or alpha) of regressing the time series of different long-short momentum returns on the CH-4 factors (MKT, SMB, HML, PMO) (Liu et al., 2019) plus each MS momentum spillover factor during sample periods of 2006-2020 and 2012-2020. Panel A reports the results of 2006-2020, while Panel B reports the results of 2012-2020. The concept momentum is excluded from this table since it is only available since 2016. The construction of the MS factor is given in subsection 4.1. The column name indicates the type of long-short momentum return (i.e., the dependent variable), while the rows name indicates the augmented CH-4 model (i.e., the original CH-4 model plus a specific MS factor). For example, the alphas in the row CH-4+Sentence_3 are the alphas from the time-series regressions of long-short portfolio returns of other momentums on MKT, SMB, HML, PMO and the Sentence_3 factor. In the last row of each panel, we include all the five momentum spillover factors (concept momentum is excluded) that are not related to news as additional explanatory variables. For brevity, we only construct the news co-mention momentum factor based on *same_sentence* type under the 3-month identification windows here. The industry momentum is based on the Shenwan-1 classification, while the geographic momentum is conducted on the province level. We do not consider the customer momentum due to the low data quality. The sample stocks include all listed stocks on the main board of the Shanghai Stock Exchange, Shenzhen Stock Exchange, and Growth Enterprise Market (GEM). ST shares are excluded. Newey and West (1987) adjusted t-statistics are shown in parentheses. Alphas with t-statistics higher than 2.00 are highlighted in bold.

Table 20: Factor spanning tests based on *same_article* type news co-mention

Panel A: Alphas of factor spanning tests (*same_article* type)										
	Article_3	Article_6	Article_9	Article_12	Analyst	Industry	Geographic	Technology	Statistical	Concept
CH-4+Article_3		-0.05	-0.14	-0.20	-0.44	-0.56	0.24	-0.33	0.18	-0.53
		(-0.62)	(-1.23)	(-1.48)	(-1.82)	(-2.42)	(1.81)	(-1.51)	(0.49)	(-1.77)
CH-4+Article_6	**0.25**		-0.09	-0.15	-0.39	-0.53	0.25	-0.32	0.18	-0.51
	(2.72)		(-1.36)	(-1.75)	(-1.74)	(-2.42)	(1.91)	(-1.46)	(0.54)	(-1.79)
CH-4+Article_9	**0.41**	**0.17**		-0.07	-0.28	-0.43	0.25	-0.22	0.23	-0.42
	(3.56)	**(2.60)**		(-1.24)	(-1.33)	(-2.06)	(1.97)	(-1.05)	(0.75)	(-1.49)
CH-4+Article_12	**0.51**	**0.27**	0.10		-0.21	-0.37	**0.26**	-0.16	0.27	-0.29
	(3.74)	**(3.05)**	(1.92)		(-0.99)	(-1.76)	**(2.07)**	(-0.75)	(0.93)	(-0.99)
CH-4+Analyst	**0.98**	**0.78**	**0.67**	**0.60**		0.11	0.24	0.17	**0.70**	0.06
	(4.85)	**(4.63)**	**(3.83)**	**(3.46)**		(0.76)	(1.83)	(0.99)	**(2.18)**	(0.28)
CH-4+Industry	**1.13**	**0.92**	**0.82**	**0.76**	0.15		0.25	0.14	**0.78**	0.33
	(5.07)	**(4.98)**	**(4.30)**	**(4.10)**	(0.96)		(1.92)	(0.87)	**(2.25)**	(1.67)
CH-4+Geographic	**1.35**	**1.18**	**1.09**	**1.05**	**0.59**	**0.55**		**0.44**	**1.05**	0.34
	(4.79)	**(4.47)**	**(3.90)**	**(3.75)**	**(2.21)**	**(2.26)**		**(2.07)**	**(2.61)**	(0.92)
CH-4+Technology	**1.23**	**1.04**	**0.95**	**0.91**	0.34	0.27	**0.27**		**0.93**	0.25
	(4.59)	**(4.38)**	**(3.77)**	**(3.62)**	(1.59)	(1.41)	**(2.05)**		**(2.50)**	(0.98)
CH-4+Statistical	**0.97**	**0.74**	**0.60**	**0.50**	0.20	0.23	0.23	0.25		0.04
	(4.04)	**(3.53)**	**(2.94)**	**(2.65)**	(0.90)	(0.97)	(1.69)	(1.24)		(0.14)
CH-4+Concept	**1.06**	**0.83**	**0.70**	**0.58**	0.29	-0.16	**0.35**	0.04	**0.92**	
	(4.07)	**(3.94)**	**(3.45)**	**(2.91)**	(1.30)	(-0.89)	**(2.19)**	(0.18)	**(2.61)**	
CH-4+Non_news	**0.89**	**0.70**	**0.51**	**0.40**						
	(3.50)	**(3.44)**	**(2.71)**	**(2.15)**						
Panel B: CH-4+Article_3 factor loading (*same_article* type)										
	Article_3	Article_6	Article_9	Article_12	Anayst	Industry	Geographic	Technology	Statistical	Concept
Article_3		**0.931**	**0.946**	**0.962**	**0.977**	**0.895**	**0.108**	**0.654**	**1.005**	**0.911**
		(40.71)	**(28.88)**	**(22.33)**	**(14.25)**	**(13.73)**	**(4.00)**	**(8.51)**	**(9.84)**	**(7.70)**
mktrf		-0.002	-0.004	-0.017	-0.081	-0.065	0.012	-0.031	-0.074	0.006
		(-0.23)	(-0.24)	(-0.93)	(-3.49)	(-2.66)	(0.89)	(-1.40)	(-1.67)	(0.15)
VMG		-0.018	-0.001	0.005	0.004	-0.014	-0.026	-0.049	0.025	0.035
		(-0.87)	(-0.02)	(0.17)	(0.07)	(-0.20)	(-0.98)	(-0.70)	(0.22)	(0.40)
SMB		0.003	0.027	0.047	0.048	0.055	-0.002	-0.029	0.072	0.050
		(0.16)	(0.90)	(1.32)	(0.76)	(0.83)	(-0.07)	(-0.52)	(0.63)	(0.57)
PMO		-0.001	-0.005	-0.019	-0.064	-0.021	-0.017	-0.049	-0.185	0.093
		(-0.05)	(-0.27)	(-0.75)	(-1.59)	(-0.47)	(-1.05)	(-1.26)	(-2.15)	(1.05)
Adj. R2		0.876	0.823	0.785	0.538	0.492	0.072	0.328	0.361	0.412
# Obs.		464	464	464	464	464	464	464	464	227

Panel A reports the intercept (or alpha) of regressing the time series of different long-short momentum returns on the CH-4 factors (MKT, SMB, HML, PMO) (Liu et al., 2019) plus each MS momentum spillover factor. The construction of the MS factor is given in subsection 4.1. The column name indicates the type of long-short momentum return (i.e., the dependent variable), while the row name indicates the augmented CH-4 model (i.e., the original CH-4 model plus a specific MS factor). For example, the alphas of the row CH-4+Ariticle_3 indicate the alphas from the time-series regressions of long-short portfolio returns of other momentums on MKT, SMB, HML, PMO and the Article_3 factor. In the last row of panel A, we include all the six momentum spillover factors that are not related to news as additional explanatory variables. News co-mention momentum factors are based on *same_article* type under identification windows including 3-month, 6-month, 9-month, and 12-month. The industry momentum is based on the Shenwan-1 classification, while the geographic momentum is conducted on the province level. We do not consider the customer momentum due to the low data quality. The sample stocks include all listed stocks on the main board of the Shanghai Stock Exchange, Shenzhen Stock Exchange, and Growth Enterprise Market (GEM). ST shares are excluded. The sample period of news co-mention momentum is 2012-2020. The sample period of concept momentum is Aug. 2016-2020. The sample periods for other momentums are 2006-2020. Newey and West (1987) adjusted t-statistics are shown in parentheses. Alphas with t-statistics higher than 2.00 are highlighted in bold. Panel B reports the factor loads of other momentum spillover factors on the CH-4+Ariticle_3 model. Coefficients with t-statistics higher than 2.00 are highlighted in bold.