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Commodity momentum: A tale of countries and sectors☆

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ABSTRACT

This paper takes a cross-country and cross-sector perspective to investigate the drivers of commodity momentum strategies. Commodity momentum strategies deployed in the U.S. and Chinese markets generate positive average returns with non-negligible correlations, but their premia are primarily local, and their return characteristics are distinct. A prevalent sector effect explains a significant fraction of momentum profits in both markets, suggesting that long-short commodity futures momentum may be riskier than previously thought. Overall, our findings suggest commodity momentum is more consistent with a risk-based explanation in U.S. markets whereas risk alone is difficult to capture the premia in China.

1. Introduction

This paper takes a multi-level deep dive to investigate the sources of commodity momentum profits. The evidence on commodity momentum is extensive (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Miffre and Rallis, 2007; Boons and Prado, 2019). However, unlike the carry (or basis) factor, which arises from hedgers' propensity to be net-long or -short and the shape of commodity futures term structure, the source of commodity momentum is more elusive. Some researchers believe that commodity momentum profits are a compensation for pervasive risk factors such as inventory levels (Gorton et al., 2013) and hedging pressure (Basu and Miffre, 2013; Bakshi et al., 2019), while others favor behavioral explanations related to inefficiencies in the way markets incorporate information into prices (Bianchi et al., 2016), as well as investor's active attention to hazard fear (Fernandez-Perez et al., 2020).[1]

Motivated by the mixed findings in the literature, our goal in this paper is to shed light on the potential drivers of momentum profits beyond basis, hedging pressure and other commodity fundamentals. To do so, we take a cross-country and cross-sector perspective to

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[1] Despite the proliferation of multi-asset/factor studies in the literature, such an approach adds limited further insights in understanding commodities momentum. While the momentum strategies in equity markets are relatively well-understood (Daniel and Moskowitz, 2016), because the institutional setting of commodity futures markets is markedly different from stocks, findings such as Goetzmann and Huang (2018) and Kelly et al. (2021) do not inform the driver of commodities momentum.

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compare momentum profits in the U.S. with those observed in China. Specifically, we first examine whether commodity momentum is primarily local, or if they also have a global component.[2] After investigating the macro source of profitability, we zoom in on commodity sectors within each country to identify a more granular source of momentum profits. Commodities are naturally grouped into sectors, but the notion that sectors can be a driver of commodity momentum has been largely neglected by the extant literature as much of the attention has gone into uncovering new factors that explain the broad cross-sectional return variations (Szymanowska et al., 2014; Fernandez-Perez et al., 2018; Boons and Prado, 2019) and how momentum can be profitably combined with other commodity fundamentals (Fuertes et al., 2010; de Groot et al., 2014; Bianchi et al., 2015; Fernandez-Perez et al., 2019).

Our work is motivated by Fan and Zhang (2020) and Kang and Kwon (2017), but we depart from these studies in the following ways. Fan and Zhang (2020) posit that unique institutional settings cause commodity factors (including momentum) in China to behave differently from the U.S. However, apart from conjecturing retail dominance being a potential driver, they do not examine *how* momentum profits in China differ from those in the U.S. In this paper, we formally test the drivers of such differences including global risk factors, macro shocks and sector versus idiosyncratic effects. Kang and Kwon (2017) also find that sector momentum plays a role in understanding commodities momentum, but rather than studying sectors within each country, they group multiple international markets together. Therefore, the sector analysis they perform answers the question of whether an international within-sector strategy can explain international momentum profits. In contrast, our work attempts to understand whether drivers of commodity momentum returns (including sectors) are consistent *across* markets.

We highlight two key findings. Our first finding points to the local nature of commodity momentum returns. While baseline momentum strategies earn positive average returns in the U.S. and Chinese markets of 2.7% and 5.2% per year, their correlation is merely 0.34. In a series of tests, we first show that spanning regressions of the Chinese strategy on the U.S. strategy (and vice versa) report economically large intercepts of 4.8% (1.2%). We then introduce a set of global factors including two global momentum strategies constructed from commodity contracts in both countries and macro factors including foreign exchange rates, global value, momentum, and carry strategies across asset classes and geographies, and find that global strategies can indeed explain the average returns associated with baseline strategies in both markets. However, we find that the U.S. commodity momentum is exposed to global inflation but the same does not hold in China. In an overlapping sample of 12 commodities traded in both the U.S. and China, we find that domestic strategies earn annual average returns of 5.0% and 3.3% respectively but continue to have a relatively low correlation of 0.43. A strategy that takes U.S. (Chinese) signals to invest in Chinese (U.S.) markets earns an annual average return of 4.5% (8.1%). The fact that cross-country signals on average perform better than domestic signals suggests that past returns in foreign markets may convey information content beyond domestic market dynamics.

The combined evidence from correlations, regressions and cross-country strategies suggests that commodity momentum is primarily local, and that their return characteristics are distinctive. The dissimilarity between the U.S. and Chinese commodity momentum manifests in several ways. First, capital flow restrictions (Makarov and Scholar, 2020), barriers-to-entry (Fan and Zhang, 2020) and trade policies imposing significant pressures on the profitability and feasibility of cash-and-carry arbitrage (Ederington et al., 2021), which prevent the convergence of commodity prices between China and the U.S. Second, the two markets' reactions to local and global inflation shocks differ substantially. Third, trading in the Chinese commodity markets is primarily driven by retail investors whereas in the U.S. markets trading is mainly driven by institutional investors (Fan and Zhang, 2020). Our findings on local characteristics are consistent with Rouwenhorst (1999), who finds that the returns and average returns of international equity momentum strategies exhibit primarily local behavior. Moreover, Asness et al. (2013) show momentum factors comove across countries and asset classes. Contrary to Asness et al. (2013), while commodity momentum strategies do share some cross-country comovement, we show that their average returns have a strongly local character. Finally, the strong local characteristics of commodity momentum premia largely explains the efficacy of cross-country diversifications demonstrated by Bianchi et al. (2021).

Our second key finding relates to commodity sector effects. Because commodity futures returns within a sector tend to be much more correlated than across sectors, momentum strategies can have large sector tilts and therefore are not well-diversified. If sector effects dominate, commodity momentum is exposed to sector concentration risk, favoring a risk-based explanation of its average returns. On the contrary, if commodity momentum were primarily driven by behavioral biases, then rational investors can earn a high Sharpe ratio with diversified positions across commodities (Moskowitz and Grinblatt, 1999).[3] Indeed, a series of tests show that sector momentum explains a significant fraction of commodity momentum profits. First, three sector-level momentum strategies using various base assets earn economically large average returns on the same order of magnitude as the baseline momentum strategies. Second, momentum strategies constructed using the idiosyncratic component of commodity returns have considerably lower average returns compared to the baseline momentum strategies. Third, a decomposition of momentum returns into a sector and an idiosyncratic component shows that 99% of the profits in the U.S. can be attributed to sectors. While strategy returns in the U.S. are mostly driven by sectors, profits in China are driven by both sector effects and individual commodity effects (i.e., 51% sector and 49% idiosyncratic). Since its individual commodity effects are more prominent, it is difficult to rationalize commodity momentum in China with only a risk-based explanation.

[2] The size and activity of the U.S. and Chinese markets – the largest and most actively traded commodity markets in the world – provide a particularly interesting setting for studying commodity momentum strategies.

[3] Theoretical models of underreaction (e.g., Barberis et al., 1998; Hong and Stein, 1999) typically posit that investors underreact to news about individual assets, not economy-wide sentiment. If we follow the premise that underreaction is more about individual assets, then individual commodity effects weakly correlated across commodities suggest that a behavioral explanation may contribute to a portion of overall momentum profits.

Our sector analysis relates to the recent work of Kang et al. (2021), who demonstrate that "crowding" effects, proxied by excess speculative pressure, can explain the recent poor performance of momentum strategies in U.S. commodity markets. Our findings suggest that the recent underperformance is due largely to sector effects rather than individual commodity effects. Since commodity momentum strategies require concentrated bets in sectors, our finding suggests a higher degree of crowding effects may be present in sectors traded by commodity momentum strategies. Moreover, our paper relates to studies linking momentum returns to sector effects. Moskowitz and Grinblatt (1999) demonstrate that industry momentum drives much of equity momentum strategies, which become significantly less profitable after controlling for industry momentum. Szymanowska et al. (2014) argue that cross-sectional and time-series variation in commodity futures returns is related not so much to sectors as to characteristics such as momentum. We find that in commodity futures markets, sector momentum contributes towards explaining the cross-sectional variation in average returns.

Kang and Kwon (2017) also find that sector momentum can account for a portion of overall commodity momentum profits. However, the authors conclude that sector effects are not as important as individual commodity effects. Our results show that sector effects are important in both the U.S. markets and the Chinese markets, but individual commodity effects differ. Several differences in research design may account for the contradictory findings. Kang and Kwon's (2017) data contain 32 U.S. and 20 Chinese commodities. Their U.S. (Chinese) sample covers 1979–2015 (2005–2015). We focus on a smaller set of 21 key commodities in the U.S. following Szymanowska et al. (2014), and a much larger cross section of 43 Chinese commodities. Since we focus on cross-country comparisons, we restrict the U.S. and Chinese samples to share a common time from January 2005 to July 2022. Kang and Kwon group sectors across countries to construct an international sector strategy, which does not allow for a comparison of sector effects across countries. In contrast, our approach focuses on sector effects within each country with the intention of facilitating cross-country comparisons.

The remainder of the paper proceeds as follows. Section 2 introduces the background and data. Section 3 investigates the commonality in commodity momentum premia in the U.S. and Chinese markets. Section 4 examines whether commodity momentum is driven by sector effects in each country. Section 5 concludes.

2. Background and data

2.1. Data

Established in the 1990s, commodity markets in China have undergone tremendous development. Commodities are of particular importance in China due to large-scale infrastructure projects driving up demand, and the Chinese commodity markets are highly active. As of 2018, the aggregate trading volume in China is more than 200 times larger than the open interest, compared to just over 20 times in North America. Six of the world's 10 most active commodity contracts trade on Chinese exchanges. Given the size and importance of the Chinese commodity markets, researchers have been increasingly interested in understanding the structure and empirical behavior of these markets.

Our Chinese sample includes the following commodities: *No.1 Soybean, No.2 Soybean, Corn, LLDPE, Soybean Meal, Palm Olein, PVC, Soybean Oil, Metallurgical Coke, Coking Coal, Plywood, Fiberboard, Egg, Iron Ore, PP*, and *Corn Starch* are traded on the Dalian Commodity Exchange (DCE). *Sugar, Cotton, Rapeseed Oil, PTA, Strong Wheat, Common Wheat, Methanol, Flat Glass, Rapeseed meal, Rapeseed, Thermal Coal, Japonica Rice, Ferrosilicon,* and *Silicon Manganese* are traded on the Zhengzhou Commodity Exchange (ZCE), and *Aluminum, Gold, Copper, Fuel Oil, Lead, Steel Rebar, Natural Rubber, Steel Wire Rod, Zinc, Silver, Bitumen, Hot-rolled Coil*, and *Tin* are traded on the Shanghai Futures Exchange (SHFE). The number of commodity contracts has grown steadily in our sample, from fewer than 10 commodities in 2005 to more than 40 commodities by 2022 (see Fig. 1). The number of commodities in every sector has increased over time.

For the U.S. sample, we consider the same set of commodities as Szymanowska et al. (2014), including *Heating Oil, Gasoline*, *Crude Oil, Gold*, *Copper*, and *Silver* traded on the New York Mercantile Exchange (NYMEX). *Feeder Cattle*, *Live Cattle*, *Lean Hogs* and *Lumber* are traded on the Chicago Mercantile Exchange (CME). *Corn*, *Oats*, *Wheat*, *Rough Rice*, *Soybean Oil*, *Soybeans*, and *Soybean Meal* are traded on the Chicago Board of Trade (CBOT), and *Coffee*, *Orange Juice*, *Cocoa*, and *Cotton* are traded on the Intercontinental Exchange (ICE).[4] For the U.S. and Chinese samples, daily settlement price, volume, and open interest on all maturities are obtained from Refinitiv Datastream.

The transfer of price risk between hedgers and speculators occurs at different maturities for the U.S. and Chinese markets. Fig. 2 illustrates the average trading volume across the futures curves for different commodities in the two countries. For the U.S. markets, the nearest contracts have the largest trading volumes compared to contracts at other maturities. This observation is consistent with the finding that in the U.S. markets, the nearest contracts tend to be the most actively traded and have the largest open interests (Dewally et al., 2013). In the Chinese markets, the nearest futures contracts do not have the highest trading volume. Instead, the second, third, or fourth nearest contracts tend to have higher average trading volumes. Fan and Zhang (2020) attribute such liquidity patterns to differential margin requirements depending on the maturity, as well as to the strict position limits for the front contracts. In

[4] Existing literature has found profitable commodity momentum strategies under different settings. Hong and Yogo (2012) find positive momentum profits for 30 U.S. commodities, and Miffre and Rallis (2007) examine 31 U.S. commodities and uncover 13 profitable momentum strategies. Although different samples can imply different empirical results, to the extent the profitability of commodity momentum is a robust feature in the data, we should observe positive premia in different samples. We construct our U.S. dataset following Szymanowska et al. (2014), who also find a positive momentum premium.

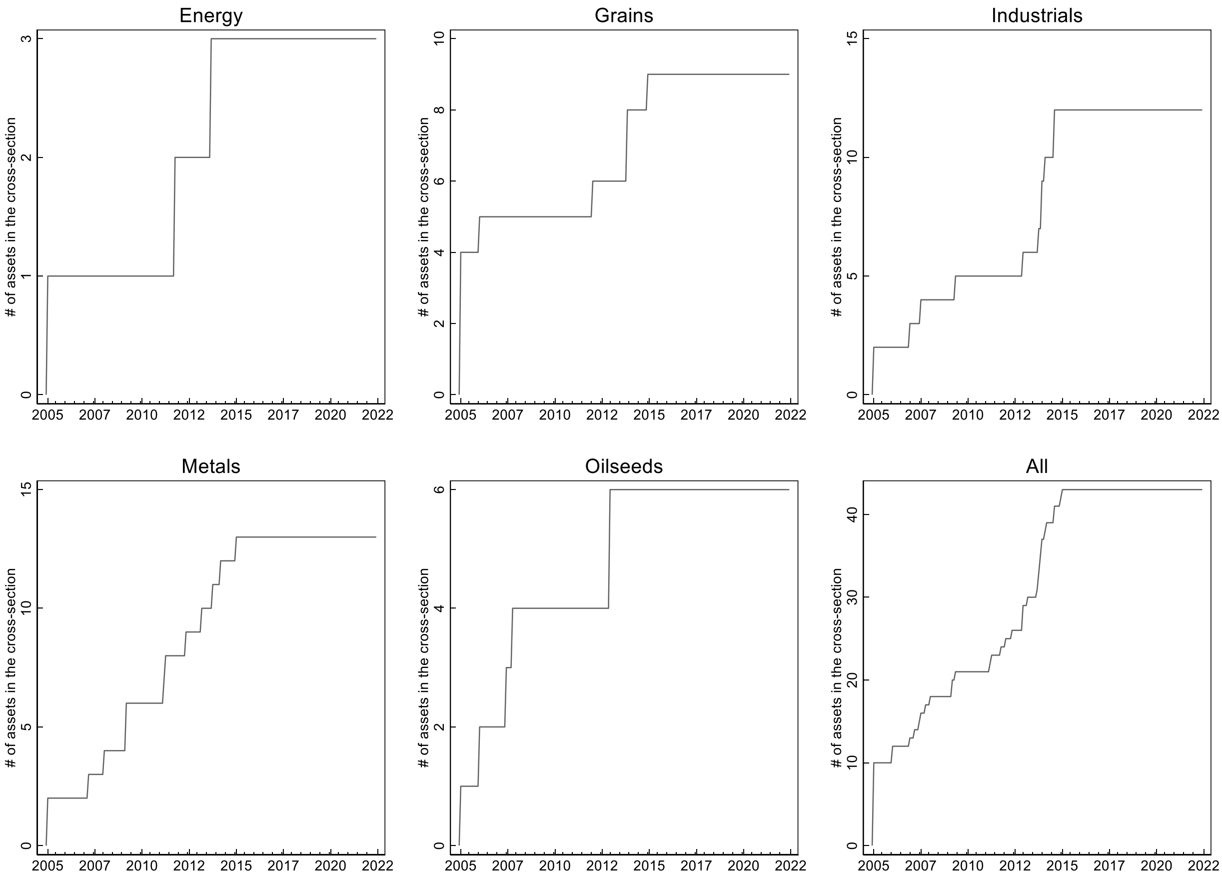


Fig. 1. The Number of Commodities in the Chinese Markets
This figure shows the number of commodities in the Chinese markets across five sectors. "All" shows the total number of commodities.

constructing portfolios, we take positions in the most liquid maturities on the curve to maximize the feasibility of the investment strategies. We roll futures positions to the most actively-traded maturity where the open interest is the highest.[5] For the majority of commodities in China, January, May, and September contracts have the highest open interest.

Table 1 presents the summary statistics for the monthly returns of commodity futures. Our sample period is from January 2005 to July 2022, because very few commodities are available in the Chinese markets before 2005. There are 21 commodities in the U.S. markets across seven sectors: energy, grains, industrials, meats, metals, oilseeds, and softs. Of these commodities, 15 have positive average returns, ranging from 0.16% to 1.21% per month, and eight have negative average returns ranging from −0.03% to −0.76%. An equal-weight portfolio across all commodities has an average return of 0.36% per month.

Our Chinese sample includes 43 commodities across five sectors: energy, grains, industrial, metals, and oilseeds. Different commodities were introduced at different times; the number of observations ranges from 88 months for tin, the most recently introduced commodity, to 210 months for sugar and LLDPE. Of the 43 commodities, 34 have positive average returns ranging from 0.04% to 1.95% per month, and 10 have negative average returns ranging from −0.04% to −0.53% per month. An equal-weight portfolio for the Chinese commodities has an average monthly return of 0.35%, in line with the U.S. markets.

2.2. *Sector returns*

We construct monthly rebalanced equal-weight portfolios for each commodity sector. Table 2 presents the summary statistics for the equal-weight sector returns. For the U.S. markets, six of the seven sectors have positive average returns in our sample, ranging between 0.12% and 0.85% per month. Meats is the only sector that shows negative average returns, at −0.34% per month. For the Chinese markets, all five sectors have positive average returns, ranging between 0.12% and 0.57% per month. For both the U.S. and

[5] See Bianchi et al. (2021) for comparisons between conventional, gradual and dynamic rolling methods and their impact on returns and capacity of factor strategies.

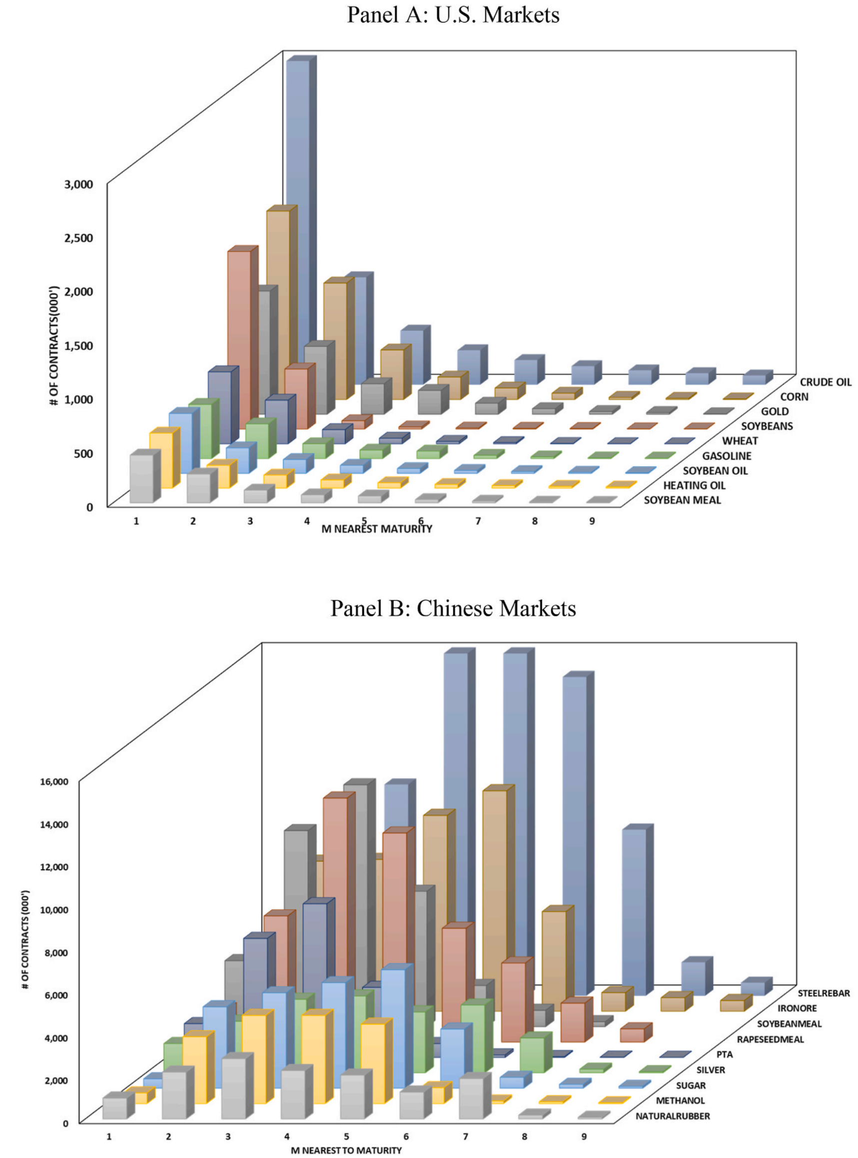


Fig. 2. Trading Volumes across Futures Curves
This figure illustrates the average trading volume of different commodities across the futures curves. The horizontal axis shows the number of months to maturity. The nearest contracts are shown on the left. Panel A includes nine commodities traded in the U.S., and Panel B includes nine commodities traded in China.

Chinese markets, commodity sector returns tend to be negatively skewed and leptokurtic.

Table 3 presents pairwise correlations of equal-weight sector returns. Pearson correlation coefficients, computed as the covariance between two variables divided by the product of their standard deviations, are shown in each cell. For comparison, Spearman's rank correlation coefficients, calculated as the Pearson correlation between the ranked variables, are shown in square brackets. For the U.S. markets, 20 of 21 Pearson correlations are positive, with values between 0.02 and 0.71. Only one Pearson correlations is negative at −0.08.19 of 21 Spearman's rank correlations are positive, with values similar to those of the Pearson correlations. The two measures show opposite signs (0.02 and −0.04) for the correlation between meats and oilseeds, highlighting the weak relation between these two sectors.

For the Chinese markets, all 10 pairwise Pearson correlations are positive, which range between 0.33 and 0.78. Spearman's rank

Table 1
Summary Statistics of Commodity Returns, This table shows the summary statistics for the monthly returns of commodity futures contracts in the U.S. (Panel A) and China (Panel B). "SD" is the standard deviation, "Skew" is the skewness, "Ex Kurt" is the excess kurtosis, and "N" is the number of available observations. The sample is from January 2005 to July 2022.

Panel A: U.S. Markets

Sector	Commodity	Mean	SD	Skew	Ex Kurt	Min	Max	N
Energy	CRUDE OIL	0.55%	9.0%	−0.27	4.02	−42.1%	43.3%	210
Energy	GASOLINE	0.90%	9.8%	−1.10	5.45	−55.0%	33.1%	201
Energy	HEATING OIL	0.42%	8.7%	−0.39	0.79	−30.9%	24.7%	210
Grains	CORN	0.40%	8.3%	0.38	0.85	−22.8%	27.8%	210
Grains	OATS	0.89%	9.3%	0.45	0.91	−26.7%	32.7%	210
Grains	ROUGH RICE	−0.04%	6.5%	−0.09	0.99	−22.8%	19.2%	210
Grains	WHEAT	−0.14%	9.1%	0.43	1.41	−25.3%	37.7%	210
Industrials	COTTON	0.34%	7.6%	−0.06	0.68	−22.6%	23.4%	210
Industrials	LUMBER	0.24%	12.1%	0.86	3.25	−36.9%	55.7%	210
Meats	FEEDER CATTLE	−0.03%	4.7%	0.02	0.19	−12.1%	15.1%	210
Meats	LIVE CATTLE	−0.24%	4.1%	−0.11	0.18	−11.1%	11.9%	210
Meats	LEAN HOGS	−0.76%	7.8%	0.00	0.18	−23.9%	20.3%	210
Metals	COPPER	0.70%	7.6%	−0.25	3.32	−36.5%	31.3%	210
Metals	GOLD	0.63%	4.9%	−0.07	0.69	−18.5%	13.8%	210
Metals	SILVER	0.76%	9.3%	0.28	0.56	−28.0%	29.9%	210
Oilseeds	SOYBEAN MEAL	1.21%	8.0%	0.48	0.84	−20.4%	30.1%	210
Oilseeds	SOYBEAN OIL	0.52%	7.2%	0.09	1.76	−25.2%	26.5%	210
Oilseeds	SOYBEANS	0.81%	7.0%	−0.11	0.61	−22.1%	20.3%	210
Softs	COCOA	0.16%	7.7%	−0.06	−0.32	−20.1%	18.8%	210
Softs	COFFEE	−0.16%	8.4%	0.81	2.53	−23.6%	42.0%	210
Softs	ORANGE JUICE	0.36%	8.7%	0.16	0.29	−21.0%	25.3%	210
	EW Portfolio	0.36%	4.2%	−0.50	2.27	−19.1%	11.6%	210

Panel B: Chinese Markets

Sector	Commodity	Mean	SD	Skew	Ex Kurt	Min	Max	N
Energy	FUEL OIL	0.50%	8.0%	−0.18	7.19	−37.4%	37.6%	207
Energy	METHANOL	−0.06%	7.3%	0.07	4.88	−21.9%	27.8%	129
Energy	THERMAL COAL	1.61%	8.4%	2.06	15.73	−23.3%	53.4%	106
Grains	CORN	0.24%	3.3%	0.18	3.34	−7.9%	10.3%	210
Grains	CORN STARCH	0.23%	4.7%	0.30	2.92	−11.1%	11.8%	91
Grains	EGG	−0.53%	5.8%	0.27	3.08	−13.8%	16.8%	104
Grains	JAPONICA RICE	0.11%	4.3%	1.69	8.16	−8.7%	19.5%	104
Grains	ONESOYBEAN	0.36%	4.7%	0.34	4.90	−15.8%	17.0%	210
Grains	STRONGGLUTEN WHEAT	−0.07%	2.9%	0.00	4.22	−10.9%	9.4%	210
Grains	SUGAR	−0.20%	5.1%	0.16	5.08	−17.7%	17.8%	198
Grains	TWOSOYBEAN	0.65%	5.3%	0.16	4.40	−19.7%	20.1%	210
Grains	WHEAT	0.04%	3.8%	1.34	8.77	−10.4%	19.2%	126
Industrial	BITUMEN	−0.43%	8.8%	−0.24	3.94	−32.8%	21.5%	105
Industrial	COTTON	−0.07%	5.7%	1.07	6.91	−15.1%	27.7%	210
Industrial	FERROSILICON	0.87%	9.7%	1.15	12.56	−31.0%	54.2%	95
Industrial	FIBERBOARD	0.79%	8.8%	1.53	10.14	−29.3%	43.8%	101
Industrial	FLAT GLASS	0.78%	6.7%	0.55	5.65	−17.8%	30.2%	115
Industrial	LLDPE	0.22%	7.0%	−1.36	11.68	−44.3%	20.3%	180
Industrial	NATURAL RUBBER	−0.33%	8.9%	0.39	4.27	−30.9%	34.5%	210
Industrial	PLYWOOD	0.27%	7.9%	−1.46	9.82	−41.6%	17.5%	103
Industrial	POLYPROPYLENE	0.79%	6.7%	0.73	4.29	−15.2%	21.2%	101
Industrial	PTA	−0.04%	7.4%	−0.06	5.84	−32.2%	30.0%	187
Industrial	PVC	0.15%	6.1%	0.47	6.83	−21.7%	27.8%	158
Industrial	SILICONMANGANES	1.05%	9.4%	0.99	6.75	−24.9%	42.2%	95
Metals	ALUMINUM	0.08%	4.8%	0.28	4.36	−13.1%	16.7%	210
Metals	COKE	1.03%	9.9%	0.83	4.67	−21.3%	39.7%	135
Metals	COKINGCOAL	1.59%	9.1%	0.58	4.03	−24.2%	29.0%	112
Metals	COPPER	0.87%	7.3%	−0.36	9.50	−40.7%	34.4%	210
Metals	GOLD	0.31%	4.8%	−0.17	4.29	−18.2%	13.2%	174
Metals	HOTROLLED COIL	1.23%	7.5%	0.22	2.94	−18.6%	24.5%	100
Metals	IRON ORE	1.95%	10.6%	0.07	2.71	−23.8%	29.5%	105
Metals	LEAD	0.11%	5.2%	1.12	9.58	−16.4%	29.1%	136
Metals	SILVER	−0.27%	7.2%	0.67	5.51	−19.1%	28.7%	122
Metals	STEEL REBAR	0.43%	6.7%	0.14	3.67	−22.1%	21.0%	160
Metals	STEEL WIRE	0.62%	7.1%	1.62	9.89	−19.3%	36.4%	156
Metals	TIN	0.76%	6.0%	−0.69	5.26	−22.7%	14.0%	88
Metals	ZINC	0.10%	6.7%	−1.09	8.20	−37.2%	19.8%	184
Oilseeds	PALM OIL	0.27%	7.3%	−0.22	4.87	−30.6%	23.1%	177
Oilseeds	RAPESEED	0.47%	4.5%	−0.35	7.49	−20.5%	15.5%	115

(*continued on next page*)

Table 1 (*continued*)

Panel B: Chinese Markets								
Sector	Commodity	Mean	SD	Skew	Ex Kurt	Min	Max	N
Oilseeds	RAPESEED MEAL	0.96%	5.8%	0.36	3.10	−12.4%	17.2%	115
Oilseeds	RAPESEED OIL	0.39%	5.7%	0.00	7.54	−22.4%	28.2%	181
Oilseeds	SOYBEAN MEAL	0.85%	5.7%	0.19	3.34	−17.9%	16.1%	210
Oilseeds	SOYBEAN OIL	0.39%	5.9%	−0.10	5.65	−22.7%	26.0%	198
EW Portfolio		0.35%	3.9%	−0.84	7.44	−21.9%	10.9%	210

Table 2

Sector Returns, This table shows the summary statistics for the monthly returns of equal-weight commodity sector portfolios. Panel A reports the results for the U.S. markets, and Panel B reports the results for the Chinese markets. N is the number of available observations. The sample is from January 2005 to July 2022.

Panel A: U.S. Markets							
	Mean	SD	Skew	Ex Kurt	Min	Max	N
Energy	0.65%	8.8%	−0.71	2.93	−42.7%	29.9%	210
Grains	0.28%	6.4%	0.03	0.72	−21.5%	17.2%	210
Industrials	0.29%	7.9%	0.44	1.31	−24.5%	30.2%	210
Meats	−0.34%	4.3%	−0.26	0.19	−14.6%	10.5%	210
Metals	0.70%	6.0%	−0.31	1.92	−25.2%	20.1%	210
Oilseeds	0.85%	6.5%	−0.06	0.71	−21.0%	19.0%	210
Softs	0.12%	5.8%	−0.06	0.28	−18.5%	15.5%	210
Panel B: Chinese Markets							
	Mean	SD	Skew	Ex Kurt	Min	Max	N
Energy	0.57%	6.6%	−0.47	6.78	−37.4%	32.4%	210
Grains	0.12%	2.9%	0.08	1.05	−9.6%	10.5%	210
Industrial	0.15%	5.3%	−0.46	3.70	−28.6%	17.4%	210
Metals	0.57%	5.2%	−0.39	3.12	−26.6%	18.9%	210
Oilseeds	0.57%	5.1%	−0.31	3.40	−23.4%	21.9%	210

Table 3

Correlations of Sector Returns, This table reports the pairwise correlations for equal-weight sector returns. In each cell, the Pearson correlation coefficient is shown on the left, and Spearman's rank correlation is shown in square brackets.

Panel A: U.S. Markets							
Pearson [Spearman]	Energy	Grains	Industrials	Meats	Metals	Oilseeds	Softs
Energy							
Grains	0.27 [0.23]						
Industrials	0.40 [0.37]	0.37 [0.36]					
Meats	0.21 [0.12]	−0.08 [-0.12]	0.08 [0.01]				
Metals	0.43 [0.39]	0.33 [0.21]	0.38 [0.35]	0.03 [0.00]			
Oilseeds	0.37 [0.37]	0.71 [0.66]	0.45 [0.42]	0.02 [-0.04]	0.37 [0.28]		
Softs	0.30 [0.28]	0.42 [0.34]	0.29 [0.24]	0.07 [0.05]	0.38 [0.27]	0.47 [0.34]	

Panel B: Chinese Markets					
Pearson [Spearman]	Oilseeds	Energy	Grains	Industrials	Metals
Oilseeds					
Energy	0.33 [0.30]				
Grains	0.65 [0.61]	0.47 [0.43]			
Industrial	0.51 [0.54]	0.38 [0.32]	0.70 [0.71]		
Metals	0.43 [0.35]	0.78 [0.72]	0.54 [0.49]	0.46 [0.38]	

correlations are also all positive, ranging between 0.30 and 0.72. Evidently, equal-weight sector returns exhibit moderately strong comovement. Positive correlations across sector returns may be indicative of a common factor, related to macroeconomic fundamentals or investor sentiment that affects all commodity sectors.[6] Comparing the two countries, the Chinese markets exhibit stronger comovement among sector returns than the U.S. markets, suggesting potentially more powerful systematic drivers of commodity returns.

[6] To the extent there is a common factor, it is not the only driver of commodity futures returns. We need multiple factors to explain comovement. A principal component analysis of Chinese commodity returns shows that the largest principal component explains only 20% of the total variance. The five largest principal components combine to explain 50% of the total variance, and we need 10 principal components to explain over 70%.

3. Are commodity momentum strategies local or global?

This section seeks to address our first research question, which relates to the similarities and differences among commodity momentum strategies in the U.S. and China. We first construct strategies in the U.S. and Chinese markets, then we examine their average returns and comovement. Finally, we study the commonality of these strategies using spanning regressions, explanatory regressions, and cross-country signals.

3.1. Baseline and within-sector momentum strategies

We construct a baseline long-short momentum strategy using the full cross section of commodities. Each month, we rank all available commodities based on their past 12-month returns. We take long positions in the top 50% of commodities by past performance, and short positions in the bottom 50%.[7] The long and short legs of this strategy are equal weighted across commodities. Separate baseline strategies are constructed for the U.S. and Chinese samples.

The performance statistics of the baseline momentum strategies are shown in Table 4. In the U.S. markets, the baseline strategy has an average return of 2.7% per year with a volatility of 13.7%, resulting in a Sharpe ratio of 0.13. The returns of this strategy are less negatively skewed compared to individual commodity returns and equal-weighted sector returns. In 53% of the months, this strategy earned a positive return. Its maximum drawdown in our sample period is −56%.

The baseline commodity momentum strategy in the Chinese markets has an average return of 5.2% per year with a volatility of 11.7%, which results in a Sharpe ratio of 0.38. Contrary to the U.S. strategy, the returns are positively skewed, and the return distribution is slightly fat tailed. In 55% of the months, the baseline momentum strategy in China has a positive return. The maximum drawdown is −36%.

Our baseline commodity momentum strategies in the U.S. and Chinese markets have return profiles consistent with the existing literature. Bhardwaj et al. (2019) construct a momentum factor using 150 years of data from 1871 to 2018. Their momentum strategy earns 7.2% per year with a volatility of 14.4% and a Sharpe ratio of 0.50. The maximum drawdown of their strategy is −58%. Kang and Kwon (2017) also explore commodity momentum strategies in the U.S. and Chinese markets, and Fan and Zhang (2020) demonstrate that commodity momentum strategies are profitable in China. Using somewhat different time periods and rolling methods, these studies find Sharpe ratios ranging from 0.6 to 1.3 for commodity momentum strategies with various holding periods in the Chinese markets. The average returns of our momentum strategies are lower than previous studies because commodity momentum strategies suffered significant loses in the past decade prior to the Covid-19 pandemic.[8]

We also construct momentum strategies within each commodity sector, following the same method as the one used for the baseline strategies. These momentum strategies are sector-neutral because the long and short positions are from the same sector, so the sector exposures from the long and short positions neutralize each other (Moskowitz and Grinblatt, 1999). The performance of within-sector momentum strategies is presented in Table 4. In the U.S. markets, only four within-sector strategies have positive average returns ranging from 1.6% to 10.2% per year, and four strategies have negative average returns ranging from −3.1% to −11.0% per year. In the Chinese markets, within-sector momentum strategies are profitable for all five sectors, ranging from 3.1% to 9.4% per year.

Compared to the baseline strategies, the within-sector momentum strategies have significantly higher volatility and typically larger drawdowns. These features may be related to more concentrated portfolio holdings. For the sectors with positive momentum returns, the return profiles are similar to the baseline momentum strategies using the full cross section of commodities: returns are fat-tailed and more than 50% of the months have positive returns.

3.2. Spanning tests

The previous section shows that commodity momentum strategies in the U.S. and Chinese markets earn positive premia, and within-sector momentum strategies are generally profitable. Are these strategies predominantly local, or do they have common global components as well? To answer this question, we first examine the return correlations of similar strategies in the U.S. and Chinese markets. The baseline commodity momentum strategies in the two countries have a correlation of 0.34, indicating that although these strategies do share some commonality, it is a rather weak relation. The correlations of within-sector momentum strategies for the five overlapping sectors also show low values: 0.36 for oilseeds, −0.07 for energy, 0.05 for grains, 0.01 for industrials, and 0.17 for metals. Overall, there is a limited degree of comovement in commodity momentum strategies across the U.S. and Chinese markets.

We proceed with a more formal test to assess the common components in commodity momentum strategies. We run spanning

[7] We use a 50% breakpoint to split commodities into halves to maintain a consistent methodology for the baseline and within-sector momentum strategies, because some sectors contain very few commodities. Baseline strategies remain profitable using alternative breakpoints (e.g., long top 20%, short bottom 20%).

[8] In light of the recent underwhelming performance of commodity momentum strategies, we apply a Bayesian analysis to assess the likelihood for commodity momentum to remain profitable. In online appendix, we show that unless one has strong beliefs to the contrary, the evidence from the U.S. and Chinese markets strongly favors the hypothesis that momentum is a profitable strategy in commodity futures markets. Even for an investor with a prior belief that momentum returns are zero in both the U.S. and China, after observing the data, her posterior view would tilt heavily towards a positive return premium in the two countries. The joint evidence in both markets offers important clues to the future profitability of momentum strategies even if the U.S. strategy has underperformed in the last decade.

Table 4
Commodity Momentum Strategies. This table presents the statistics of various commodity momentum strategies. “Baseline” is a strategy that invests in the full cross section of commodities, taking long positions in the top 50% of commodities by performance over the past 12 months and short positions in the bottom 50%. The strategy is rebalanced monthly, and the long and short legs are equal weighted across commodities. Within-sector momentum strategies are monthly rebalanced long-short strategies that invest in the top 50% of commodities in that sector, ranked by past 12-month performance, and short positions in the bottom 50% of commodities. The sample period is January 2005 to July 2022.

Panel A: U.S. Markets

	Baseline	Energy	Grains	Industrial	Meats	Metals	Oilseeds	Softs
Annual Average Returns	2.7%	−3.1%	−7.1%	10.2%	2.6%	1.6%	5.6%	−11.0%
Volatility	13.7%	13.7%	21.9%	44.2%	18.8%	23.8%	21.3%	32.5%
Sharpe Ratio	0.13	−0.29	−0.44	0.01	0.05	−0.05	0.16	−0.51
Skewness	−0.05	−0.08	−0.37	0.30	−0.22	0.39	0.26	−0.11
Excess Kurtosis	0.58	7.12	0.48	1.56	0.17	1.05	1.68	0.19
% of Positive Months	53%	47%	47%	54%	55%	47%	53%	46%
Maximum Drawdown	−56%	−60%	−81%	−81%	−41%	−58%	−48%	−98%

Panel B: Chinese Markets

	Baseline	Energy	Grains	Industrial	Metals	Oilseeds
Annual Average Returns	5.2%	9.4%	3.4%	3.1%	5.2%	8.3%
Volatility	11.7%	29.7%	12.1%	19.9%	19.2%	15.7%
Sharpe Ratio	0.38	0.17	0.22	0.06	0.17	0.45
Skewness	0.09	0.27	−0.10	0.78	0.59	−0.23
Excess Kurtosis	1.19	1.34	2.33	5.99	4.49	0.79
% of Positive Months	55%	54%	54%	53%	54%	59%
Maximum Drawdown	−36%	−48%	−34%	−54%	−53%	−39%

regressions for commodity momentum returns:

$$f_t^{Ch} = \alpha^{Ch} + \beta^{Ch} f_t^j + \varepsilon_t^{Ch}, j = US \quad (1)$$

$$f_t^{US} = \alpha^{US} + \beta^{US} f_t^k + \varepsilon_t^{US}, k = Ch \quad (2)$$

where f_t^{Ch} and f_t^{US} are returns to commodity momentum strategies in China and the U.S, and explanatory factors f_t^j and f_t^k can be country-level or global strategies. If the explanatory factors and baseline strategies share significant comovement, we would expect large and positive regression coefficients β^{Ch} and β^{US}, as well as large R-squareds. If the explanatory factors fully explain the average returns of f_t^{Ch} and f_t^{US}, we would expect the regression intercepts α^{Ch} and α^{US} to be small or negative. Alternatively, large and positive intercepts would indicate that the average returns of the baseline strategies cannot be explained.

Momentum strategies tend to have long left tails (Daniel and Moskowitz, 2016; Arnott et al., 2019), so strategy returns are not normally distributed. The baseline strategy in China strongly rejects the null of normality in Shapiro-Wilk and D'agostino's tests with p-values that are zero to three decimal places. If we were to run a spanning regression involving this strategy, while the point estimates of coefficients remain unbiased, standard errors calculated under the normality assumption can be misleading. To overcome this issue, we use a bootstrap approach to test the statistical significance of regression coefficients. For each spanning regression, we draw 10,000

Table 5
Spanning Regressions of Commodity Momentum Strategies.
This table presents spanning regressions for the monthly returns of commodity momentum strategies in the U.S. on the strategy returns in China, and vice versa.

$$f_t^{Ch} = \alpha^{Ch} + \beta^{Ch} f_t^j + \varepsilon_t^{Ch}, j = US$$
$$f_t^{US} = \alpha^{US} + \beta^{US} f_t^k + \varepsilon_t^{US}, k = Ch$$

Baseline shows spanning regressions for baseline momentum strategies, whereas Energy, Grains, Industiral, Metals and Oilseeds show within-sector momentum strategies. Bootstrap p-values are shown in square brackets. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

	Baseline		Energy		Grains		Industrial		Metals		Oilseeds	
	China	US	China	US	China	US	China	US	China	US	China	US
α^{Ch}	4.8%**		8.4%		3.6%		3.6%		4.8%		7.2%**	
	[0.05]		[0.19]		[0.11]		[0.28]		[0.15]		[0.04]	
α^{US}		1.2%		−6.0%		−7.2%		9.6%		0.0%		2.4%
		[0.42]		[0.12]		[0.10]		[0.17]		[0.45]		[0.33]
β_t^{US}	0.288***		−0.142		0.025		0.007		0.140		0.266***	
	[0.00]		[0.43]		[0.49]		[0.83]		[0.13]		[0.00]	
β_t^{Ch}		0.393***		−0.039		0.082		0.033		0.216		0.496***
		[0.00]		[0.44]		[0.50]		[0.84]		[0.08]		[0.00]
R^2	0.113		0.006		0.002		0.000		0.030		0.132	
N	198		117		198		198		198		186	

samples from the original time series with replacement. Each sample is constructed to have the same time-series dimension as the original data. We rerun regressions on each sample and record the coefficients. We then compute the *p*-values using the distributions of the bootstrap coefficients.

Table 5 presents the regression results for the baseline and within-sector momentum strategies. A regression of the Chinese baseline strategy on the U.S. baseline strategy yields a coefficient of 0.288 and an R-squared of 0.113. The intercept is 4.8% per year, significant at the 5% level. A regression of the U.S. baseline strategy on the Chinese strategy yields a coefficient of 0.393. The intercept is 1.2% per year, but the estimate is statistically indistinguishable from zero. This pair of spanning regressions illustrates some comovement between the two strategies, consistent with the finding that momentum strategies are correlated across geographic regions (Asness et al., 2013). At the same time, nearly 90% of the return variation in these strategies remain unexplained. Large intercepts on the same order of magnitude as the raw average returns of the baseline strategies, along with low explanatory power, suggest that commodity momentum premia in the China and U.S. contain economically large local components.

We could easily draw incorrect conclusions if we are not careful about inference. *T*-statistics and *p*-values from ordinary least squares, under the assumption that the regression errors are normally distributed, would imply that the regression intercept is indistinguishable from zero for both the Chinese and the U.S. baseline strategies. Without inspecting the distributions of the dependent and independent variables, one may attribute the weak statistical significance to having relatively few data points and dismiss the economically large intercepts as unimportant. Bootstrap *p*-values show that the spanning regression intercept for the Chinese strategy is not only economically large, but also statistically different from zero.

Turning to the results on within-sector momentum strategies in the five overlapping sectors. For each sector, we run a pair of spanning regressions comparing the explanatory power of the U.S. strategy for the Chinese strategy and vice versa. We observe a similar pattern compared to the baseline strategies: Low R-squared, suggesting there is a limited comovement among within-sector strategies in the U.S. and Chinese markets, and economically large intercepts for the Chinese strategies ranging between 3.6% and 8.4% per year. Due to greater variability of returns, the intercepts of within-sector spanning regressions are generally not statistically significant, except for the case of oilseeds.

3.3. Global factors and comovement

Table 5 contains univariate tests of explanatory power, but does not tell us whether these strategies are exposed to other possible common drivers. We explore commonalities in U.S. and Chinese momentum strategies through explanatory regressions including macroeconomic and global factors. A global momentum strategy is constructed on the entire cross section of available commodities, including all U.S. and Chinese markets. A 50/50 combination of the baseline strategies in China and the U.S. is computed as a portfolio that invests equally among the two strategies. Global strategies combine the characteristics of both the U.S. and Chinese commodity markets, increasing the likelihood of explaining average returns in each country. We then expand our set of global factors to include prominent risk factors proposed in the literature such as value, momentum and carry strategies across asset classes and geographies (Asness et al., 2013; Koijen et al., 2018).

Table 6 reports the factor loadings of Chinese (Panel A) and U.S. (Panel B) commodity momentum strategies on macro and global factors. Regressions of the baseline momentum strategies on the global strategy show much stronger explanatory power. A regression of the Chinese baseline strategy on the global strategy yields a coefficient of 0.897, significant at the 1% level and an R-squared of 0.67. Likewise, a regression of the U.S. baseline strategy on the global strategy (Panel B) has a coefficient of 0.887 and an R-squared of 0.481. The intercepts in these regressions are economically small and statistically indistinguishable from zero. Evidently, the baseline momentum strategies in the Chinese and U.S. markets both load on, and their average returns explained by, the global strategy.[9] We observe similar results for the regressions of baseline strategies on the 50/50 combination; the regression coefficients and R-squareds are large. The intercepts are omitted as they are economically and statistically small. The baseline momentum strategies are spanned by the 50/50 strategy.

Regressions involving the global and 50/50 strategies provide useful comparisons to regressions including only the baseline momentum strategies. The Chinese baseline strategy is 0.82 correlated with the global strategy and 0.74 correlated with the 50/50 strategy, but it is only 0.34 correlated with the U.S. baseline strategy. Similarly, the U.S. baseline strategy is 0.69 and 0.84 correlated to the global and 50/50 strategies. Comparing the regression R-squareds, it is clear that while the global and 50/50 strategies can explain the return variation and average returns associated with the two baseline momentum strategies, the baseline strategies are not able to explain the return variation nor average returns of each other.

We now turn to inflation and global factors across asset classes. From the univariate regressions, the Chinese and U.S. momentum strategies load positively on U.S. inflation. For the U.S. strategy, these results hold when global multi-asset strategies are controlled for. We also find that both the Chinese and U.S. strategies load negatively on global value and positively on global momentum across asset classes, consistent with the findings in Asness et al. (2013). For the Chinese strategy, the explanatory power of the global carry factor remains if we include the U.S. strategy, suggesting that the U.S. commodity momentum does not fully explain Chinese momentum. But once we include global or 50/50 combo the explanatory power of other variables disappears, suggesting that global commodity momentum captures all the variation associated with the Chinese strategy. We observe a somewhat different pattern for the U.S. strategy: Global momentum is significant when we control for the Chinese commodity momentum, but the significance weakens when

[9] This result is not mechanical. The global strategy can take on different long and short positions compared to the baseline strategies. A commodity could have a long position in the global strategy but a short position in the respective baseline strategy.

Table 6
Loadings on Macro and Global Factors, This table reports the loadings of monthly returns of commodity momentum strategies on macro and global factors. Panel A reports results on momentum in China whereas Panel B reports results in the US. Global represents a momentum strategy constructed on the entire cross section of available commodities, including both U.S. and Chinese markets. 50/50 presents an equal combination of the baseline strategies in China and the U.S. Inflation is represented by changes in monthly CPIs in each respective country. Global value, momentum and carry are obtained from AQR Capital's website. Momentum and value are constructed as per Asness et al. (2013), carry is based on Koijen et al. (2018). The USD/RMB exchange rate is obtained from the St. Louis Fed. *p*-values are shown in square brackets. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Panel A: Chinese momentum strategy

	$baseline_t^{Ch}$	$baseline_t^{Ch}$	$baseline_t^{Ch}$	$baseline_t^{Ch}$	$baseline_t^{Ch}$	$baseline_t^{Ch}$	$baseline_t^{Ch}$	$baseline_t^{Ch}$	$baseline_t^{Ch}$	$baseline_t^{Ch}$	$baseline_t^{Ch}$	$baseline_t^{Ch}$	$baseline_t^{Ch}$	$baseline_t^{Ch}$	$baseline_t^{Ch}$
$baseline_t^{US}$	0.288***									0.197***			0.169**		
	[0.00]									[0.00]			[0.00]		
$global_t$		0.897***									0.914***			0.933***	
		[0.00]									[0.00]			[0.00]	
$50/50_t$			0.884***									0.900***			0.930***
			[0.00]									[0.00]			[0.00]
$inflation_t^{Ch}$				0.003						0.000	0.000	0.000			
				[0.53]						[0.96]	[0.99]	[0.99]			
$inflation_t^{US}$					0.015*								0.008	−0.005	−0.007
					[0.05]								[0.26]	[0.24]	[0.14]
$global\ value_t$						−0.627*				−0.047	−0.230	−0.072	−0.035	−0.239	−0.079
						[0.02]				[0.91]	[0.28]	[0.77]	[0.93]	[0.26]	[0.74]
$global\ mom_t$							0.648***			0.482	−0.175	−0.116	0.523	−0.199	−0.152
							[0.00]			[0.09]	[0.21]	[0.47]	[0.05]	[0.15]	[0.35]
$global\ carry_t$								0.510		0.546*	0.080	0.083	0.460*	0.133	0.151
								[0.09]		[0.03]	[0.59]	[0.62]	[0.05]	[0.35]	[0.34]
USD/RMB_t									0.003	0.002	−0.003	−0.001	0.003	−0.003	−0.001
									[0.53]	[0.62]	[0.35]	[0.73]	[0.59]	[0.37]	[0.74]
R^2	0.113	0.670	0.616	0.003	0.031	0.040	0.088	0.020	0.002	0.169	0.675	0.618	0.177	0.678	0.624
N	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198

Panel B: The U.S. momentum strategy

	$baseline_t^{US}$	$baseline_t^{US}$	$baseline_t^{US}$	$baseline_t^{US}$	$baseline_t^{US}$	$baseline_t^{US}$	$baseline_t^{US}$	$baseline_t^{US}$	$baseline_t^{US}$	$baseline_t^{US}$	$baseline_t^{US}$	$baseline_t^{US}$	$baseline_t^{US}$	$baseline_t^{US}$	$baseline_t^{US}$
$baseline_t^{Ch}$	0.359***									0.246**			0.199**		
	[0.00]									[0.00]			[0.01]		
$global_t$		0.887***									0.811***			0.754***	
		[0.00]									[0.00]			[0.00]	
$50/50_t$			1.114***									1.074***			1.040***
			[0.00]									[0.00]			[0.00]
$inflation_t^{Ch}$				0.004						0.000	0.000	0.000			
				[0.41]						[0.96]	[0.99]	[0.99]			
$inflation_t^{US}$					0.028***								0.027***	0.015*	0.008
					[0.00]								[0.00]	[0.01]	[0.15]
$global\ value_t$						−0.884***				0.082	−0.052	−0.053	0.117	−0.025	−0.040
						[0.00]				[0.78]	[0.86]	[0.82]	[0.64]	[0.92]	[0.86]
$global\ mom_t$							0.987***			0.957***	0.338	0.171	1.021***	0.411*	0.210
							[0.00]			[0.00]	[0.11]	[0.26]	[0.00]	[0.05]	[0.17]
$global\ carry_t$								0.408		0.500*	0.112	−0.004	0.176	−0.044	−0.084
								[0.16]		[0.05]	[0.63]	[0.98]	[0.48]	[0.84]	[0.63]
USD/RMB_t									0.006	0.006	0.001	0.002	0.006	0.001	0.002
									[0.31]	[0.25]	[0.80]	[0.64]	[0.32]	[0.78]	[0.66]
R^2	0.096	0.481	0.705	0.003	0.086	0.059	0.149	0.009	0.005	0.221	0.497	0.711	0.290	0.517	0.716
N	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198

the global commodity momentum factors are present.[10] Overall, Table 6 suggests that the U.S. momentum is exposed to global inflation shocks, but the Chinese momentum is not. Taken together, our analysis supports the argument that Chinese and U.S. commodity momentum are distinctive despite being somewhat correlated.

3.4. Cross-country signals

Up until this point, we have constructed baseline strategies in the U.S. and China by selecting long and short positions using the past returns of each domestic markets and invest in these same commodities. Some commodities are traded in both markets, including corn, wheat, and silver. How would cross-country signals perform? If soybean returns in China have been strong relative to other commodities, would a strategy that invests in U.S. soybean futures have positive average returns? We explore this idea in Table 7.

A strategy that uses U.S. signals to invest in U.S. markets is the U.S. baseline strategy, and a strategy that uses Chinese signals to invest in Chinese markets is the Chinese baseline strategy. From Table 4, these strategies earn annual average returns of 5.2% and 2.7%, respectively, and report a correlation of 0.34. There are 12 overlapping commodities in the U.S. and Chinese markets in our sample. In this overlapping sample, these strategies earn annual average returns of 5.0% and 3.3% respectively and still report a modest correlation of 0.43. A strategy that takes U.S. signals to invest in Chinese markets earns an annual average return of 4.5%, whereas a strategy that takes Chinese signals to invest in U.S. markets earns an annual average return of 8.1%. The fact that cross-country signals report higher returns implies that past returns in foreign markets may contain information content beyond domestic market dynamics. This may also help explain why the correlation between the U.S. and Chinese momentum is relatively low even in a seemingly identical set of commodities.

Commodities such as corn, soybean meal, copper, and cotton are traded in both countries. To the extent commodities are fungible across geographic borders, the returns to these overlapping commodities may be expected to be similar across the U.S. and Chinese markets. Similar underlying return series would lead to similar momentum strategies. Fan and Zhang (2020) identify 14 commodities traded in the U.S. and Chinese market and examine their pairwise correlations. The authors find an average correlation of 0.46, indicating that although the commodity names are identical, the futures contracts in the U.S. and China do not behave similarly. Since individual commodities in the U.S. and Chinese markets exhibit limited comovement, it is not surprising that momentum strategies constructed on these commodities also exhibit limited comovement. Several factors may contribute to this dissimilarity. First, the infeasibility of cash-and-carry arbitrage prevents the convergence of commodity prices between China and the U.S. Second, as shown in Table 6, commodity momentum in China and U.S. respond differently to global inflation shocks. Third, trading in the Chinese commodity markets is primarily driven by retail investors whereas in the U.S. markets trading is mainly driven by institutional investors (Fan and Zhang, 2020).

Overall, the combined evidence of correlations, regressions, and cross-country signals shows that while commodity momentum strategies across borders share some comovement, they are primarily local in nature. Furthermore, the strong local characteristics of commodity momentum premia largely explains the efficacy of cross-country diversifications demonstrated by Bianchi et al. (2021). The moderate correlations observed between the U.S. and Chinese momentum profits suggest that investors around the globe can improve their risk-return tradeoff by diversifying into Chinese commodity futures markets. Since commodity momentum returns exhibit a strong local component, we further examine whether its profitability is driven by the sector or idiosyncratic effects within each local market.

4. Sector and idiosyncratic components of commodity momentum profits

The previous section explored the similarities and differences among commodity momentum strategies in the U.S. and Chinese markets. In this section, we examine whether the profitability of commodity momentum strategies can be attributed to sector effects or individual commodity effects. We first examine the profitability of several sector-level momentum strategies and make comparisons to the baseline momentum strategies. We then construct momentum strategies based only on the idiosyncratic component of commodity returns, and we assess the relative importance of sector effects versus individual commodity effects to understand whether commodity momentum is more likely driven by risk or behavioral factors.

4.1. Sector-level momentum strategies

Commodity markets are naturally divided into sectors that behave similarly. Return correlations of commodities within a sector are considerably higher than return correlations across sectors. To what extent are commodity momentum premia driven by sector effects?

Table 8 presents three momentum strategies at the sector level. We begin with a sector momentum strategy that takes equal-weight sector returns as basis assets. We rank the past 12-month returns of the equal-weight sector portfolios and take long and short positions in the winners and losers, rebalancing the strategy monthly. In the U.S. markets, there are seven sector portfolios, so the sector

[10] The Chinese momentum strategy generates an alpha of 6% per year relative to global value (significant at 5%) and 4.8% per year to global carry (significant at 10%), though it becomes insignificant when considering global momentum. Meanwhile, the U.S. commodity momentum strategy does not generate statistically significant alphas to any global risk factors considered. These findings are in line with Bianchi et al. (2021) where the authors find that the investable commodity premia in China expand the opportunity set of global investors and offer meaningful diversification benefits.

Table 7
Momentum Strategies using Alternative Signals This table presents the statistics of commodity momentum strategies constructed using alternative signals. Each strategy uses either the past returns of U.S. commodities or the past returns of Chinese commodities as the portfolio formation signal, and then invests in one of these markets. For example, "U.S. Strategy, Chinese Signals" refers to a strategy formed using the past returns of Chinese commodities that invests in the U.S. markets. The sample period is January 2005 to July 2022.

	U.S. Strategy, U.S. Signals	Chinese Strategy, Chinese Signals	U.S. Strategy, Chinese Signals	Chinese Strategy, U.S. Signals
Annual Average Returns	5.0%	3.3%	8.1%	4.5%
Volatility	15.4%	11.7%	16.5%	12.4%
Sharpe Ratio	0.25	0.21	0.41	0.30
Skewness	0.36	−0.26	0.42	0.08
Excess Kurtosis	1.08	1.33	1.43	1.32
% of Positive Months	55%	59%	56%	58%
Maximum Drawdown	−58%	−28%	−34%	−31%

Table 8
Sector-Level Momentum Strategies, This table reports momentum strategies at the sector level. "Sec Mom" is a momentum strategy that uses equal-weight sector returns as basis assets. "EW WSM" is an equal-weight portfolio of within-sector momentum strategies in Table 4. "WSM Mom" is a momentum strategy using within-sector momentum strategies as basis assets. All strategies are rebalanced monthly.

Panel A: U.S. Markets			
	Sec Mom	EW WSM	WSM Mom
Annual Average Returns	3.7%	0.2%	−6.4%
Volatility	16.1%	9.6%	21.2%
Sharpe Ratio	0.15	−0.03	−0.41
Skewness	0.17	0.57	0.13
Excess Kurtosiss	0.59	2.70	0.43
% of Positive Months	54%	46%	47%
Maximum Drawdown	−63%	−39%	−79%
Panel B: Chinese Markets			
	Sec Mom	EW WSM	WSM Mom
Annual Average Returns	7.3%	4.3%	5.5%
Volatility	17.7%	12.2%	11.0%
Sharpe Ratio	0.33	0.29	0.45
Skewness	−0.23	0.07	0.55
Excess Kurtosis	0.50	1.01	3.55
% of Positive Months	53%	56%	59%
Maximum Drawdown	−33%	−49%	−30%

momentum strategy is long three sectors and short three sectors. This strategy has an average return of 3.7% per year, a volatility of 16.1%, and a Sharpe ratio of 0.15. These performance statistics are generally in line with those of the baseline momentum strategy (2.7%, 13.7%, and 0.13). In the Chinese markets, a sector momentum strategy earns somewhat higher average returns than the baseline momentum strategy (7.3% vs. 5.2%), with a higher annual volatility (17.7% vs. 11.7%) and comparable Sharpe ratios (0.33 vs. 0.38). Indeed, in both U.S. and Chinese markets, sector momentum exhibits a high correlation of 0.74 with the baseline individual momentum.

Second, we form an equal-weight portfolio of within-sector momentum strategies. In the U.S. markets, this strategy merely earns an annual average return of 0.2%, lower than that of the baseline strategy. In the Chinese markets, the equal-weight within-sector strategy has an annual average return of 4.3%, slightly lower than the baseline strategy's 5.2%. Its volatility of 12.2% is similar to the baseline strategy's 11.7%. As a result, the Sharpe ratio of this equal-weight within-sector momentum strategy is lower than that of the baseline momentum strategy. We also find that the U.S. within-sector momentum strategy is only moderately correlated with the baseline strategy at 0.57, while the Chinese strategy is highly correlated with the baseline strategy at 0.83.

Third, we construct a momentum strategy using the within-sector momentum strategies as basis assets, rebalanced monthly. We rank the past 12-month returns of the within-sector momentum strategies, and take long positions in the best-performing strategies and short positions in the worst-performing ones. In the U.S. markets, this strategy has an annual average loss of 6.4%, significantly underperforming the baseline momentum strategy, while reporting a higher volatility of 21.2% compared to the baseline strategy. The volatility of a long-short portfolio of within-sector strategies is nearly as high as those of the individual within-sector momentum strategies, indicating a limited degree of diversification. We observe a different pattern in the Chinese markets, with an annual return of 5.5% and a volatility of 11.0% per year, which appears to outperform the baseline strategy. Not surprisingly, we observe a much lower level of correlation between the third strategy and the baseline momentum strategies in both countries at 0.19 and 0.32, respectively.

Our finding that momentum strategies constructed using sector portfolio show average returns on the same order of magnitude as the baseline commodity momentum premia echoes a similar finding in equity momentum. Moskowitz and Grinblatt (1999) demonstrate that in equity markets, momentum strategies constructed using industry portfolios exhibit economically large average returns on the same order of magnitude as the equity momentum return premium. Our result hints at the possibility that sector momentum contributes to the overall profitability of commodity momentum strategies. We delve more deeply into this possibility in the following sections.

4.2. Sector effects versus individual commodity effects

The baseline commodity strategies (see Table 4) are constructed through ranking the 12-month total returns of individual commodities, which have a sector component and a commodity-specific component. We augment the portfolio construction procedure to remove the sector component: rather than ranking on total returns, we rank on the past returns of individual commodities minus the equal-weight returns of their respective sectors. This step neutralizes the sector effects in commodity returns and allows us to focus on the commodity-specific returns. We then construct excess sector momentum strategies by ranking on the excess sector returns over the past 12 months, taking long positions in the top 50% of commodities by performance and short positions in the bottom 50%.

Table 9 shows the results of the excess sector momentum strategies. In the U.S. markets, the excess sector strategy earns an average return of −0.4% per year with a volatility of 9.6%. After removing the sector component of past returns, commodity momentum in the U.S. is no longer profitable. In the Chinese markets, the excess sector strategy earns 4.6% per year, similar to the 5.2% of the baseline momentum strategy. Evidently, after removing the sector component of past returns, commodity momentum in the Chinese markets continue to be profitable.

Our second test to compare the relative importance of sector effects and individual commodity effects is based on portfolio constructions that offset sector and individual commodity effects. We select the best performing sectors, and within each winning sector, invest in the worst performing commodities. We also select the worst performing sectors, and within these sectors, short the best performing commodities. If sector effects dominate, we would expect to see a positive average return to such a strategy since we took long positions in the best sectors and short positions in the worst sectors. If individual commodity effects dominate, we would expect a negative average return because we took long positions in the worst performing commodities and short positions in the best performing commodities. Table 9 shows that in the U.S. markets, such a strategy earns an average return of 3.4% per year with a volatility of 17.6%, whereas in the Chinese markets this strategy earns −0.1% per year with a volatility of 11.0%. These findings suggest that sector effects are stronger than individual commodity effects in the U.S. markets, whereas individual commodity effects are somewhat stronger compared to sector effects in the Chinese markets.

4.3. Return decomposition

Momentum is a trading strategy that goes long commodities that have outperformed the average commodity in the portfolio formation period and short commodities that have underperformed. There are various ways of constructing momentum portfolios. Thus far, we have followed the most popular methodology in the literature: rank assets by their past returns and go long the top performers and short the bottom performers, placing equal weights on the commodities within the two groups. This methodology offers a simple interpretation, but it does not lend itself to a straightforward return decomposition. Alternative approaches allow for more tractable return decomposition. One approach involves constructing self-financing portfolios with weights that are linear

Table 9
Comparing Sector and Idiosyncratic Effects, This table presents two momentum strategies that compare sector effects against idiosyncratic commodity effects. “Excess Sector” is constructed by ranking on individual commodity returns in excess of their respective equal-weight sector returns. “High-Sector Losers minus Low-Sector Winners” selects the best performing sectors, and within each winning sector, take long positions in the worst performing commodities. This strategy also takes short positions in the best performing commodities within the worst performing sectors. All strategies are rebalanced monthly.

Panel A: U.S. Markets		
	Excess Sector	High-Sector Losers minus Low-Sector Winners
Annual Average Returns	−0.4%	3.4%
Volatility	9.6%	17.6%
Sharpe Ratio	−0.09	0.11
Skewness	0.05	0.18
Excess Kurtosis	0.87	1.37
% of Positive Months	49%	54%
Maximum Drawdown	−37%	−63%
Panel B: Chinese Markets		
	Excess Sector	High-Sector Losers minus Low-Sector Winners
Annual Average Returns	4.6%	−0.1%
Volatility	9.7%	11.0%
Sharpe Ratio	0.43	−0.07
Skewness	−0.33	−0.17
Excess Kurtosis	3.94	0.94
% of Positive Months	57%	51%
Maximum Drawdown	−28%	−43%

functions of past returns – a commodity that performed especially well receives a larger weight relative to a commodity that barely outperformed the average (Lo and MacKinlay, 1990). However, such a strategy may place considerable weight on the extremes. To limit the effect of outliers and generate more stable portfolio returns, we used a rank-based weighting approach (Asness et al., 2013; Koijen et al., 2018). The weight placed on commodity i at time t is given as follows:

$$w_t^i = \delta_t \left(rank\left(mom_t^i\right) - \frac{N_t + 1}{2} \right) \tag{3}$$

where mom_t^i is the momentum signal for commodity i at time t, N_t is the number of available commodities, and δ_t is a scalar such that the sums of long and short positions are 1 and -1, respectively.

To compare the relative importance of sector effects and idiosyncratic commodity effects, we can rewrite the portfolio weight on commodity i as a combination of a sector part and an idiosyncratic part:

$$w_t^i = w_t^m + \left(w_t^i - w_t^m\right) \tag{4}$$

where w_t^m is the average weight for all commodities in the same sector as commodity i, and $(w_t^i - w_t^m)$ is the portfolio weight adjusted for sector exposure. In this construction, momentum returns can be readily decomposed into a sector component and an idiosyncratic

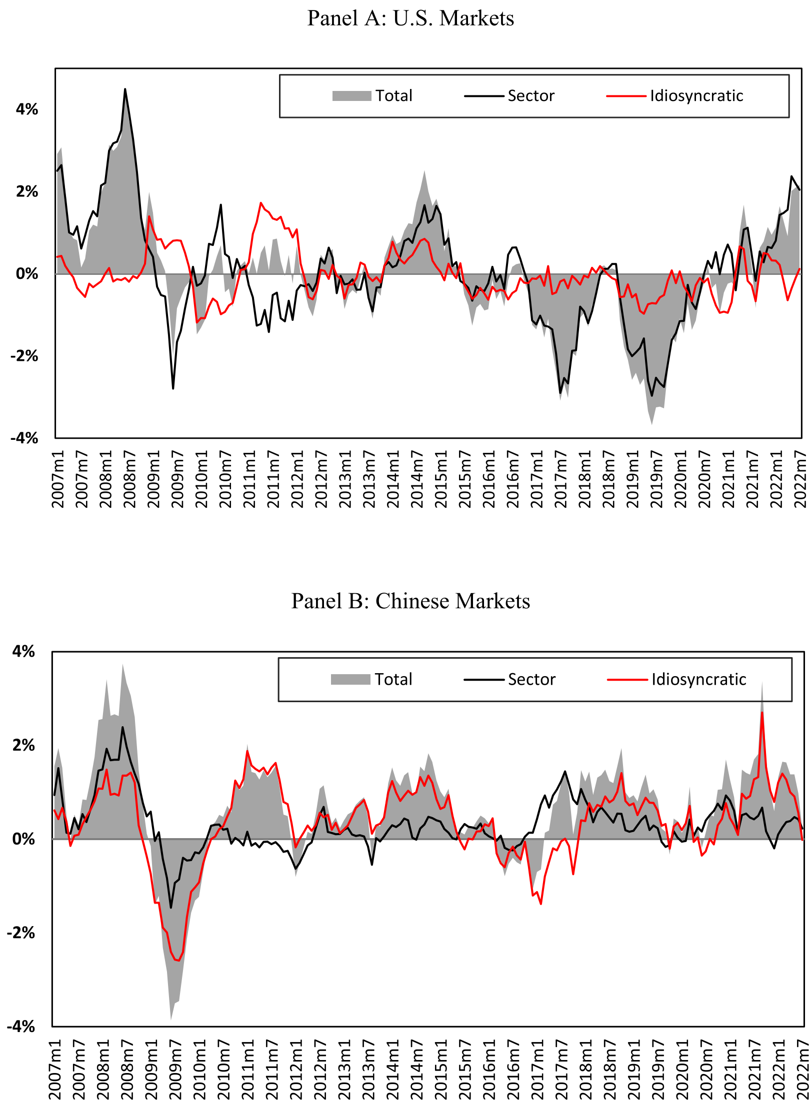


Fig. 3. Return Decomposition of Momentum Strategies
This figure plots the 12-month moving averages of rank-based momentum returns. The total portfolio returns are shown in grey shading. Total returns are decomposed into sector and idiosyncratic components, which are plotted separately.

component:

$$r_{t+1} = \sum_i w_t^i r_{t+1}^i = \underbrace{\sum_i w_t^m r_{t+1}^i}_{\substack{\text{Sector} \\ \text{Component}}} + \underbrace{\sum_i \left(w_t^i - w_t^m\right) r_{t+1}^i}_{\substack{\text{Idiosyncratic} \\ \text{Component}}} \tag{5}$$

The rank-based momentum returns are highly correlated with the returns from portfolio sorts. The portfolio returns from the two methods have a correlation of 0.92 for the U.S. markets and 0.96 for the Chinese markets. Fig. 3 plots the rank-based momentum returns, along with the sector and idiosyncratic components. For ease of viewing, the returns are smoothed using a 12-month window. There exists significant time variation in momentum profits. Years preceding to the Great Recession saw great returns for both the U.S. and Chinese strategies, and both strategies suffered drawdowns during the Great Recession. The drawdown in the U.S. markets was less severe and lasted for a shorter period, as sector and idiosyncratic components offset one another. Around the same time in the Chinese markets, both the sector and idiosyncratic components contributed negatively to a deeper drawdown. The recent underperformance in the U.S. markets can be largely attributed to a large negative sector component. In terms of economic magnitude, the rank-based method shows average returns of 2.1% for the U.S. and 8.4% for China. 99% of momentum profits in the U.S. can be attributed to the sector component. In the Chinese markets, the split is 51% and 49% for the sector and idiosyncratic components, respectively.

4.4. *Diversification*

Asness et al. (2013) show that momentum strategies are positively correlated across asset classes and geographic regions, and they attribute the positive correlations to a common explanation of momentum returns. We examine the correlations of within-sector momentum strategies in order to understand whether there is a common driver to commodity momentum returns across sectors.

Table 10 reports the pairwise correlations of within-sector momentum strategies. In each cell, the Pearson correlation coefficient is shown on the left and Spearman's rank correlation is shown in square brackets. In the U.S. markets, Pearson and Spearman correlation are economically small, ranging between −0.12 and 0.09. In the Chinese markets, the Pearson correlations average to 0.12, whereas the Spearman correlations average to 0.11. The Spearman correlations range between −0.13 and 0.25. The small magnitude of correlations illustrates the rather weak relations among within-sector momentum strategies. Unlike the findings for momentum strategies across asset classes in Asness et al. (2013), within-sector momentum strategies do not appear to share much comovement. The lack of comovement in within-sector momentum strategies stands in contrast to the comovement exhibited by sector returns (see Table 3); within-sector momentum strategies exhibit even lower comovement compared to equal-weight sector returns.

We further investigate the comovement of within-sector momentum strategies by examining the left tail of these return distributions. Fig. 4 compare the drawdowns of sector returns and within-sector momentum strategies in the Chinese markets. Panel A illustrates that drawdowns tend to occur at the same time across several sectors: energy, industrials, metal, and oilseeds all simultaneously suffered a sharp drawdown in 2009. Although its magnitude was less dramatic, the grains sector also experienced a smaller drawdown at the same time as the other sectors. From 2015 to 2017, all five sectors had continuous losses. Because sector-level drawdowns tend to happen at the same time, an equal-weight portfolio of sector returns cannot alleviate this tail risk – an equal-weight sector portfolio shows a maximum drawdown of 46.3%. This equal-weight portfolio experienced a prolonged period of underperformance, from 2008 to 2020, as individual sectors perform persistently poorly.

In contrast to sector returns, within-sector momentum strategies tend not to be highly correlated with one another. Panel B of Fig. 4 illustrates that the drawdowns of within-sector momentum strategies also do not tend to occur at the same time. When industrials and metals suffered 54% and 53% drawdowns in 2009, the other three sectors show gains rather than losses. Similarly, in 2014 when

Table 10
Correlations of Within-sector Momentum Strategies, This table reports the pairwise correlations for within-sector momentum strategies. In each cell, the Pearson correlation coefficient is shown on the left, and Spearman's rank correlation is shown in square brackets.

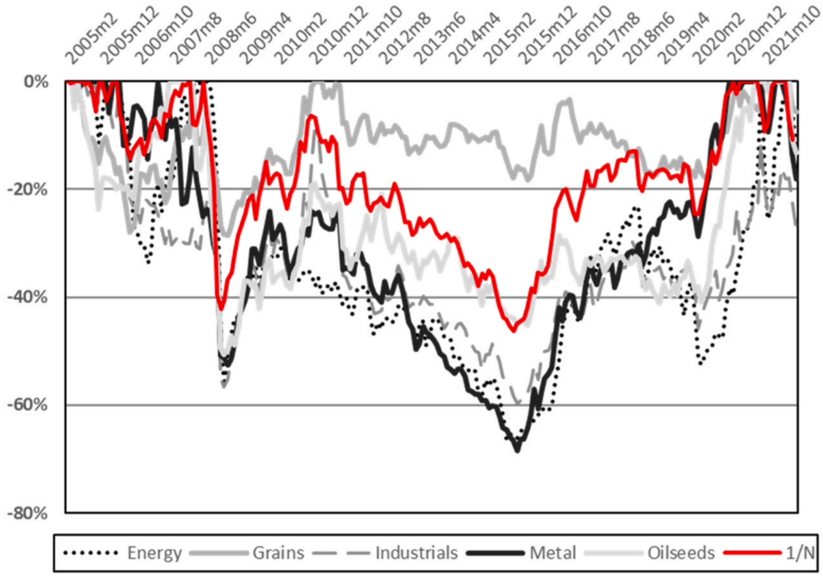
Panel A: U.S. Markets

Pearson [Spearman]	Energy	Grains	Industrials	Meats	Metals	Oilseeds	Softs
Energy							
Grains	0.06 [0.09]						
Industrials	0.03 [-0.02]	−0.07 [-0.09]					
Meats	−0.01 [0.00]	0.01 [0.07]	0.04 [0.02]				
Metals	−0.05 [0.00]	−0.05 [-0.03]	0.01 [0.00]	−0.06 [-0.09]			
Oilseeds	−0.03 [-0.06]	0.06 [0.09]	0.00 [-0.04]	0.04 [0.09]	0.00 [-0.02]		
Softs	0.06 [-0.01]	−0.11 [-0.12]	−0.01 [-0.01]	−0.08 [-0.04]	0.05 [0.03]	−0.01 [-0.03]	

Panel B: Chinese Markets

Pearson [Spearman]	Oilseeds	Energy	Grains	Industrials	Metals
Oilseeds					
Energy	0.06 [0.10]				
Grains	0.34 [0.24]	0.21 [0.10]			
Industrial	0.28 [0.25]	0.10 [0.05]	0.29 [0.25]		
Metals	0.16 [0.11]	−0.17 [-0.13]	−0.01 [0.07]	0.04 [0.02]	

Panel A. Drawdowns of Sector Returns



Panel B. Drawdowns of Within-sector Momentum Strategies

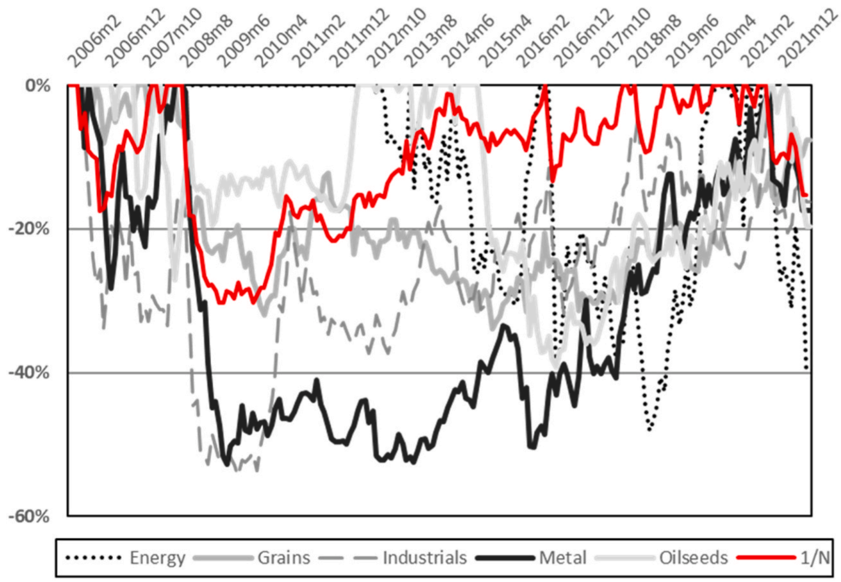


Fig. 4. Left Tails of Sector Returns and Momentum Strategies
This figure compares the left tails of sector returns and momentum strategies, as measured by drawdowns, in the Chinese markets. In Panel A, equal-weight sector returns are shown in greyscale, and the red line represents an equal-weight portfolio of sector returns. In Panel B, within-sector momentum strategies are shown in greyscale, and the red line represents an equal-weight portfolio of these momentum strategies. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

energy and grains started to have drawdowns, industrials and oilseeds performed well. Due to excellent diversification across within-sector momentum strategies, an equal-weight portfolio of these strategies has a maximum drawdown of 30%, markedly smaller than the individual within-sector momentum strategies.

The lack of correlation across within-sector momentum strategies – and their diversification benefits for one another – suggests momentum returns in commodity sectors are not driven by an economy-wide factor. It is possible that within-sector momentum strategies are employed by different investor segments across sectors, as to cause different return behavior across sectors. We cannot rule out the possibility that momentum strategies within sectors may have a common economic driver, whether risk-based or behavioral, but it appears such a driver manifests itself in different ways across different commodity sectors.

4.5. Discussions and extension

The evidence from sector-level momentum strategies, tests comparing sector and individual commodity effects, and return decomposition support the hypothesis that sector effects make up a large component of momentum premia in commodity markets. Moskowitz and Grinblatt (1999) find that in equity markets, industry momentum drives much of momentum strategy returns, and momentum strategies are less profitable after controlling for industry momentum. We find similar results in commodity markets: sector momentum contributes to the total profits in commodity momentum strategies. Szymanowska et al. (2014) show that cross-sectional and time-series variation in commodity futures returns is related not so much to sectors as characteristics such as past returns. We

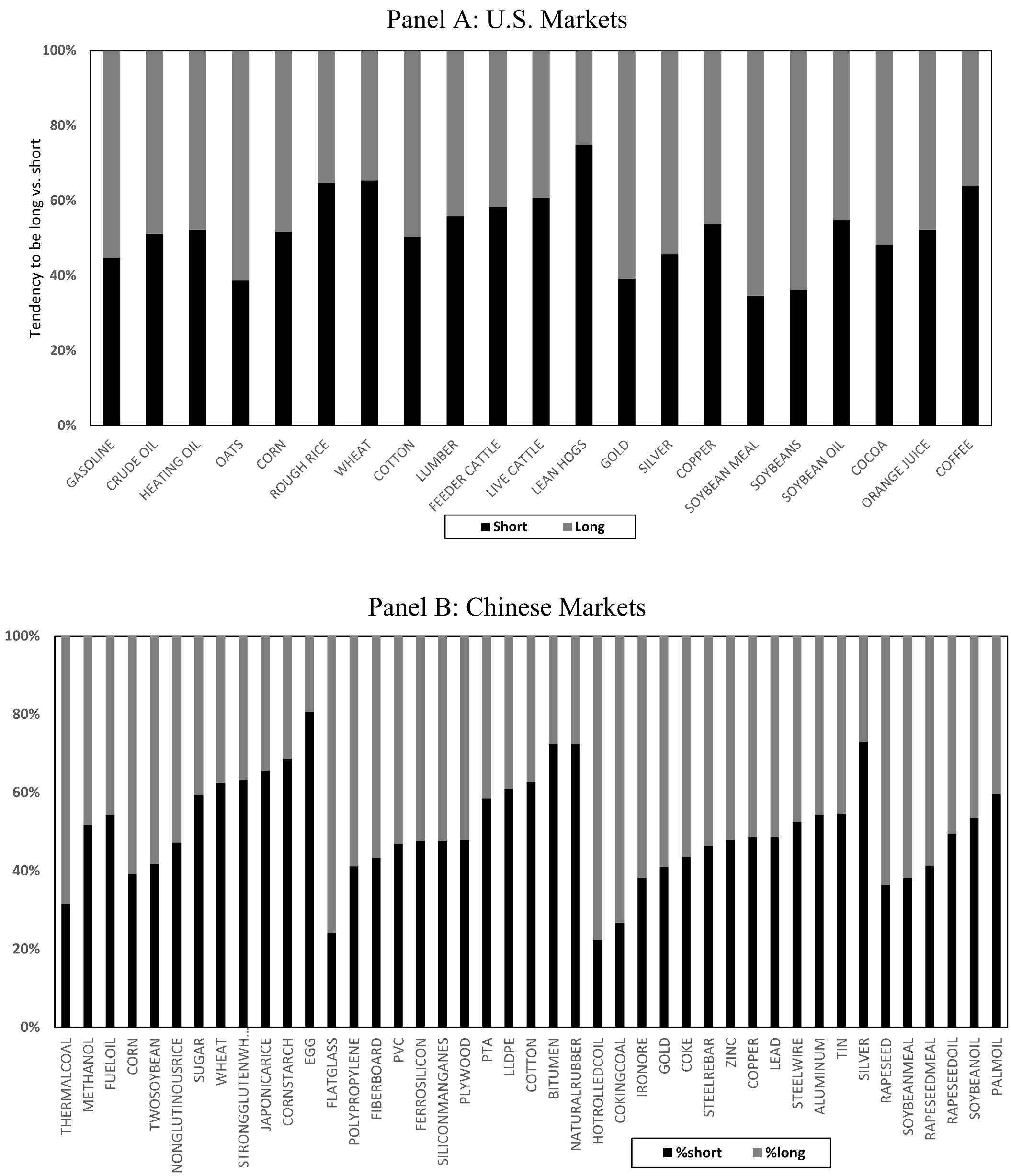


Fig. 5. Percentage Long vs. Short
This figure shows the fraction of months that different commodities are likely to be long or short in the baseline momentum strategy in the U.S. (Panel A) and China (Panel B). The dark bars show the short positions as a percentage of the total number of positions taken; the light bars show the long positions as a percentage of the total positions.

complement their results by demonstrating that sector effects contribute to explaining the cross-sectional variation in commodity returns through the momentum anomaly.

Because commodity futures returns are more correlated within a sector than across sectors, commodity momentum profits driven by sector effects are not well-diversified. An investor cannot form well-diversified long and short portfolios of past winners and losers because she would still be exposed to the vagaries of sector performance. In other words, the existence of sector momentum in commodity markets imposes limits to arbitrage for rational investors who want to exploit momentum profits (Grinblatt and Moskowitz, 1999); momentum in commodity markets is not an arbitrage. In the Chinese markets, significant commodity-specific effects imply that a common risk factor model is unlikely to fully explain the cross-sectional variation in commodity returns.

Kang and Kwon (2017) also find that sector momentum can account for a portion of overall commodity momentum profits. However, the authors conclude that sector effects are not as important as individual commodity effects. Our results show that sector effects are important in both the U.S. markets and the Chinese markets, but individual commodity effects differ. In the U.S. markets, sector effects completely explain the profitability of commodity momentum strategies; a momentum strategy based on the idiosyncratic component of commodity returns is no longer profitable. In contrast, both individual commodity effects and sector effects are strong in the Chinese markets, and individual commodity effects appear somewhat stronger. Even if we neutralize the sector effects, the excess sector momentum returns remain positive and economically large.

Several differences in sample selection may account for the contradictory findings in our work and Kang and Kwon's. Kang and Kwon's (2017) data contain 32 U.S. commodities and 20 Chinese commodities. Their U.S. sample starts in January 1979 and ends in June 2015, and their Chinese sample starts in January 2005 and ends in June 2015. We have a somewhat smaller set of commodities in the U.S. markets, 21, following Szymanowska et al. (2014), and we have a much larger cross section in the Chinese markets, totaling 43 commodities. Since we focus on cross-country comparisons, we restrict the U.S. and Chinese samples to share a common period from January 2005 to July 2022.

Although dissimilar samples may account for some differences in empirical results, the most crucial distinction lies in the research design. To investigate sector contribution to momentum profits, Kang and Kwon group sectors across countries to construct an international sector strategy; agricultural commodities in the U.S. and Chinese markets are clustered as one, along with those traded in the U.K., India, and Japan. This methodology does not allow for a comparison of sector effects across countries. In contrast, our approach focuses on sector effects within each country with the intention of facilitating cross-country comparisons. The methodological differences stem from differences in motivation. Kang and Kwon (2017) focus on the question of whether commodity momentum exists internationally, whereas our work tries to examine whether drivers of commodity momentum returns are consistent across markets.

As a further test of the importance of individual commodity effects in the U.S. and Chinese markets, we examine the long and short positions for the baseline momentum strategies. If individual commodity effects drive the overall profits of commodity momentum strategies, we may expect to observe concentrated positions in specific commodities. Fig. 5 shows the fraction of time each commodity is long or short. For both the U.S. and China, most commodities are traded both in the long and short portfolios, and the fraction of longs and shorts appear balanced. The baseline momentum strategies do not take many extreme positions, suggesting momentum profits are spread across sectors rather than concentrated in individual commodities. However, there are some exceptions in the Chinese markets. The baseline strategy in the Chinese markets exhibit more unbalanced positions across commodities, indicating stronger influence of individual commodity effects for the overall momentum profits.

Stronger commodity-specific effects in the Chinese markets may be related to greater participation of retail investors. By the end of 2016, 86% of open interest was held by individual accounts in the Chinese markets compared to less than 15% in the U.S. markets (Bhardwaj et al., 2016; Fan and Zhang, 2020). Using CFTC trader positions data, Kang et al. (2020) find that speculators (non-commericals) are on average momentum traders. Since momentum strategies are based on past returns and retail investors can greatly influence past returns, momentum strategy profits are dependent on the behavior of retail investors. To the extent retail investors are less sophisticated than institutional investors and behave more like "uninformed traders" (De Long et al., 1990), there could be more positive feedback trading in the Chinese markets, which leads to more persistent and more extreme price deviations from fundamental values. Positive feedback trading would imply positive autocorrelation at shorter horizons for individual commodity returns.[11] We test this implication in our data.

Table 11 shows the first-order autocorrelation coefficients for individual commodity returns in the U.S. and Chinese markets. We observe clear differences between the two countries. In the U.S. markets, the autocorrelation coefficients appear to be small. Daily returns show an average autocorrelation coefficient of just 0.02. Six of 21 commodities exhibit a positive and significant coefficient, whereas four have a negative and significant coefficient. At the weekly or monthly frequencies, the average autocorrelation coefficient continues to be close to zero. Almost all of the individual coefficients are indistinguishable from zero. In the Chinese markets, the autocorrelation coefficients are markedly larger. At the daily frequency, 41 of 43 commodities show a positive and significant coefficient. The daily autocorrelation average of 0.18 is a magnitude larger compared to 0.02 in the U.S. markets. The weekly and monthly

[11] For individual commodity in the U.S., the CFTC Commitment of Traders (CoT) Report outlines the weekly long and short positions held by different type of traders, e.g., commercials (hedgers) and noncommercials (speculators). Chinese exchanges (such as the ZCE) publish the daily long and short positions held by individual futures companies/brokers, but they do not disclose more granular levels of data. At present, the CSRC (China's top financial markets regulator) has not indicated the availability of such data. In the absence of positions data by trader type, the autocorrelation test is a simple but powerful tool to quantify the extend of positive feedback trading in China, especially when deployed in parallel with U.S. commodity markets.

Table 11
Autocorrelations of Commodity Returns, This table shows the first-order autocorrelations of commodity returns in the U.S. and Chinese markets. Statistically significant values at the 5% level are shown in bold. The *t*-statistics are reported in parenthesis and are based on Newey-West standard errors with three lags.

Panel A: U.S. Markets

	Daily		Weekly		Monthly	
Commodity	AR (1)	t (AR (1))	AR (1)	t (AR (1))	AR (1)	t (AR (1))
HEATING OIL	0.00	0.2	0.01	0.4	−0.25	−4.7
GASOLINE	−0.02	−1.0	0.04	1.1	−0.08	−1.1
CRUDE OIL	−0.07	−3.6	−0.01	−0.3	0.14	1.5
FEEDER CATTLE	0.03	1.6	0.00	0.0	0.04	0.6
LIVE CATTLE	0.05	2.5	0.08	2.4	0.04	0.6
LIVE HOGS	−0.08	−3.1	−0.01	−0.3	0.21	3.1
GOLD	0.10	4.5	−0.07	−1.4	−0.03	−0.3
COPPER	−0.04	−1.9	0.06	0.9	0.20	3.2
SILVER	0.00	0.1	−0.05	−1.3	−0.12	−1.7
CORN	−0.03	−1.7	0.00	0.0	0.24	3.6
OATS	0.03	1.6	0.01	0.2	−0.02	−0.2
WHEAT	0.03	1.7	−0.06	−1.9	0.01	0.2
ROUGH RICE	0.17	7.9	0.05	1.3	0.13	1.5
SOYBEAN OIL	0.09	4.9	0.03	0.9	0.05	0.9
SOYBEANS	0.06	3.0	0.02	0.7	−0.13	−2.4
SOYBEAN MEAL	0.10	5.5	0.06	1.4	−0.03	−0.4
COFFEE	−0.03	−1.1	−0.02	−0.5	−0.02	−0.3
ORANGE JUICE	0.01	0.3	−0.02	−0.4	0.00	0.1
COCCOA	0.01	0.4	−0.01	−0.3	0.03	0.4
COTTON	0.03	1.5	−0.02	−0.3	0.02	0.3
LUMBER	0.01	0.4	0.04	1.5	−0.08	−1.2
US Average	0.02	1.1	0.01	0.2	0.02	0.2

Panel B: Chinese Markets

	Daily		Weekly		Monthly	
Commodity	AR (1)	t (AR (1))	AR (1)	t (AR (1))	AR (1)	t (AR (1))
SUGAR	0.13	5.9	−0.04	−1.1	0.05	1.0
COTTON	0.19	5.2	0.02	0.7	−0.03	−0.5
RAPESEED OIL	0.17	7.1	0.02	0.5	0.15	1.7
PTA	0.09	3.6	−0.06	−1.7	−0.17	−2.2
STRONGGLUTEN WHEAT	0.07	3.1	0.03	0.8	0.02	0.2
WHEAT	0.13	2.0	0.15	2.0	0.01	0.1
METHANOL	0.23	8.0	0.09	1.5	0.01	0.1
FLATGLASS	0.12	7.1	0.07	2.1	0.12	2.0
RAPESEED MEAL	0.21	8.3	0.15	3.3	0.11	1.3
RAPESEED	0.18	7.7	0.04	0.8	−0.09	−1.6
NONGLUTINOUS RICE	0.13	6.7	0.07	1.4	0.15	1.8
THERMAL COAL	0.16	3.8	0.05	0.8	−0.02	−0.1
JAPONICA RICE	0.23	9.0	0.08	1.4	0.03	0.3
FERROSILICON	0.06	2.3	0.01	0.3	0.24	2.5
SILICONMANGANES	0.24	8.5	0.07	1.5	0.06	0.6
ONESOYBEAN	0.33	15.3	0.09	2.3	−0.03	−0.4
TWOSOYBEAN	0.31	13.9	0.08	1.9	0.08	0.9
CORN	0.18	8.8	0.05	1.1	−0.16	−2.0
LLDPE	0.30	8.8	0.04	0.7	0.20	2.3
SOYBEAN MEAL	0.15	2.4	−0.14	−2.6	−0.19	−2.0
PALM OIL	0.19	7.7	0.04	0.7	−0.05	−0.9
PVC	0.13	6.8	0.03	1.0	0.06	1.0
SOYBEAN OIL	0.28	12.3	0.07	2.0	−0.01	−0.1
COKE	0.16	6.3	0.02	0.4	0.11	1.4
COKING COAL	0.19	9.5	0.03	0.8	0.18	3.0
PLYWOOD	0.18	7.1	0.08	1.2	−0.08	−1.3
FIBERBOARD	0.00	0.1	−0.07	−1.5	−0.06	−0.7
EGG	0.17	7.2	0.09	2.0	−0.12	−1.4
IRON ORE	0.27	12.5	0.08	2.1	−0.02	−0.3
POLYPROPYLENE	0.23	10.2	−0.01	−0.3	0.04	0.4
CORN STARCH	0.00	−0.1	−0.03	−0.6	0.15	1.5
ALUMINIUM	0.23	13.2	0.07	1.6	0.12	1.5
GOLD	0.16	5.1	0.13	1.8	0.00	0.0
COPPER	0.17	4.9	0.14	2.6	0.02	0.3
LEAD	0.18	4.1	0.00	0.0	0.29	2.1
STEEL REBAR	0.20	8.9	0.03	0.8	0.05	0.7
NATURAL RUBBER	0.22	12.2	0.08	1.8	0.11	1.4

(*continued on next page*)

Table 11 (*continued*)

Panel B: Chinese Markets						
	Daily		Weekly		Monthly	
STEEL WIRE	0.23	7.6	0.06	1.1	0.00	0.0
ZINC	0.10	3.9	0.05	1.1	−0.11	−1.3
SILVER	0.04	1.9	0.08	1.6	0.00	0.0
BITUMEN	0.15	7.3	0.03	0.8	0.08	1.2
HOTROLLED COIL	0.28	4.1	0.12	1.1	−0.01	−0.1
TIN	0.17	8.5	0.03	0.7	−0.03	−0.6
CN Average	0.18	7.0	0.05	0.9	0.03	0.3

autocorrelations are somewhat smaller, but 11 and 7 individual commodities still show positive and significant coefficients at these frequencies, respectively. The autocorrelation patterns in Table 11 are consistent with the notion that a market dominated by retail investors is more prone to positive feedback trading. Stronger price trends at the individual commodity level can translate into a larger commodity-specific component in momentum strategies.

5. Conclusion

This paper takes a cross-country and cross-sector perspective to understand the behavior of commodity momentum beyond established commodity fundamentals. Commodity momentum strategies in the U.S. and China show some return comovement, but their premia are primarily local. The distinction of commodity momentum in the U.S. and China originates from the impairment of cross-broader cash-and-carry arbitrage, as well as substantial differences in market participants and sensitivity to global inflation shocks. The strong local characteristics also shed light on the efficacy of cross-country diversification offered by commodity momentum strategies.

Zooming in on each country to identify a more granular source of momentum profits, we find that sector momentum explains a large portion of the average returns to commodity momentum strategies. Whereas individual commodity effects contribute to the overall profitability of momentum strategies in China, they are much weaker in the U.S. markets. Stronger individual commodity effects in China hint at the difficulty for common risk factor models to fully explain the cross-sectional return variation. While the commodity pricing literature has neglected the role of sectors, we highlight that sectors can help us better understand variation in the average returns of commodity futures through a link to momentum profits.

We also demonstrate that the recent underperformance of momentum strategies in the U.S. is largely explained by the underperformance of the sector component. Despite a mediocre performance of U.S. momentum strategies in the past decade, a Bayesian analysis (in online appendix) strongly favors the hypothesis that commodity momentum remains profitable. Furthermore, since drawdowns of within-sector momentum strategies do not tend to occur at the same time, a within-sector momentum strategy deployed across sectors diversifies sector concentration risk, presenting a better alternative to traditional momentum strategies.

Credit statement

John Hua Fan: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Software, Visualization, **Xiao Qiao**: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Software, Visualization

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcomm.2023.100315.

This table presents spanning regressions for the monthly returns of commodity momentum strategies in the U.S. on the strategy returns in China, and vice versa.

$$f_t^{Ch} = \alpha^{Ch} + \beta^{Ch} f_t^j + \varepsilon_t^{Ch}, j = US$$

$$f_t^{US} = \alpha^{US} + \beta^{US} f_t^k + \varepsilon_t^{US}, k = Ch$$

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