1-2022

Concept links and return momentum

Qianqian DU
Southwestern University of Finance and Economics

Dawei LIANG
Southwestern University of Finance and Economics

Zilin CHEN
Southwestern University of Finance and Economics

Jun TU
Singapore Management University, tujun@smu.edu.sg

Concept links and return momentum

Qianqian Du[a], Dawei Liang[a], Zilin Chen[b], Jun Tu[c]

a Research Institute of Economics and Management, Southwestern University of Finance and Economics, Chengdu 611130, China
b School of Finance, The Southwestern University of Finance and Economics, Chengdu 611130, China
c Lee Kong Chian School of Business, Singapore Management University, 178899, Singapore

Published in Journal of Banking & Finance, January 2022, 134, 106329, pp. 1-13

Abstract

Unlike traditional asset categories (e.g., industry classifications) that are generally defined clearly, some groups of stocks are tied to certain loosely defined “concepts” (e.g., e-commerce). When investors find it difficult to analyze ambiguous concept-oriented information, information diffuses slowly, creating “concept momentum”. Based on unique concept data in the Chinese stock market, this study constructs a concept-momentum strategy that involves buying stocks from past winning concepts and selling stocks from past losing concepts, which can generate pronounced abnormal returns. Neither risk factors, firm-level momentum, nor industry-level momentum can explain concept momentum. Furthermore, we find that both the underreaction and cross-stock lead-lag effect channels can cause slow information diffusion and drive concept momentum. Moreover, the concept momentum effect is stronger for relatively ambiguous concepts, for concepts that attract less investor attention, and following high-sentiment periods.

Keywords:

Asset classifications, Category learning, Concept stocks, Momentum effects

1. Introduction

Investors in financial markets focus considerable attention on classifying financial assets into categories. Attention is a scarce cognitive resource (Kahneman, 1973), so categorization simplifies portfolio-allocation decisions and helps investors process vast amounts of information efficiently (Mullainathan, 2002). Many studies have analyzed the investor decision-making process theoretically across various asset categories (e.g., Mullainathan, 2002; Barberis and Shleifer, 2003; Peng and Xiong, 2006).

Cooper et al. (2001) show that, during the Internet bubble period (1998–1999), firms that had adopted dot.com names without embracing specific internet-related investment strategies earned significantly positive abnormal returns around their name-change announcements. This evidence indicates that asset categorizations that matter to investors can be tied not only to traditional industries or products, linked by “hard” or physical characteristics, but also to technologies or business models, such as the internet in the 1990s and e-commerce in recent years. The latter represent softer or more “concept”-oriented links.[1]

Unlike the traditional hard or physical characteristics-oriented categorizations that typically are clearly defined, one “concept” generally refers to a category of stocks that share a particular trend or fad in the market based in loosely defined fundamental connections (e.g., e-commerce). This makes it difficult for investors to analyze news related to an ambiguous concept. This difficulty with information processing may lead to underreaction to good (bad) news related to “winner” (“loser”) concepts. Therefore, we may expect to observe ex-ante strong return momentum effects across winner and loser concepts. Nevertheless, detailed data pertaining to concept-oriented asset categories in the US stock market seem unavailable. In this study, equipped with unique concept data in the Chinese stock market, we are able to investigate a new type of momentum-based trading strategy, namely concept momentum. Using web-crawling technology, we collect from the Joinquant website more than 800 unique concepts and historical lists of firms in each concept.2 For example, many concepts are related to technology, such as 5 G, artificial intelligence (AI), and blockchain. There are also many concepts based on business models, including e-commerce, the sharing economy, the stall economy, and others.

[1] The most widely used asset categorization proxies in the literature, i.e., those under the Standard Industry Classification (SIC), fail to reclassify efficiently over time as firms and markets evolve (Hoberg and Phillips, 2016, 2018). Hoberg and Philips (2016) develop asset categories in what they call Text-Based Network Industry Classifications (TNIC) based on product similarity measures using textual analyses of firms’ 10-K product descriptions. TNIC captures product similarities in a time series, but unlike “concept” categorizations it is not directly visible to investors.

The concept portfolio we construct is equal-weighted across the stocks within each concept. Following Moskowitz and Grinblatt (1999), we devise concept-momentum strategies by sorting concept portfolios into quintiles based on their return performance in recent months (the formation period, i.e., F), buying stocks from the top quintile of concepts while shorting stocks from the bottom quintile, holding those concepts for the following several months (the holding period, i.e., H), and rebalancing portfolios every month. We construct 32 momentum strategies using combinations of formation and holding periods and find a strong and prevalent momentum effect based on these concept-momentum strategies.[3] For instance, one concept-momentum strategy, where $F = 6$ months and $H = 6$ months while skipping one month between the formation and holding periods, generates an average monthly raw return of 1.35% (with a t-statistic of 4.48), and a Fama and French (2015) five-factor adjusted return of 1.25% (with a t-statistic of 5.53). These results are robust to formulating concept-momentum strategies based on an alternative construction method and applying the Liu et al. (2019) four-factor model to adjust returns.

In addition, we explore whether the concept-momentum effect could be explained by firm-level momentum or industry-level momentum. First, we find that firm-level momentum on the intermediate horizon is nonsignificant in China, which is consistent with previous findings reported in the literature (e.g., Griffin et al., 2003; Chui et al., 2010). Second, following Moskowitz and Grinblatt (1999), we construct industry-momentum strategies by buying winner-industry portfolios and shorting loser-industry portfolios. We find that industry-momentum strategies are unable to produce significant profits in the Chinese stock market. Overall, the concept-momentum effect cannot be explained by either nonsignificant industry momentum or firm-level momentum.

We also conduct a placebo test in which we reshuffle all the sample firms in each month and randomly assign a stock to replace the stock within a given concept to form "placebo concept momentum" portfolios. The strategies included in the placebo test generate nonsignificant returns, indicating that the concept momentum we document stems from the concept effect rather than the construction mechanism.

We next conduct a Fama and MacBeth (1973) regression to investigate the concept momentum effect. After controlling for a set of well-documented indicators, including size, the book-to-market equity ratio (BTM), institutional ownership, turnover, gross profitability, and the investment-to-asset ratio, the relationship between concept-level past cumulative returns and future returns is consistently significant.

We then explore the mechanism underlying the concept momentum effect in greater depth. We find that the winner concept quintile generates significantly higher standardized unexpected earnings than the loser quintile, indicating that concept momentum is likely to be driven by investor underreaction to earnings information related to concept stocks. We further find that such mispricing is partly corrected following earnings announcements. Moreover, we find that investors fail to fully incorporate return information related to peer firms associated with the same concept, which may also be the factor that drives the concept-momentum effect. Furthermore, we find that concept momentum exhibits a long-term reversal pattern, consistent with Hong and Stein's (1999) prediction.

Further analyze show that, for relatively ambiguous concepts and concepts that attract less investor attention, the concept-momentum effect is more pronounced, consistent with the investor underreaction argument. Following Baker and Wurgler (2006), we construct a monthly investor sentiment index using Chinese stock market data and find that the concept-momentum strategy is more profitable following high-sentiment periods. We further analyze the persistence of the concepts and find that concepts become less persistent over the following 6 and 12 months, consistent with the persistence of industry momentum in the US market.

This study contributes to the momentum literature. It has been well-documented that the momentum effect exists almost everywhere. It occurs both cross-sectionally (Jegadeesh and Titman,1993) and in time series (Moskowitz et al., 2012); it is prevalent across asset classes (Asness et al., 2013) and industries (Moskowitz and Grinblatt, 1999). Many studies also find that momentum is pervasive not only in the US market but also around the world (e.g., Chan et al., 2000; Griffin et al., 2003; Chui et al., 2010; Gong et al., 2015). Our findings further extend the frontier of the momentum literature by employing novel data to investigate a new type of momentum effect. This study also adds to the category-investment literature by proposing a new type of category investment strategy, the concept-momentum strategy, which might be driven by difficulty in information processing given a lack of the investor expertise that is needed to analyze relatively ambiguous concept categories.

The remainder of this paper is organized as follows. In Section 2, we describe the data and portfolio construction. Section 3 presents the main empirical results. In Section 4 we show how we conduct mechanism analyze. In Section 5, we offer some further analyses. Section 6 concludes.

2. Data and summary statistics

2.1. Data description

Concept-oriented asset classification is a widely accepted practical classification system, but it differs greatly from traditional industry-asset classifications that are time-series constant and follow rigid classification rules. Most influential Chinese financial websites and trading apps provide information about concept-oriented asset classifications and detailed lists of firms within each concept based on their analyses. For these classifications, the basic rule for including a firm or excluding a firm from association with a given concept is whether the firm's business is closely related to the concept or not. The Joinquant database integrates concept information from the main Chinese financial websites and trading apps.[4] New concepts are often created soon after certain emergencies occur. For instance, the Mask concept appeared in the database on February 4, 2020 immediately following the COVID-19 pandemic outbreak in China. New concepts are also initiated because of certain news events, such as the Winter Olympics.[5]

Although trading in concepts is very popular among Chinese investors, data related to such concepts are not directly available. To the best of our knowledge, the Joinquant database is the only source providing historical data related to concepts, whereas the concept information provided by other financial websites and trading apps can be scraped back up to only three months in the past. In this study, we employ web-crawling technology and scrape the historical detailed firm lists for the concept-oriented asset cate-

[3] Some firms are labelled with more than one concept. For the main results, when we calculate a portfolio's holding return, we retain the firms within the concept that has achieved the best past performance. In Section 2.1, we use alternative means to address the cross-concept problem.

[4] The Joinquant database integrates data from many Chinese financial websites and trading apps, including https://finance.sina.com.cn/stock/, http://q.stock.sohu.com/, Eastmoney, Tonghuashun, Dazhihui, et al.

[5] Beijing was selected as the host city for the 2022 Winter Olympic Games on July 31, 2018, whereas the concept of the Winter Olympics was created on May 23, 2018, reflecting investors' expectations related to the associated events.

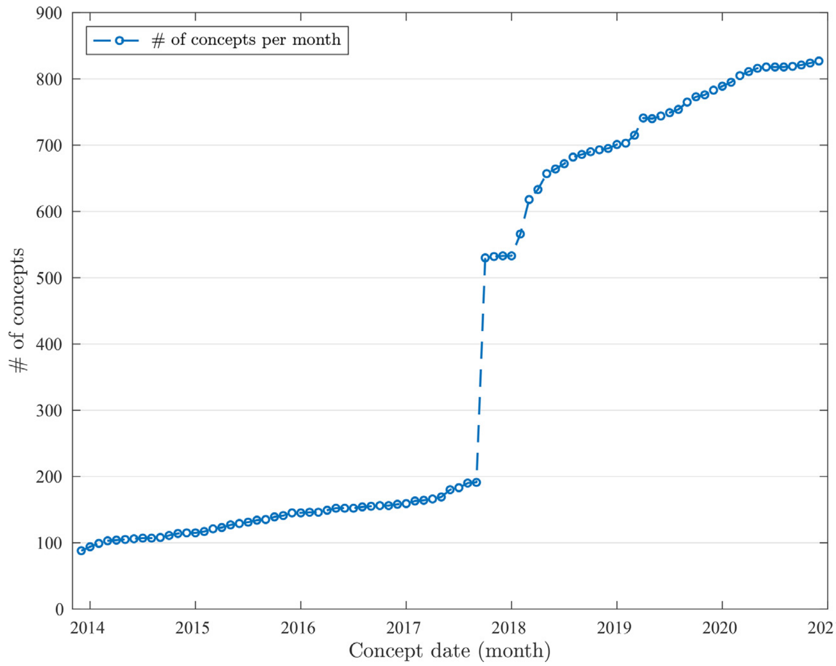

Fig. 1. Distribution of concept categories.
This figure depicts the number of concept categories across time. The sample period runs from December 2013 through December 2020.

gories from the Joinquant database. The concept data provided in Joinquant are integrated from financial websites and trading apps. Therefore, the concept data resolve the concern about disagreement between concept lists from different resources and largely represent the market's overall opinion regarding concept-level asset classifications.

Our sample of concept stocks spans a period that runs from December 2013 through December 2020. Fig. 1 depicts the distribution of the concepts, where the number of concepts continues expanding during our sample period.[6] Within each concept, the lists of firms are not constant over time. Firms are added to or dropped from particular concepts according to their businesses' closeness to those concepts. Fig. 2 indicates how the number of firms associated with a specific concept changes over time, where we exclude concepts for the first month after they appear in the database to illustrate changes in concept size. The circles (crosses) indicate the number of added (excluded) firms, and the squares indicate that the number of firms within a particular concept has not changed during that month. Generally, we find that the number of firms associated with a given concept is quite volatile. For example, the number of firms within the MSCI China concept has increased by more than 1000 firms in May 2019, as MSCI increased the weight of China A shares on MSCI indices from 5% to 10% and added China Large Cap shares with a 10% inclusion factor.

Insofar as 73.4% of firms in the concept portfolio sample are labelled with more than one concept, we need to address a cross-labeling problem. In this study's main tests we construct winner or loser portfolios based on concepts' past return performance, which is quite consistent with investor trading behavior in the Chinese stock market. That is, investors observe the return on a given concept, which is provided directly by most of the apps. In calculating holding returns, if a firm is cross-labelled, we retain the firm within the concept that achieves the best performance among the cross-labelled concepts in the formation period. To check robustness, we apply an alternative symmetric method for sorting cross-labelled firms: if a firm is labelled within N concepts, we allocate the weight 1/N to the focal firm when calculating return performance in both the formation period and the holding period.

To construct a momentum strategy, we further remove stocks that hit price limits on the last trading day of each month, which generates price momentum mechanically.[7] In the sample for the main test, we have on average 254 concepts per month and 10.3 stocks per concept, which represent 83.77% of the firms listed on the Shanghai and Shenzhen stock exchanges.[8] The return data and accounting data for firms listed on these exchanges are derived from the CSMAR database, which is one of the most widely used databases in Chinese stock market research. Table 1 presents the summary statistics for the main variables at the concept level. Size has a mean of 12,918.45 (million *yuan*) and a median of 9234.61 (million *yuan*). BTM has a mean of 0.60 and a median of 0.59. The descriptive statistics indicate that our sample is comparable to those used in other studies, such as Liao et al. (2014) and Liu and Pi (2007).

2.2. Portfolio formation

In this study, we construct firm-level, industry-level, and concept-level momentum strategies. When we examine firm-level momentum effects, we construct overlapping momentum portfolios following Jegadeesh and Titman (1993). For the beginning of each month, the firms in our sample are sorted into quintile groups based on returns in the previous F months and held for the following H months. The returns on the momentum strategy are

[6] The number of concepts increased sharply in October 2017. According to the explanation the database offered, the sharp increase can be attributed to an expansion of data resources where the concept data were integrated. The database does not however disclose further information about the names of the expanded data resources.

[7] In the A-share market, the price limit for stocks on both main boards and the growth enterprises board was 10% per day before August 24, 2020; after August 24, 2020, the price limit for stocks on the growth enterprises board changed to 20% per day.

[8] The monthly mean of the listed firms on the Shanghai and Shenzhen stock exchanges with trading data available in our sample period is 3,123. Our sample therefore generally accounts for 83.77% of the listed firms.

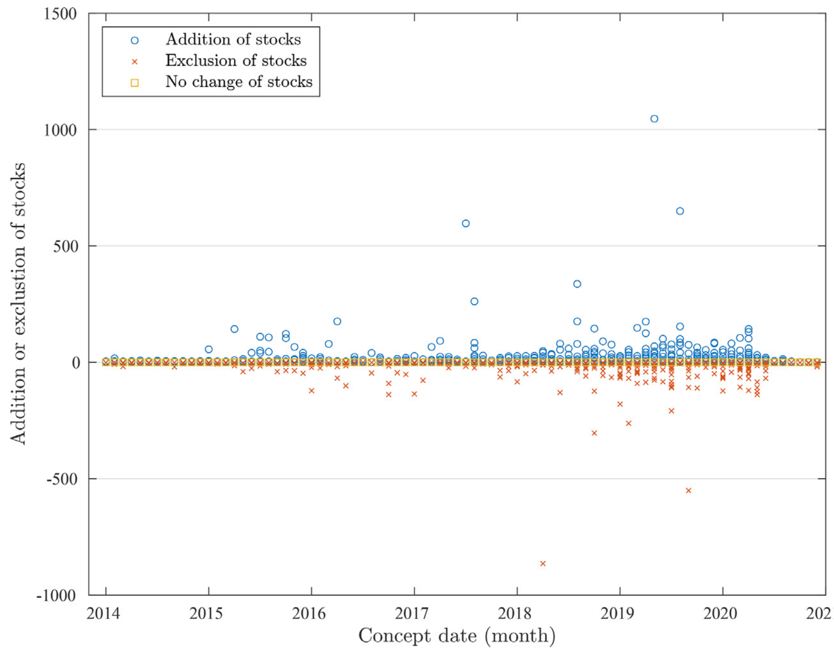

Fig. 2. Addition and exclusion of stocks per concept over time.
This figure depicts changes in the number of firms associated with a specific concept over time. The circles (crosses) indicate the number of added (excluded) firms associated with a concept and the squares indicate the number of firms associated with the concept that did not change in a given month.

Table 1
Summary statistics.
This table presents summary statistics for the main variables at the concept level. *Size*, denominated in millions of *yuan*, is the natural logarithm of a firm's market capitalization. *BTM* is the book-to-market equity ratio estimated at the end of the previous year. *Institutional ownership* is the percentage of institutional investors holding a stock. *Investment-to-assets* is the ratio of capital investment to assets. *Gross profitability* is net income scaled by total assets. *Trading volume* is total trading volume scaled by shares outstanding. *Ambiguity* is monthly analyst forecast dispersion scaled by a firm's stock price on the end date of the previous fiscal year, where its magnitude is multiplied by 10. The sample period runs from December 2013 through December 2020.

	Mean	Std.	25%	Median	75%
Size (million)	12,918.45	12,586.54	5956.70	9234.61	14,540.38
BTM	0.6	0.17	0.48	0.59	0.71
Institutional ownership	0.06	0.03	0.04	0.06	0.08
Investment-to-asset	0.05	0.02	0.03	0.04	0.06
Gross profitability	0.3	0.11	0.23	0.29	0.35
Trading volume	364.11	229.65	193.33	302.4	477.69
Ambiguity	0.05	0.05	0.02	0.04	0.06

based on portfolios with overlapping holding periods. In particular, in each month, we change 1/H of the securities in the entire portfolio and carry over the rest. To minimize the effects of short-term reversals (Chui et al., 2010), for the main results we construct portfolios by skipping one month between the formation period and the holding period. We also form portfolios with no gap between the formation period and the holding period to check robustness.

Industry-momentum strategies are constructed following Moskowitz and Grinblatt (1999). We sort industry portfolios into quintiles based on their past F-months return performance, buy the winner quintile and short the loser quintile, hold for the following H months, and rebalance portfolios monthly. Concept-momentum strategies are constructed similarly to the industry-momentum strategy, based on the F-months lagged returns on concept portfolios and held for the following H months.[9]

[9] When we construct a momentum strategy, we need the concepts to have been in the database for at least F (F = 3, 6, 9, or 12) months to calculate the formation-period performance.

3. Main empirical findings

3.1. Concept-momentum effect

In this section, we begin the presentation of our empirical analyses by exploring how the investment strategy based on concept-level momentum performs. The concept portfolio is equal-weighted across the stocks within each concept. Inspired by Moskowitz and Grinblatt (1999), we construct concept-momentum strategies by sorting concept portfolios based on their return performance in the formation period (F months) into quintiles. We buy stocks from the top quintile of concepts (Winners) while shorting stocks from the bottom quintile (Losers), holding this position for the following H months and rebalancing the portfolios monthly. We construct both concept-momentum strategies with one-month skipping between the formation period and the holding period and concept-momentum strategies without such one-month skipping, and present the return performances of the strategies in Table 2.

Table 2
Concept-momentum effect.
This table presents results indicating the performance of concept-momentum strategies in China. Panel A presents equal-weighted average monthly raw returns in percentages for the winner, loser, and winner-minus-loser portfolios of the concept-momentum strategies over varying formation and holding and periods. Panel B presents average monthly Fama and French (2015) five-factor adjusted returns for the portfolios. For W – L portfolios' raw returns and adjusted returns, statistical significance at the 5% level is indicated in bold. Newey and West (1987) *t*-statistics are shown in parentheses. The length of a lag depends on H, where $H = 3$, 6, 9, or 12 months. For winner-minus-loser portfolios' raw returns and adjusted returns, statistical significance at the 5% level is indicated in bold. The sample period runs from December 2013 through December 2020.

Panel A Monthly raw return

		Without skipping				Skipping one month			
		$H = 3$	$H = 6$	$H = 9$	$H = 12$	$H = 3$	$H = 6$	$H = 9$	$H = 12$
$F = 3$	W	0.43	0.54	0.57	0.54	0.62	0.73	0.70	0.65
		(0.39)	(0.58)	(0.57)	(0.52)	(0.55)	(0.74)	(0.66)	(0.60)
	L	−0.29	−0.38	−0.37	−0.32	−0.27	−0.40	−0.33	−0.27
		(−0.27)	(−0.37)	(−0.33)	(−0.28)	(−0.24)	(−0.37)	(−0.29)	(−0.24)
	W-L	**0.73**	**0.93**	**0.94**	**0.86**	**0.88**	**1.12**	**1.02**	**0.93**
		(2.03)	**(2.98)**	**(3.16)**	**(2.80)**	**(2.92)**	**(4.52)**	**(3.71)**	**(3.54)**
$F = 6$	W	0.75	0.83	0.78	0.69	0.72	0.79	0.68	0.61
		(0.66)	(0.84)	(0.73)	(0.64)	(0.63)	(0.79)	(0.63)	(0.56)
	L	−0.47	−0.50	−0.43	−0.37	−0.58	−0.57	−0.46	−0.41
		(−0.41)	(−0.45)	(−0.36)	(−0.31)	(−0.51)	(−0.52)	(−0.39)	(−0.35)
	W-L	**1.22**	**1.32**	**1.21**	**1.06**	**1.30**	**1.35**	**1.14**	**1.03**
		(3.51)	**(4.08)**	**(3.80)**	**(3.36)**	**(4.26)**	**(4.48)**	**(3.68)**	**(3.48)**
$F = 9$	W	0.74	0.67	0.56	0.49	0.55	0.42	0.33	0.26
		(0.63)	(0.67)	(0.53)	(0.46)	(0.47)	(0.42)	(0.32)	(0.26)
	L	−0.65	−0.72	−0.65	−0.56	−0.90	−0.90	−0.81	−0.73
		(−0.56)	(−0.67)	(−0.57)	(−0.50)	(−0.77)	(−0.86)	(−0.77)	(−0.70)
	W-L	**1.39**	**1.39**	**1.21**	**1.06**	**1.44**	**1.32**	**1.14**	**1.00**
		(3.88)	**(4.27)**	**(3.77)**	**(3.06)**	**(4.29)**	**(4.26)**	**(3.63)**	**(3.02)**
$F = 12$	W	0.41	0.33	0.26	0.16	0.44	0.41	0.31	0.22
		(0.33)	(0.32)	(0.25)	(0.15)	(0.34)	(0.36)	(0.27)	(0.20)
	L	−1.00	−1.00	−0.95	−0.90	−0.91	−0.93	−0.84	−0.81
		(−0.86)	(−0.99)	(−0.92)	(−0.89)	(−0.77)	(−0.88)	(−0.79)	(−0.77)
	W-L	**1.41**	**1.33**	**1.20**	**1.06**	**1.35**	**1.33**	**1.15**	**1.04**
		(3.96)	**(4.18)**	**(3.45)**	**(2.84)**	**(4.27)**	**(4.45)**	**(3.34)**	**(2.79)**

Panel *B* Fama and French (2015) five-factor adjusted returns

		Without skipping				Skipping one month			
		$H = 3$	$H = 6$	$H = 9$	$H = 12$	$H = 3$	$H = 6$	$H = 9$	$H = 12$
$F = 3$	W	−0.76	−0.58	−0.56	−0.60	−0.58	−0.46	−0.49	−0.53
		(−3.59)	(−3.44)	(−3.92)	(−4.45)	(−3.01)	(−3.01)	(−3.28)	(−3.84)
	L	−1.18	−1.37	−1.37	−1.32	−1.29	−1.48	−1.40	−1.36
		(−4.66)	(−5.99)	(−6.13)	(−5.70)	(−5.92)	(−7.35)	(−6.45)	(−6.32)
	W-L	0.42	**0.79**	**0.80**	**0.73**	**0.71**	**1.02**	**0.91**	**0.83**
		(1.10)	**(2.66)**	**(3.08)**	**(2.77)**	**(2.42)**	**(4.90)**	**(4.02)**	**(4.17)**
$F = 6$	W	−0.49	−0.40	−0.46	−0.53	−0.46	−0.39	−0.50	−0.55
		(−2.23)	(−2.38)	(−3.04)	(−4.14)	(−2.34)	(−2.48)	(−3.29)	(−4.39)
	L	−1.53	−1.59	−1.53	−1.47	−1.63	−1.63	−1.53	−1.49
		(−6.93)	(−7.01)	(−6.56)	(−6.34)	(−8.26)	(−7.69)	(−6.86)	(−6.82)
	W-L	**1.04**	**1.19**	**1.07**	**0.94**	**1.18**	**1.25**	**1.03**	**0.94**
		(2.87)	**(4.21)**	**(4.07)**	**(3.72)**	**(4.18)**	**(5.53)**	**(4.27)**	**(4.23)**
$F = 9$	W	−0.37	−0.41	−0.50	−0.55	−0.37	−0.47	−0.53	−0.58
		(−1.83)	(−2.37)	(−3.38)	(−4.37)	(−1.91)	(−2.80)	(−3.44)	(−4.15)
	L	−1.51	−1.61	−1.54	−1.46	−1.57	−1.60	−1.51	−1.44
		(−6.27)	(−7.13)	(−6.43)	(−5.78)	(−6.67)	(−7.10)	(−6.48)	(−5.90)
	W-L	**1.14**	**1.20**	**1.04**	**0.91**	**1.20**	**1.13**	**0.98**	**0.86**
		(3.32)	**(4.31)**	**(3.97)**	**(3.31)**	**(3.85)**	**(4.45)**	**(3.90)**	**(3.30)**
$F = 12$	W	−0.50	−0.49	−0.54	−0.63	−0.49	−0.47	−0.56	−0.63
		(−2.50)	(−2.98)	(−3.36)	(−3.94)	(−2.98)	(−2.81)	(−3.20)	(−3.49)
	L	−1.56	−1.59	−1.55	−1.51	−1.61	−1.63	−1.56	−1.53
		(−6.84)	(−6.79)	(−6.11)	(−5.70)	(−7.84)	(−7.41)	(−6.68)	(−6.32)
	W-L	**1.06**	**1.10**	**1.01**	**0.88**	**1.12**	**1.16**	**1.00**	**0.90**
		(3.30)	**(4.21)**	**(3.53)**	**(2.85)**	**(4.47)**	**(5.09)**	**(3.73)**	**(3.08)**

For Table 2, as we mentioned above, for each month, when we calculate the holding period return, if a firm is labelled with more than one concept, we retain the firm within the concept that yields the best performance among the cross-labelled concepts in the formation period. In Panel A of Table 2 we report equal-weighted average monthly raw returns on the winner, loser, and winner-minus-loser portfolios of the concept-momentum strategies, which are constructed over varying formation ($F = 3$, 6, 9, or 12 months) and holding ($H = 3$, 6, 9, or 12 months) periods. Whether we include the skipping of one month between the formation periods and holding periods or exclude such skipping, the winner-minus-loser portfolios consistently generate significant profits.[10]

In Panel B of Table 2 we report average monthly Fama and French (2015) five-factor adjusted returns for the winner, loser,

[10] Grundy and Martin (2001) find that industry momentum using SIC is not robust if we take a portfolio formation period with one lagged month into consideration. Our concept-momentum effects are robust when we skip one month.

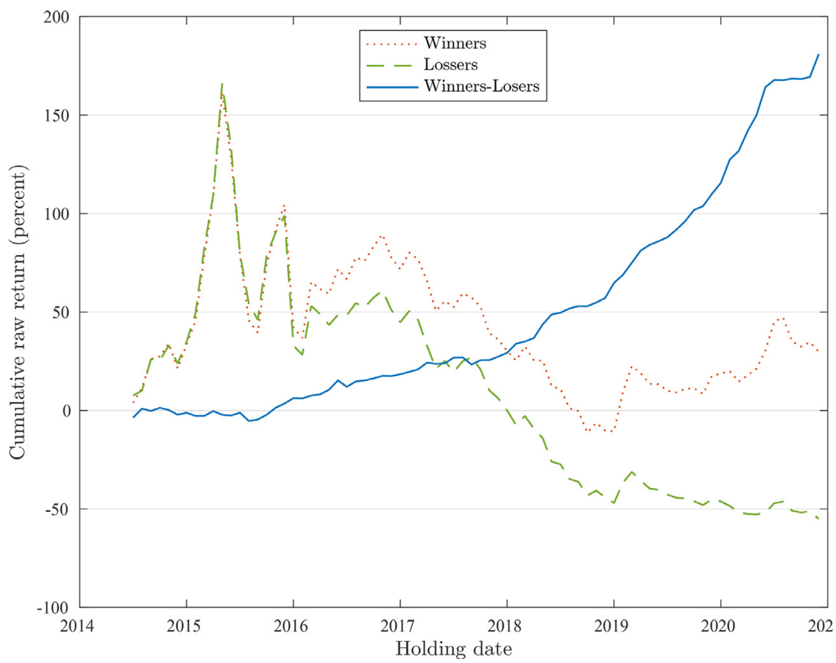

Fig. 3. Cumulative returns on concept momentum.
This figure depicts the cumulative returns on winner, loser, and winner-minus-loser portfolios for the concept-momentum strategy in which $F = 6$ months, $H = 6$ months, and we skip one month. The vertical axis represents cumulative returns (in percentages), and the horizonal axis represents holding time.

and winner-minus-loser portfolios of the 32 concept-momentum strategies.[11] The winner-minus-loser portfolios persistently generate positive and significant adjusted returns. For instance, the concept-momentum strategy in which $F = 6$ months, $H = 6$ months, and one month is skipped generates an average monthly Fama and French (2015) five-factor adjusted return of 1.25% (with a t-statistic of 5.53), which yields a significant yearly abnormal return of 15%. This result indicates that the concept-momentum effect is remarkably pronounced. Fig. 3 plots the cumulative returns of winner, loser, and winner-minus-loser portfolios for the concept-momentum strategy in which $F = 6$ months, $H = 6$ months, and we skip one month, showing the robust return patterns of this concept-momentum strategy over time.

Table 3 presents the results of a battery of robustness checks. For Panel A we apply an alternative method to address cross-labelled firms. If a firm is labelled with N concepts, we allocate the weight 1/N to the focal firm in calculating both formation and holding performance. For the sake of brevity, we report only average monthly adjusted returns for the winner, loser, and winner-minus-loser portfolios for the concept-momentum strategies in which $F = 6$ months and $H = 3$, 6, 9, or 12 months. The average monthly Fama and French (2015) five-factor adjusted returns for the winner minus loser portfolios are statistically significant. For example, the concept-momentum strategy in which $F = 6$ months, $H = 6$ months, and we skip one month generates a Fama and French (2015) five-factor adjusted return of 0.81% (with a t-statistic of 2.92) per month. The magnitudes of the spreads are smaller but comparable to those reported in Table 2, indicating that the concept-momentum effect is robust to the alternative construction method.

Liu et al. (2019) construct size and value factors for the Chinese stock market that demonstrate superior performance over the Fama and French three-factor model. For Panel B of Table 3, we apply Liu et al. (2019) four-factor model to calculate the adjusted returns.[12] The magnitude and significance of adjusted returns on the concept strategies are consistent with those reported in Table 2. For instance, the concept-momentum strategy in which $F = 6$ months, $H = 6$ months, and we skip one month generates an adjusted return of 1.56% (with a t-statistic of 5.64) per month, where the magnitude is slightly larger than that of the Fama and French (2015) five-factor adjusted returns achieved with the corresponding strategy. These results indicate that this concept-momentum strategy is robust to using alternative factor models. We further provide value-weighted portfolio performance results in the Internet Appendix (Table IA.1), where we show a consistently pronounced concept-momentum effect.

3.2. Firm-level momentum

In the previous section we document a pronounced concept-momentum effect. The question arises, though, whether concept momentum is really a new category-investment anomaly in the Chinese stock market or could be explained by other anomalies, such as firm-level momentum. We investigate the firm-level momentum effect in the Chinese stock market. In Internet Appendix Table IA.2 we report equal-weighted average monthly raw returns on portfolios (W–L) over various holding and formation periods. The results indicate that firm-level momentum at intermediate horizons cannot generate significant profits in China, which is consistent with findings reported in the literature (e.g., Griffin et al. 2003, Chui et al. 2010).[13] Chui et al. (2010) use the "individualism" culture perspective to explain the varying momentum patterns across countries and claim that a country where there is a low-individualism culture experiences nonsignificant momentum

[11] The Chinese version of the Fama and French (2015) five factors are available in the CSMAR database.

[12] The factors are provided at http://finance.wharton.upenn.edu/~stambaug/.

[13] Several papers argue that the momentum effect is pronounced in the Chinese stock market using alternative construction methods (e.g., Kang et al. 2002, Naughton et al. 2008). The nonsignificant momentum effect in China is however well documented in the literature (e.g., Wang and Zhao 2001, Griffin et al. 2003, Liu and Pi 2007, Chui et al. 2010).

Table 3
Robustness checks.
This table presents results of robustness checks for concept-momentum strategies. For panel *A*, we apply an alternative symmetric method to address cross-labelled firms. If a firm is labelled in *N* concepts, we allocate the weight 1/N to the focal firm in calculating both formation and holding performance. In panel *B*, we apply Liu et al. (2019) four-factor model to calculate adjusted returns. Newey and West (1987) *t*-statistics are shown in parentheses. The length of a lag depends on *H*, where H = 3, 6, 9, or 12 months. For winner-minus-loser portfolio returns, statistical significance at the 5% level is indicated in bold. The sample period runs from December 2013 through December 2020.

Panel *A* Fama and French (2015) five-factor adjusted returns based on an alternative construction method									
		Without skipping				Skipping one month			
		$H = 3$	$H = 6$	$H = 9$	$H = 12$	$H = 3$	$H = 6$	$H = 9$	$H = 12$
$F = 6$	W	−0.33	−0.33	−0.38	−0.44	−0.31	−0.32	−0.41	−0.46
		(−1.06)	(−1.12)	(−1.34)	(−1.54)	(−1.00)	(−1.14)	(−1.43)	(−1.59)
	L	−1.19	−1.18	−1.06	−1.04	−1.23	−1.13	−1.03	−1.03
		(−4.34)	(−4.06)	(−3.63)	(−3.62)	(−4.55)	(−3.89)	(−3.55)	(−3.58)
	W-L	**0.86**	**0.85**	**0.69**	0.62	**0.93**	**0.81**	**0.62**	0.57
		(2.53)	**(2.89)**	**(2.24)**	(1.89)	**(2.92)**	**(2.92)**	**(2.05)**	(1.80)

Panel B Liu et al. (2019) four-factor adjusted returns									
		Without skipping				Skipping one month			
		$H = 3$	$H = 6$	$H = 9$	$H = 12$	$H = 3$	$H = 6$	$H = 9$	$H = 12$
$F = 6$	W	0.13	0.17	0.11	0.00	0.14	0.19	0.06	−0.02
		(0.61)	(0.94)	(0.69)	(0.01)	(0.66)	(1.13)	(0.35)	(−0.12)
	L	−1.32	−1.37	−1.30	−1.20	−1.36	−1.38	−1.26	−1.19
		(−6.55)	(−6.05)	(−5.40)	(−4.75)	(−6.72)	(−5.83)	(−5.10)	(−4.69)
	W-L	**1.45**	**1.54**	**1.40**	**1.21**	**1.50**	**1.56**	**1.32**	**1.17**
		(4.48)	**(5.29)**	**(5.05)**	**(4.26)**	**(5.16)**	**(5.64)**	**(4.60)**	**(4.18)**

effect. According to Chui et al. (2010), Chinese investors score relatively low on the individualism scale and overall lack overconfidence, and therefore the firm-level momentum effect is not pronounced in the Chinese stock market. Because firm-level momentum effect is nonsignificant in the Chinese stock market, it is unlikely to be the source of concept momentum.

3.3. *Industry momentum*

Moskowitz and Grinblatt (1999) document a strong industry momentum effect that accounts for much firm-level momentum in the US market. Grundy and Martin (2001) find, however, that the industry-momentum effect using SIC is not robust when considering the bid–ask bounce and a portfolio-formation period with one lagged month. Insofar as some concepts in the Chinese stock market are related to specific industries, it might seem possible that industry momentum could be the source of the observed concept momentum. To resolve this concern, we explore whether the industry-momentum effect is significant in the Chinese stock market.

We form an industry portfolio using the China SEC industry classification code (2012), which classifies the A-share listed firms into 90 industries. We sort industry portfolios into quintiles based on cumulative returns for the previous F months, where the top quintile portfolio is the winner portfolio and the bottom quintile portfolio is the loser portfolio. For the sake of brevity, in Table 4 we report only monthly raw returns for the portfolios formed according to returns achieved in the previous 6 months, where $F = 6$ months, $H = 3$, 6, 9, or 12 months, with or without skipping one month. All the winner-minus-loser portfolios generate nonsignificant raw returns, indicating that the industry-momentum effect is not pronounced in the Chinese stock market. Therefore, industry momentum cannot be the force driving the concept-momentum effect.

We next compare the names of China SEC industries and concepts. First, we find that all industry names based on the SEC industry classification differ from the concept names, so there are no perfect matches. Second, we apply the word-segmentation technique, which is commonly used in natural language processing (e.g., Loughran and McDonald, 2011) to further compare the words in the names. Specifically, we tokenize all industry and concept names into single words and drop the stop words. There are then 162 words left for industry names and 965 words left for concept names. We find that only 4.15% of the words among the concept names are matched with words among the industry names, indicating that a large proportion of the words in the concept names differ from those among the industry names.

Generally, the industry classification differs from the concept-oriented asset classification. The nonsignificance of the momentum effect based on the industry classification might be caused by its failure to reclassify efficiently over time as firms and markets evolve. Therefore, static industry classifications cannot represent market perceptions of the asset classifications and are inappropriate for testing category-level investment behaviors.

3.4. *Placebo test*

In this section, we further test the concept-momentum effect by conducting a placebo test in which we reshuffle all the firms in each month and randomly assign a stock to replace the stock that falls within a given concept. After we replace the firms in the concept portfolios by the matched firms, we follow the procedures for constructing concept-momentum strategies presented in Section 3.1 and form "placebo concept-momentum portfolios". If the winner-minus-loser portfolios in the placebo concept-momentum strategy are significant, the results run against our argument that the return pattern we document is a new type of anomaly based on concept stocks.

In the Internet Appendix Table IA.3, we report average monthly raw returns for the winner, loser, and winner-minus-loser portfolios for the placebo concept-momentum strategies. We find that all the winner-minus-loser portfolios for the placebo concept-momentum strategies generate nonsignificant returns, indicating that the placebo concept-momentum effect is not statistically prominent. The results further support out conclusion that the concept momentum effect we document stems from the concepts themselves rather than the construction mechanism.

Table 4
Industry momentum.
This table presents average monthly raw returns in percentages for industry-momentum strategies in China. Following Moskowitz and Grinblatt (1999), we sort industry portfolios into deciles based on their cumulative returns for the previous 6 months. The top decile portfolio is the winner portfolio and the bottom decile portfolio is the loser portfolio. Newey and West (1987) *t*-statistics are shown in parentheses. The length of a lag depends on H, where $H = 3$, 6, 9, or 12 months. The sample period runs from December 2013 through December 2020.

		Without skipping				Skipping one month			
		$H = 3$	$H = 6$	$H = 9$	$H = 12$	$H = 3$	$H = 6$	$H = 9$	$H = 12$
$F = 6$	W	1.23	1.47	1.46	1.44	1.40	1.49	1.43	1.42
		(1.16)	(1.51)	(1.35)	(1.30)	(1.30)	(1.49)	(1.31)	(1.27)
	L	1.39	1.26	1.28	1.30	1.19	1.17	1.24	1.25
		(1.33)	(1.24)	(1.20)	(1.21)	(1.13)	(1.14)	(1.17)	(1.17)
	W-L	−0.16	0.21	0.18	0.14	0.20	0.32	0.20	0.17
		(−0.59)	(0.98)	(0.90)	(0.75)	(0.67)	(1.52)	(0.93)	(0.86)

3.5. Regression analyze

The results we have reported so far show a significant concept-momentum effect based on the portfolio analysis, but this effect might be influenced by important variables that cannot be captured by the portfolio-analysis approach. Therefore, we follow the Fama and MacBeth (1973) regression approach to investigate the concept-momentum effect by controlling for variables that might influence future returns. Specifically, for each concept portfolio in month t we run the following cross-sectional Fama and MacBeth (1973) regression:

$$AveReturn_{i,\ t+1:t+6} = \beta_0 + \beta_1 CumReturn_{i,t-6:t-1} + \beta_2 Controls_{i,t} + \varepsilon_{i,t} \quad (1)$$

Here $AveReturn_{i,\ t\ +\ 1:t\ +\ 6}$ is the average monthly raw return on concept portfolio i in the following 6 months for a given month t, and $CumReturn_{i,\ t\text{-}6:t\text{-}1}$ denotes the cumulative raw return on a concept portfolio in the previous 6 months for a given month t. *Controls* include *size, BTM, institutional ownership, turnover, gross profitability,* and *investment-to-assets* at the end of month $t - 1$. *Size* is the natural logarithm of a firm's market capitalization. *BTM* is the book-to-market equity ratio. *Institutional ownership* is the percentage of institutional investors holding a stock. *Investment-to-assets* is the ratio of capital investment to assets. *Gross profitability* is net income scaled by total assets. *Trading volume* is total trading volume scaled by shares outstanding. All the control variables are constructed at the concept level, which are the means of the firm-level variables within each concept portfolio.

We report the regression results in Table 5. For specification (1), we conduct a univariable test and find that the regression coefficient of *CumReturn* is positive and statistically significant. For specification (2), after we control for additional variables including *size, BTM, institutional ownership, turnover, gross profitability* and *investment-to-assets*, the estimated coefficient of *CumReturn* is 0.29 with a *t*-statistic of 3.79. Overall, the results are consistent with those of the portfolio analyses reported in Tables 2 and 3, suggesting the strong predictability of a concept-level portfolio's past returns for future returns even after controlling for a set of firm-level characteristics.

4. Mechanism analyze

4.1. Concept momentum and earnings information

In this section, we conduct mechanism analyses to explore the sources of the concept-momentum effect. First, following Chan et al. (1996), we examine whether the concept-momentum effect is driven by underreaction to earnings information by comparing standardized unexpected earnings (SUE) on various concept quintiles. SUE is constructed as an individual firm's latest quarterly earnings minus quarterly earnings from 4 quarters in the past scaled by the standard deviation of unexpected earnings for the previous 8 quarters. The results reported in Panel A of Table 6 show that, in the current quarter, SUE in the winner quintile is 0.19 while SUE in the loser quintile is only −0.75, and the difference between the winner and loser quintiles is significant (with a *t*-statistic of 6.43). The pattern is consistent with that reported in Chan et al. (1996), indicating that concept momentum is closely aligned with underreaction to past earnings information related to the concept firms in our sample. In the following quarter, SUE continues to be higher in the winner quintile than in the loser quintile, consistent with Bernard and Thomas's (1990) finding that seasonal earnings information is time-series correlated and investors underreact to such earnings information.

We further compare cumulative three-day abnormal returns (CAR) around earnings announcement dates for various quintile portfolios. The results reported in Panel B of Table 6 indicate that CAR is significantly higher in the winner quintile than in the loser

Table 5
Fama and MacBeth regression analyze.
This table presents the Fama and MacBeth (1937) regression results. The dependent variable *AveReturn* is the average monthly raw return on concept portfolio *i* for the following 6 months. *CumReturn* denotes the cumulative return on the concept portfolio for the previous 6 months. Control variables include *Size, BTM, Institutional ownership, turnover, Gross profitability,* and *Investment to assets* at the concept level. *Ambiguity* is monthly analyst forecast dispersion scaled by a firm's stock price on the end date of the previous fiscal year. All the estimated coefficients are multiplied by 10. Newey and West (1987) *t*-statistics adjusted for a lag of 6 months are shown in parentheses. The estimated coefficients are marked with *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Intercept	−0.04	0.10	0.38
	(−0.52)	(0.43)	(1.12)
CumReturn	0.33***	0.29***	0.30***
	(3.46)	(3.79)	(3.08)
Size		−0.02	−0.04
		(−1.12)	(−1.34)
BTM		0.04	−0.14
		(0.60)	(−0.99)
Institutional ownership		0.80***	0.79***
		(2.54)	(2.41)
Turnover		−0.08	0.02
		(−1.14)	(0.29)
Gross profitability		−0.01	−0.08
		(−0.11)	(−0.46)
Investment-to-assets		−0.15	−0.01
		(−0.54)	(−0.05)
CumReturn*Ambiguity			16.91***
			(2.59)
Ambiguity			2.29
			(0.84)

Table 6
Earnings information and concept-momentum portfolios.
Panel *A* presents standardized unexpected earnings (SUE) for multiple concept-momentum portfolios for the contemporaneously current quarter and the following quarter, where the momentum strategy is $F = 6$ months, $H = 6$ months, and one month is skipped. Because firms within particular concepts might differ from quarter to quarter, the reported results are based on firms that are included within the same concept for both quarters. The magnitude of the SUE is multiplied by 10. Panel *B* presents cumulative three-day abnormal returns (CAR) around earnings-announcement dates, where the results are based on firms that are included within the same concept for the reported announcements. For W–L portfolio returns, statistical significance at the 5% level is indicated in bold.

Panel A Standardized unexpected earnings (SUE) for multiple concept quintiles							
	L	2	3	4	W	W-L	*t*-statistics
Current quarter	−0.75	−0.60	−0.38	0.01	0.19	**0.94**	**6.43**
Following quarter	−1.04	−0.41	−0.07	0.01	0.27	**1.31**	**8.54**
Panel B CAR in different concept quintiles							
	L	2	3	4	W	W-L	*t*-statistics
Current quarter	−0.85	−0.61	−0.47	−0.46	0.45	**1.31**	**13.02**
Following quarter	−0.83	−0.47	−0.25	−0.37	−0.39	**0.44**	**4.20**

quintile in both the portfolio-formation quarter and the following quarter. This finding indicates that mispricing caused by investor underreaction is partly corrected following earnings announcement dates.[14] Overall, the results reported in Table 6 indicate that underreaction to earnings information can drive concept momentum, which is consistent with the underreaction mechanism posited in the momentum literature (e.g., Chan et al., 1996; Barberis et al., 1998; Hong and Stein, 1999).[15]

4.2. Concept momentum and the cross-stock lead-lag effect

From the investor perspective, firms associated with the same concept are economically correlated peers. The literature documents that delayed information recognition causes significant lead-lag return predictability between economically correlated firms, such as within customer–supplier relationships (Cohen and Frazzini, 2008) or through technology linkages (Lee et al., 2019). To explore whether concept momentum is driven by the cross-stock lead-lag effect, we take other firms in a given concept as a focal firm's peers (Leary and Robert, 2014; Du and Shen, 2018) and conduct the following regression analysis:

$$Ret_{i,t} = \beta_0 + \beta_1 Concept\,Ret_{-i,t-1} + \varepsilon_{i,t} \tag{2}$$

where $Ret_{i,t}$ is the focal firm's raw return in month t and $ConceptRet_{-i,\ t-1}$ is the concept's raw return in month t – 1 excluding the focal firm.

In untabulated results, we find that the estimated coefficient of *ConceptRet* is 0.18 with a Newey-West corrected *t*-statistic of 38.36 when lagged one month and with a Newey-west *t*-statistic of 14.76 when lagged 6 months. These results indicate the presence of a significant cross-stock lead-lag effect within the concept, which might be a channel for the concept momentum we observe. Combining the findings reported in Section 4.1 with the findings reported in this section, it is possible in general that investors underreact to or fail to fully incorporate news about both the focal firm and its economically related firms that are associated with the same concept. Therefore, both the underreaction and cross-stock lead-lag effect channels can cause slow information diffusion and drive concept momentum.

4.3. Long-term performance

The momentum literature indicates that the momentum effect is accompanied by long-term reversals (e.g., Hong and Stein 1999, Jegadeesh and Titman, 2001). In this subsection, we explore whether the concept-momentum effect is followed by a long-term contrarian trend. In Table 7, we report the long-term performance of the concept-momentum strategy. For the sake of brevity, we report only the adjusted returns on the strategy in which $F = 6$ months and we skip one month.

The results reported in Table 7 show that the concept-momentum effect generates significant negative five-factor adjusted returns when holding stocks from months 25 through 48, while generating nonsignificant negative adjusted returns when holding stocks from months 13 through 24 and from months 49 through 60. Overall, these results show that concept momentum tends to be followed by long-term reversals, which is similar to the pattern of long-term reversals for the firm-level momentum strategy documented in the literature (e.g., Jegadeesh and Titman, 2001) and is consistent with Hong and Stein's (1999) prediction.[16]

5. Further analyze

5.1. Ambiguity and concept momentum

Differing from traditional categorizations, such as SIC classification, which commonly are defined clearly, concept-oriented categorizations are often loosely defined, which makes it difficult for investors to acquire the expertise they would need to incorporate news related to an ambiguous concept. We expect that, for relatively ambiguous concepts, investors will need more time to in-

[14] Such mispricing cannot however be fully corrected following earnings announcements, because investors may also underreact to earnings surprise information in earnings announcements, resulting in predictable return patterns, such as post-earnings-announcement drift (PEAD), which is well documented in the literature (e.g., Daniel et al. 2020).

[15] Other mechanisms, such as overconfidence or overreaction, might also drive the concept-momentum effect. A long-term reversal rather than short-term momentum is, however, more likely to be driven by overreaction to news. It seems that the literature often hypothesizes that investors tend to "overreact to private information signals and underreact to public signals" (Daniel et. 1998) rather than overreacting to public signals as in past returns on concept winners.

[16] Based on our finding (reported in Table 7) that the magnitude of the reversal is smaller than the magnitude of the momentum, it is possible that an initial underreaction is followed by an overreaction (both of which contribute to the momentum part) and we then have the reversal to correct the magnitude of the overreaction.

Table 7
Long-term performance of the concept-momentum strategy.
In this table we report average monthly Fama and French (2015) five-factor adjusted returns for the concept strategy in which $F = 6$ months and one month is skipped. For W–L portfolio returns, statistical significance at the 5% level is indicated in bold. The sample period runs from December 2013 through December 2020.

		Months 1 to 12	Months 13 to 24	Months 25 to 36	Months 37 to 48	Months 49 to 60
$F = 6$	W	−0.55	−1.42	−1.58	−1.39	−1.37
		(−4.39)	(−8.71)	(−8.16)	(−7.77)	(−3.34)
	L	−1.49	−1.32	−1.23	−1.09	−1.18
		(−6.82)	(−4.55)	(−4.47)	(−4.76)	(−4.46)
	W-L	**0.94**	−0.19	**−0.43**	**−0.29**	−0.19
		(4.23)	(−1.25)	**(−3.38)**	**(−2.08)**	(−1.31)

corporate such information, and therefore investor underreaction will be stronger and the concept-momentum effect will be more pronounced. We construct an indicator variable, *Ambiguity,* which is the concept-level mean of analyst forecast dispersion scaled by a firm's stock price, as a proxy for the ambiguity of a concept.[17] For each concept portfolio in month *t*, we run the following cross-sectional Fama and MacBeth (1973) regression:

$$AveReturn_{i,\ t+1:t+6} = \beta_0 + \beta_1 CumReturn_{i,\ t-6:t-1} + \beta_2 CumReturn_{i,\ t-6:t-1} \times Ambiguity_{i,t} + \beta_3 Ambiguity_{i,t} + \beta_4 Controls_{i,t} + \varepsilon_{i,t} \quad (3)$$

where β_2 is of our interest, indicating how the ambiguity of concepts impact the concept-momentum effect. $AveReturn_{i,\ t+1:t+6}$, $CumReturn_{i,\ t\text{-}6:t\text{-}1}$ and $Controls_{i,t}$ are defined as they are in model (1). The regression results are presented in specification (3) of Table 5. The estimated coefficient of the intersection between $CumReturn_{i,\ t\text{-}6:t\text{-}1}$ and $Ambiguity_{i,t}$ is 16.91 (with a *t*-statistic of 2.59), indicating that the concept-momentum effect is more pronounced for concepts that are associated with wider analyst dispersion.

5.2. Investor attention and concept momentum

If investor attention to concept news influences the information-diffusion process, we expect that, for concepts that attract more investor attention, the incorporation of concept-level information will be more efficient and the concept-momentum effect will be less significant. Prior literature posits three commonly used measures of investor attention: analyst coverage, size, and institutional ownership (e.g., Lee et al., 2019). We expect concepts that attract greater analyst reporting coverage, involve higher institutional holdings, or exhibit larger market capitalization to attract greater investor attention.

For each month in our sample period, we sort concept portfolios into terciles according to concept-level attention and then construct a concept-momentum strategy within each attention group following the procedures presented in Section 3.1. Table 8 presents the portfolio returns on concept-momentum strategies under various attention proxies. For the sake of brevity, we report only average monthly returns on the concept-momentum strategy in which $F = 6$ months and $H = 6$ months while skipping one month between the formation period and the holding period. For Panel A, we use concept-level analyst coverage as the proxy for investor attention. We find that the Fama and French (2015) five-factor adjusted return on the winner-minus-loser portfolio in the high-(low-)attention group is 0.88% (3.29%), and the difference between the adjusted return in the high- and low-attention groups is statistically significant (with a *t*-statistic of −2.79). For Panel B, concept-level market capitalization is used as the proxy for investor attention. We find that the concept-momentum strategy is more pronounced for concept stocks marked by small market capitalization, where the difference in raw returns between the high- and low-attention groups is 1.37%, with a *t*-statistic of −2.36, and the difference in the adjusted returns is 1.57% with a *t*-statistic of −3.43. In Panel *C*, the results we report show that the concept-momentum effect is more pronounced for firms with lower institutional ownership shares, and the difference between returns in the high- and low-attention groups is statistically significant. These findings are

Table 8
Investor attention and concept momentum.
In this table we report portfolio returns in percentages for concept-momentum strategies in the subsamples that are subject to varying investor-attention proxies. We construct concept-level analyst coverage, size, and institutional ownership as proxies for investor attention. We sort concepts into terciles based on investor attention and construct a concept momentum strategy for each attention group. We report equal-weighted average monthly raw returns and Fama and French (2015) five-factor adjusted returns for the portfolios. Newey and West (1987) *t*-statistics are reported in parentheses. The length of a lag depends on H, where $H = 3$, 6, 9, or 12 months. For W–L portfolio returns, statistical significance at the 5% level is indicated in bold. The sample period runs from December 2013 through December 2020.

Panel *A* Analyst coverage and concept momentum						
	Raw returns			Adjusted returns		
	H	*L*	H-L	*H*	*L*	H-L
W	1.20	2.45	−1.24	−0.07	1.57	−1.64
	(1.07)	(1.87)	(−1.32)	(−0.23)	(1.78)	(−1.66)
L	0.02	−0.90	0.92	−0.95	−1.73	0.78
	(0.02)	(−0.75)	(1.63)	(−4.16)	(−4.95)	(2.06)
W-L	**1.18**	**3.35**	**−2.17**	**0.88**	**3.29**	**−2.42**
	(3.29)	**(4.23)**	**(−2.47)**	**(3.42)**	**(4.23)**	**(−2.79)**
Panel B Size and concept momentum						
	Raw returns			Adjusted returns		
	H	L	H-L	H	L	H-L
W	1.11	1.67	−0.56	−0.13	0.62	−0.75
	(1.13)	(1.77)	(−1.32)	(−0.48)	(1.77)	(−1.65)
L	−0.00	−0.82	0.81	−1.12	−1.95	0.82
	(−0.00)	(−0.73)	(1.68)	(−2.90)	(−8.14)	(1.82)
W-L	**1.12**	**2.49**	**−1.37**	**0.99**	**2.57**	**−1.57**
	(2.07)	**(5.47)**	**(−2.36)**	**(2.76)**	**(6.18)**	**(−3.43)**
Panel C Institutional ownership and concept momentum						
	Raw returns			Adjusted returns		
	H	L	H-L	H	L	H-L
W	1.20	2.96	−1.76	−0.07	1.85	−1.92
	(1.00)	(2.70)	(−1.73)	(−0.13)	(2.92)	(−1.90)
L	−0.04	−0.46	0.42	−1.15	−1.40	0.26
	(−0.04)	(−0.41)	(0.87)	(−3.13)	(−4.43)	(0.51)
W-L	**1.24**	**3.42**	**−2.18**	**1.08**	**3.26**	**−2.18**
	(2.39)	**(5.37)**	**(−2.33)**	**(2.56)**	**(5.47)**	**(−2.48)**

[17] Analyst dispersion has been posited in the literature as a proxy for information uncertainty, as in Zhang (2006).

Table 9
Sentiment and concept momentum.
In this table, we report results obtained after exploring the performance of concept momentum following high or low investor sentiment. Following Baker and Wurgler (2006), we construct a monthly investor sentiment index, BW_{PRC}, using the first principal component of the six investor sentiment proxies in the Chinese stock market. Following Stambaugh et al. (2012), we define month t as a high (low) sentiment period if the investor sentiment index BW_{prc} for that month is above (below) the sample median. We report equal-weighted average monthly raw returns and Fama and French (2015) five-factor adjusted returns in percentages for the portfolios. t-statistics are reported in parentheses. The length of a lag depends on H, where $H = 3$, 6, 9, or 12 months. For W–L portfolio returns, statistical significance at the 5% level is indicated in bold. The sample period runs from December 2013 through December 2020.

	Raw returns			Adjusted returns		
	High	Low	H-L	High	Low	H-L
	sentiment	sentiment	sentiment	sentiment	sentiment	Sentiment
W	−0.27	1.70	−1.96	0.10	−0.63	0.73
	(−0.24)	(0.93)	(−0.78)	(0.76)	(−2.86)	(2.88)
L	−2.04	0.97	−3.01	−1.66	−1.25	−0.41
	(−1.84)	(0.50)	(−1.21)	(−5.70)	(−4.10)	(−1.05)
W-L	**1.77**	**0.72**	**1.04**	**1.76**	**0.62**	**1.14**
	(5.87)	**(2.17)**	**(2.35)**	**(7.63)**	**(2.20)**	**(3.01)**

consistent with our expectation that attention plays a crucial role in the information-diffusion process, i.e., the greater the investor attention the less pronounced is the concept-momentum effect.[18]

5.3. Investor sentiment and concept momentum

Previous literature indicates that the momentum effect is stronger following high-sentiment periods (Stambaugh et al., 2012; Antoniou et al., 2013). In this subsection, we explore whether concept-momentum performance varies following high- and low-sentiment periods. Following Baker and Wurgler (2006), we construct a monthly investor sentiment index BW_{PRC} using the first principal component of the six investor sentiment proxies from the Chinese stock market. The six proxies are the close-end fund discount rate (CEFD), share turnover (TURN), the number of IPOs (NIPO), first-day returns on IPOs (RIPO), the dividend premium (PDND), and the equity share in new issues (EQTI). Following Stambaugh et al. (2012), we define month t as a high- (low-) sentiment period if the investor sentiment index in that month is above (below) the median of BW_{PRC}.

In Table 9 we report average monthly portfolio returns for the concept-momentum strategy following high- and low-sentiment periods. We find that the concept-momentum strategy generates significantly higher adjusted returns in high-sentiment periods than in low-sentiment periods (with a difference of 1.14% and a t-statistic of 3.01). This finding is consistent with evidence documented in the previous literature that the momentum effect is more pronounced following high-sentiment periods (e.g., Stambaugh et al., 2012).[19]

5.4. Discussion: transaction costs

Insofar as the concept-momentum strategy is rebalanced monthly, we need to consider transaction costs when we estimate long–short spreads (Novy-Marx and Velikov, 2016). Compared with what occurs when pursuing an annual rebalanced strategy, here higher transaction costs will be involved with the monthly rebalancing strategy. Those costs include the commission fee, the stamp duty, and the transfer tax, which equal 2.5 basis points, 10 basis points, and 0.2 basis points, respectively, in the A-share market.[20] The magnitude of the concept-momentum effect continues to be pronounced if we take the additional transaction costs into consideration. For instance, the concept strategy in which $F = 6$ months, $H = 6$ months, and we skip one month generates an average monthly Fama and French (2015) five-factor adjusted return of around 1.20% and Liu et al. (2019) four-factor adjusted return of around 1.51% after we further deduct the transaction costs. These results are comparable to or higher than the profits earned by trading strategies in the A-share market as documented in the literature (Liu et al., 2019). Furthermore, most of the strategies documented in the literature do not consider the shorting cost. It is, however, costly to short stocks in China. For example, for individual investors the average cost of borrowing security is around 8% per year. Nevertheless, for institutional investors the cost should be much lower because of the greater borrowing size, say 4%, because such investors take out larger loans.[21] After deducting the shorting cost, the commission fee, the stamp duty, and the transfer tax, the yearly Fama and French (2015) five-factor adjusted return is around 10.40%, while the Liu et al. (2019) four-factor adjusted return is around 14.12%. These results indicate that the concept-momentum strategy is profitable even after we consider transaction and shorting costs.

5.5. Discussion: persistence

We investigate the persistence of winner and loser concepts and show in Table 10 the transition matrix of the concept-momentum strategy with a formation period of 6 months, which estimates the probability that concepts remain in the same quintile or migrate to other quintiles in the following period. In Panel *A*, Panel *B*, and Panel *C*, we report the probability of remaining or migrating in the following 1 month, 6 months, and 12 months, respectively. In Panel A, 68% (68.98%) of the concepts in the loser (winner) quintile remain in the same quintile for the following month. As seen in Panel *B* and Panel *C*, we find that concepts become less persistent in terms of estimating the following 6 and

[18] Following a referee's suggestion, we calculate Liu et al. (2019) four-factor adjusted returns on the momentum strategy for various attention subgroups and report the results in the Internet Appendix (Table IA.4), showing consistent patterns.

[19] Following a referee's suggestion, we calculate the Liu et al. (2019) four-factor adjusted returns on the momentum strategy for varying sentiment periods in the Internet Appendix (Table IA.5) and find consistent results.

[20] The average monthly turnover ratio is 31.02% for a long leg (32% for a short leg), and therefore the actual commission fee is about 1.58 basis points. In the A-share market, only selling the stocks is assessed the stamp duty, while purchasing the stock is not.

[21] We obtained this ballpark number of 4% after consulting several fund managers, as we are unable to find these specific data in the database.

Table 10
The transition matrix.
This table presents the transition matrix for the concept-momentum strategy in which $F = 6$ months. The matrix estimates the probability that a concept remains in the same quintile or migrates to another quintile in the following period. In Panel A, Panel B, and Panel C we report the probability of remaining or migrating in the following 1 month, 6 months and 12 months, respectively.

Panel *A* Persistence estimated for the following 1 month					
	Rank in month $t+1$				
Rank in month t	*L*	2	3	4	*W*
L	68.00%	22.00%	5.91%	1.96%	0.73%
2	22.18%	42.66%	23.20%	8.16%	1.52%
3	5.40%	23.35%	39.16%	24.07%	5.20%
4	1.96%	8.90%	23.71%	43.40%	19.23%
W	0.79%	1.91%	5.82%	19.44%	68.98%
Panel B Persistence estimated for the following 6 months					
	Rank in month $t+6$				
Rank in month t	L	2	3	4	*W*
Loser	23.40%	20.40%	16.82%	15.95%	14.46%
2	18.80%	19.51%	19.38%	17.36%	15.40%
3	16.04%	19.80%	19.16%	19.29%	15.30%
4	16.35%	18.01%	18.25%	18.32%	18.11%
Winner	15.92%	15.25%	15.99%	18.50%	23.15%
Panel *C* Persistence estimated for following 12 months					
	Rank in month $t+12$				
Rank in month t	*L*	2	3	4	*W*
L	18.96%	18.00%	14.91%	16.05%	15.45%
2	17.91%	17.63%	17.43%	15.79%	14.28%
3	17.37%	18.41%	16.66%	14.74%	15.17%
4	16.30%	16.42%	15.60%	18.15%	15.54%
W	14.70%	14.90%	15.90%	17.00%	18.78%

12 months. Specifically, fewer than 20% of concepts in the winner (loser) group remain in the same groups for the following 12 months.

Following Moskowitz and Grinblatt (1999), we use data from CRSP to replicate the industry-momentum strategy in the US market and estimate the persistence of the industry portfolio. In the Internet Appendix Table IA.6, Panel *A* we report the return performance of the industry-momentum strategy based on 2-digit SIC industry classification, where the significance and magnitude are consistent with what Moskowitz and Grinblatt (1999) report. We report the probability of remaining in the same quintile or migrating to another quintile in the following 1 month, 6 months, and 12 months, respectively, in Panel *B*, Panel *C*, and Panel *D*. We replicate industry momentum using Moskowitz and Grinblatt (1999) 20 industry classifications and report the results of persistence in the Internet Appendix Table IA.7. The persistence patterns reported in Tables IA.6 and IA.7 are similar to those reported in Table 10, showing that both industries and concepts become less persistent in the following 6 and 12 months.

6. Conclusion

Although investors care about asset categorizations that are based not only on traditional industry classifications but also on concept-oriented classifications, detailed data on concept-oriented asset categories are not available for the US stock market. Using unique web-crawled data on concept stocks in the Chinese stock market, we document a new type of momentum effect based on a concept-level classification that generates significant and robust profits. We demonstrate that the pronounced concept-momentum effect we observe cannot be explained by risk-factor models, firm-level momentum, or industry-level momentum. We show that the concept-momentum effect is stronger for relatively ambiguous concepts, which require investors to take more time to gain the expertise they need to incorporate concept-level information into their analyses. Furthermore, in the mechanism analyses, we find that both the underreaction and cross-stock lead-lag effect channels can cause gradual information diffusion and drive concept-momentum effect. Finally, we find that the concept momentum effect is more pronounced for relatively ambiguous concepts, for concepts that attract less investor attention, and following high-sentiment periods.

Declaration of Competing Interest

None.

CRediT authorship contribution statement

Qianqian Du: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Funding acquisition. **Dawei Liang:** Conceptualization, Methodology, Investigation, Software, Validation, Writing – review & editing, Visualization. **Zilin Chen:** Writing – review & editing, Visualization. **Jun Tu:** Supervision, Methodology, Project administration, Writing – review & editing.

Funding

We appreciate helpful comments and suggestions from George Dai, Xinrui Duan, Lin Huang, Han Li, Lin Liao, Liwei Shan, Rui Shen, Yean Zhou, and participants at the 1st Behavioral and Experiment conference in Hangzhou and the 2019 RIEM Seminar in Chengdu. Du acknowledges funding from National Natural Science Foundation of China (Project No. 72102190) as well as funding from a research grant (Grant No. JBK2101015) supported by Fundamental Research Funds for the Central Universities.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2021.106329.

References

Antoniou, C., Doukas, J.A., Subrahmanyam, A., 2013. Cognitive dissonance, sentiment, and momentum. J. Financ. Quant. Anal. 48, 245–275.
Asness, C.S., Moskowitz, T.J., Pedersen, L.H., 2013. Value and momentum everywhere. J. Financ. 58, 929–985.
Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Financ. 61, 1645–1680.
Barberis, N., Shleifer, A., 2003. Style investing. J. Financ. Econ. 68, 161–199.
Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. J. Financ. Econ. 49, 307–343.
Bernard, V.L., Thomas, J.K., 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. J. Account. Econ. 27, 1–48.
Chan, K., Hameed, A., Tong, W., 2000. Profitability of momentum strategies in the international equity markets. J. Financ. Quant. Anal. 35, 153–172.
Chan, L.K.C., Jegadeesh, N., Lakonishok, J., 1996. Momentum strategies. J. Financ. 51, 1681–1713.
Chui, A.C.W., Titman, S., Wei, K.C.J., 2010. Individualism and momentum around the world. J. Financ. 65, 363–392.
Cohen, L., Frazzini, A., 2008. Economic links and predictable returns. J. Financ. 63, 1977–2011.
Cooper, M.J., Dimitrov, O., Rau, P.R., 2001. A rose.com by any other name. J. Financ. 56, 2371–2388.
Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. J. Financ. 53, 1839–1885.
Daniel, K., Hirshleifer, D., Sun, L., 2020. Short- and long-horizon behavioral factors. Rev. Financ. Stud. 33, 1673–1736.
Du, Q., Shen, R., 2018. Peer performance and earnings management. J. Bank. Financ. 89, 125–137.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116, 1–22.

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. J. Political Econ. 81, 607–636.
Gong, Q., Liu, M., Liu, Q., 2015. Momentum is really short-term momentum. J. Bank. Financ. 50, 169–182.
Griffin, J.M., Ji, X., Martin, J.S., 2003. Momentum investing and business cycle risk: evidence from pole to pole. J. Financ. 58, 2515–2547.
Grundy, B.D., Martin, J.S., 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. Rev. Financ. Stud. 14, 29–78.
Hoberg, G., Phillips, G., 2016. Text-based network industries and endogenous product differentiation. J. Political Econ. 124, 1423–1465.
Hoberg, G., Phillips, G., 2018. Text-based industry momentum. J. Financ. Quant. Anal. 53, 2355–2388.
Hong, H., Stein, J.C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. J. Financ. 54, 2143–2184.
Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. J. Financ. 48, 65–91.
Jegadeesh, N., Titman, S., 2001. Profitability of momentum strategies: an evaluation of alternative explanations. J. Financ. 56, 699–720.
Kahneman, D., 1973. Attention and Effort. Prentice-Hall, Englewood Cliffs, NJ.
Kang, J., Liu, M.H., Ni, S.X., 2002. Contrarian and momentum strategies in China stock market: 1993–2000. Pacific Basin Financ. J. 10, 243–265.
Leary, M.T., Roberts, M.R., 2014. Do peer firms affect corporate financial policy? J. Financ. 69, 139–178.
Lee, C.M.C., Sun, S.T., Wang, R., Zhang, R., 2019. Technological links and predictable returns. J. Financ. Econ. 132, 76–96.
Liao, L., Liu, B., Wang, H., 2014. China's secondary privatization: perspectives from the split-share structure reform. J. Financ. Econ. 113, 500–518.
Liu, B., Pi, T., 2007. Momentum and contrarian strategies: the evidence from the stock markets in Shanghai and Shenzhen in China (translated from Mandarin). J. Financ. Res. 8, 154–166.
Liu, J., Stambaugh, R.F., Yuan, Y., 2019. Size and value in China. J. Financ. Econ. 134, 48–69.
Loughran, T., McDonald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. J. Financ. 66, 35–65.
Moskowitz, T.J., Grinblatt, M., 1999. Do industries explain momentum? J. Financ. 54, 1249–1290.
Moskowitz, T.J., Ooi, Y.H., Pedersen, L.H., 2012. Time series momentum. J. Financ. Econ. 104, 228–250.
Mullainathan, S., 2002. Thinking Through Categories. Massachusetts Institute of Technology, Cambridge, MA Unpublished working Paper..
Naughton, T., Truong, C., Veeraraghavan, M., 2008. Momentum strategies and stock returns: chinese evidence. Pacific Basin Financ. J. 16, 476–492.
Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Novy-Marx, R., Velikov, M., 2016. A taxonomy of anomalies and their trading costs. Rev. Financ. Stud. 29, 104–147.
Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. J. Financ. Econ. 80, 563–602.
Stambaugh, R.F., Yu, J., Yuan, Y., 2012. The short of it: investor sentiment and anomalies. J. Financ. Econ. 104, 288–302.
Wang, Y., Zhao, X., 2001. An empirical analysis of "Inertial Strategy" and "Reverse Strategy" in China's stock market (translated from Mandarin). Econ. Res. J. 6, 56–89.
Zhang, X.F., 2006. Information uncertainty and stock returns. J. Financ. 61, 105–136.