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RESEARCH ARTICLE

Commodity network and predictable returns

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Abstract
We investigate the lead–lag relation in the cross-section of commodity returns. We estimate dynamic and directional networks for 32 commodities and then construct a new predictor termed commodity network momentum, exploring cross-commodity information spillover. Network momentum positively and significantly predicts future commodity returns, controlling for existing commodity characteristics. Unlike previous lead–lag studies, the predictive relation is consistent with overreaction rather than underreaction. The relation is stronger for attention-grabbing commodities and commodities with lottery-like properties and with higher limits to arbitrage. Extrapolation from connected commodities contributes to this predictive relation. Overall, our paper highlights the role of information spillover in commodity return predictability.

KEYWORDS
commodity futures, extrapolation, investor attention, lead–lag relation, network momentum

1 | INTRODUCTION

Asset prices do not move in isolation. Existing studies provide ample evidence about the potential links between different asset prices through various economic relationships. For instance, Cohen and Frazzini (2008) show that the customer–supplier relationship implies a cross-sectional lead–lag effect in stock returns due to the limited attention of investors and the underreaction of news. An increasing number of follow-up studies, including Jiang et al. (2016), Cao et al. (2016), and Lee et al. (2019) among others, consider various forms of economic links, including R&D networks, strategic alliances, patent networks, and so forth. The rich evidence of the lead–lag relation or cross-asset momentum (or cross-momentum hereafter) suggests that the link between the network and cross-asset return predictability seems to be prevalent.

In this paper, we investigate cross-asset return predictability in commodity futures markets. Since the financialization in 2004, commodity futures have become one of the most important asset classes and attract various attention from academics. A large number of commodity return predictors have been introduced in the literature, see Miffre (2016) for a comprehensive review. One important feature in commodity markets, especially in the post-financialization era, is that commodities present strong comovement, as documented by Cheng and Xiong (2014). Similar to equity markets, the supply chain also plays a critical role in commodity markets. Moreover, different commodities are also linked through substitution and complementary relationships. Casassus et al. (2013) show that these commodities with economic linkages present strong comovements. Therefore, we expect the relationship between network and cross-sectional return predictability may also hold in commodity markets.

The economic motivations and potential explanations for the predictive relation between network and commodity returns are as follows. First, commodity investors may underreact to news, similar to existing evidence in equity markets. Kahneman (1973) suggests that attention is a scarce cognitive resource. A few theoretical studies including Merton (1987), Hirshleifer and Teoh (2003), and Peng and Xiong (2006) among others consider the implications of limited attention on asset prices. Due to the limited attention capacity, investors cannot process all information. Therefore, when the news arrives on a focal commodity's connected commodities, investors may underreact to the news and hence generate the predictive pattern, due to the gradual incorporation of news into asset prices. This explanation is consistent with the slow information diffusion as mentioned by Hong and Stein (1999) and is also in line with equity market evidence as shown in Cohen and Frazzini (2008). Second, commodity investors may overreact to news. More recent theoretical and empirical studies suggest that investors tend to extrapolate from the past performance. Greenwood and Shleifer (2014) document that investors tend to extrapolate from historical stock returns and form expectations. Barberis et al. (2015) and Hirshleifer et al. (2015) theoretical highlight the effect of extrapolative beliefs on asset prices. In the commodity market, existing studies, such as Han et al. (2016), show that technical trading rules or trend-following strategies are commonly used. These strategies essentially extrapolate from the past performance, hence extrapolative beliefs should play a critical role. We conjecture that if investors extrapolate from the past performance of not only the focal commodity but also connected commodities, then the extrapolation-generated overreaction could lead to temporal predictive price continuation, followed by a reversal. Whether our findings in commodity markets are consistent with underreaction or overreaction is an empirical question. Therefore, we resort to the following formal empirical analyses to better understand the economic driving mechanisms.

One empirical challenge is that, unlike the equity market, the cross-commodity relation is more complicated and there is no readily available information about the clear supply-chain relation for a large cross-section of commodities. To overcome this empirical obstacle, we resort to an econometric perspective to measure commodity networks. We employ two approaches: adaptive lasso (least absolute shrinkage and selection operator) regression approach developed by Zou (2006) and forecast error variance decomposition method of the vector autoregressive model (VAR) used by Diebold and Yilmaz (2009). Using 32 commodities, we construct dynamic and directional commodity networks. We find that the extracted network is close to the real-world economic network among different commodities, validating its role in capturing potential information spillover in commodity markets.

We then construct a new commodity return predictor: network momentum, which is the weighted average of past returns of connected commodities for a focal commodity. The predictor summarizes lagged news shock for a commodity from its network. We find that sorting commodities into five portfolios according to the network momentum signal reveals the positive predictive relationship between network momentum and future returns. A long–short strategy of buying commodities with the highest network momentum signal and shorting commodities with the lowest signal generates positive and statistically significant profits of 11.7% per year. Using time-series factor-spanning tests, we show that the long–short network momentum portfolio return spread cannot be explained by existing systematic risk premia in commodity markets. Employing Fama–MacBeth cross-sectional regressions, we show that the positive network momentum–return predictive relation remains. A one standard deviation increase in network momentum is associated with a 0.24 standard deviation increase in the next month's returns when the adaptive lasso-based measure is used. Our findings remain strong when various existing commodity characteristics as well as network properties are controlled. In short, our findings support that network momentum contains incremental return predictive power for commodity returns.

We next formally explore the underlying economic mechanism for the predictive relation between network momentum and future commodity returns. We first check whether our results are consistent with the news underreaction effect in the literature. We find that the positive predictable return of the network momentum decreases rapidly after holding the portfolios beyond the 1-month horizon. The relation turns insignificant after 3 months and then turns negative. This pattern is in sharp contrast with the investor underreaction of news and slow information diffusion explanation, as commonly employed in the existing literature about economic link and cross-momentum, such as Cohen and Frazzini (2008) and follow-up studies. We further validate this finding using a modified (reciprocal) underreaction coefficient. Our results again support overreaction rather than underreaction. Therefore, our findings imply that new explanations beyond the existing slow information diffusion hypothesis are needed to better explain the network momentum effect we observed.

One may wonder why existing cross-momentum studies in equity markets generally observe the underreaction effect while our analysis in commodity markets instead reveals the overreaction effect. We suggest that the different institutional features between equity and commodity markets may help reconcile the observed differential effects. First, unlike equity markets where retail investors are more important, commodity markets are dominated by institutional investors.[1] Compared with retail investors, institutional investors are more sophisticated, therefore, they are more likely to have a better ability and capacity to process information. Hence, the underreaction of news due to overlooking information is less likely to happen in commodity markets. Instead, institutional investors may tend to overinterpret news and hence could lead to overreaction. Second, unlike equity markets, in which stocks have clear fundamentals from the financial statement, commodity price formation is more complicated. There is rich evidence that commodity investors frequently employ technical trading rules and trend-following strategies.[2] Namely, these investors are more likely to extrapolate from the historical performance. Hence, they tend to overreact. Third, while commodity futures markets allow the ease of short selling, the markets also make margin trading and leverage easier. Therefore, when good news arrives, investors may trade on margins (and hence leverage up) to amplify their bets, which could also lead to overreaction. In short, the heterogeneous news reaction patterns in equity and commodity markets could be driven by their differential institutional features.

We then consider a set of additional tests to further understand the underlying driving mechanisms. We first check the role of investor attention. Using internet search volume, abnormal turnover, extreme return, and skewness, we provide evidence that the network momentum effect is consistently stronger for commodities with higher rather than low-attention measures. This finding again suggests that the existing underreaction effect due to limited attention does not explain our findings. Instead, investors tend to hold those attention-grabbing commodities. This finding is consistent with more recent evidence by Bali et al. (2021) and Barber et al. (2022) that irrational investors tend to hold attention-grabbing assets for speculative purposes. As a result, lottery preference and speculative demand play important roles to understand the predictive relation. Namely, those commodities are more likely to attract speculative demand from irrational traders and their prices are temporally appreciated due to buying pressure, and then they experience a reversal when the horizon extends. We also find that limits to arbitrage matter for the predictive relation. The network momentum effect is consistently stronger when idiosyncratic volatility and illiquidity are high. Namely, the mispricing-driven predictability is stronger when it is more difficult for rational arbitragers to correct for mispricing.

To further explore why the *network* momentum in particular matters, we consider the role of extrapolation. A few recent studies, such as Greenwood and Shleifer (2014), Barberis et al. (2018), Cassella and Gulen (2018), Da et al. (2021), and Liao et al. (2022), highlight the crucial role of extrapolative belief bias in asset pricing. We conjecture that investors may not only extrapolate from the asset's historical performance but may also extrapolate from the connected assets' past performance. Therefore, we expect that the network momentum should be stronger when the network (weighted average) measure of attention (speculative demand) is high and when the degree of extrapolation (DOX) is high. Our empirical analysis confirms this conjecture. Therefore, our analysis suggests that cross-asset extrapolation is critical to understanding the predictive relation between network momentum and commodity returns.

We then conduct a set of comprehensive robustness checks. Our results remain qualitatively unchanged when an alternative network approach, different conjunction methods, different nearby contracts, alternative momentum formations, subsample periods, out-of-sample tests, transaction costs, and extreme illiquidity are taken into consideration. Hence our findings are robust across different specifications. We also show that our findings cannot be attributed to disaster risk.

The overall contribution of our paper is threefold. First, we enrich the commodity asset pricing literature by introducing a novel cross-sectional commodity return predictor extracted from the commodity network. Our results show that the new predictor contains incremental predictive information beyond existing commodity characteristics. Our findings imply the need to search for commodity return predictors beyond the commodity's own characteristics. Second, our paper also relates to the literature on network analysis. A large number of studies develop various econometric tools to measure the information spillover effects across different assets, including commodity futures. We show that these information spillover effects can be used to construct commodity network momentum predictors and portfolio strategies, hence supporting one potential way to quantify the economic value of using the information spillover effect in practice. Third, our paper extends the fast-growing literature on economic links and the cross-asset momentum effect, especially in stock markets. We provide arguably one of the first empirical investigations of the cross-momentum effect in commodity markets. Different from existing equity market studies, due to the absence of well-organized and clear economic link data

[1]For instance, see the GameStop stock frenzy due to the Robinhood retail investor crowd in March 2020. In contrast, commodity futures markets are dominated by commercial traders (hedgers) and non-commercial traders (speculators, large institutions, such as money managers), while retail investors rarely participate, see, for instance, Fernandez-Perez et al. (2018).

[2]See, for instance, Han et al. (2016) and references therein.

in commodity markets, we instead rely on econometric tools to quantify the commodity network. Most importantly, our analysis shows that conventional investor underreaction and the slow information diffusion mechanism may not be the sole driving force behind the lead–lag relation. Instead, we highlight that investors may extrapolate from connected commodities and generate predictive cross-asset return patterns. Hence our analysis offers a potentially alternative economic mechanism underlying the cross-momentum effect.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and variables. Section 4 presents our main empirical findings about the network momentum effect in commodity markets. Section 5 conducts additional tests to understand the source of predictability. Section 6 carries out a set of robustness tests. Section 7 draws some concluding remarks.

2 | RELATED LITERATURE

In this section, we review the literature related to our study. We consider four streams of the literature including commodity return predictors, financial network and the lead–lag return relation, market underreaction and overreaction, as well as extrapolation. We also highlight our contributions to these four strands of the literature.

2.1 | Commodity return predictors

Since the financialization of commodity markets in 2004, see, for instance, Cheng and Xiong (2014) for more details, the increasingly important role of commodity futures as a major asset class inspires a large number of studies considering cross-sectional commodity return predictors.[3] While compared with equity markets, the number of return predictors in commodity markets remains small, existing studies demonstrate that various commodity characteristics contain strong predictive power for the cross-section of commodity returns. Miffre (2016), for instance, provides a comprehensive overview of commodity return predictors and factors, including commodity futures term structure (or basis), momentum, and hedging pressures.

Term structure (TS) was initially proposed by Kaldor (1976). The measure captures the logarithm difference between the first front and the second front month contract prices. The economic intuition is related to the classical storage theory put forward by Kaldor (1939), Working (1949), and Brennan (1976), as the term structure reflects the information about convenience yield. In addition, another prominent commodity return predictor is momentum. Similar to equity momentum, commodity momentum (MOM) constructed by Miffre and Rallis (2007) reflects the continuation of historical performance in the future. Hedging pressure (HP), which was proposed by Cootner (1960), is based on the theory of hedging pressure in the futures market. Keynes (1930) and Hicks (1975) propose that to achieve effective hedging between futures and spots, hedgers in the futures market hope to smooth the basis when the futures are close to expiry. The magnitude of this pressure varies with market conditions. Besides the hedging pressure for hedgers, existing studies also use hedging pressure for speculators.

In addition to these classical return predictors, existing studies also introduce several new commodity return predictors. These variables include basis momentum by Boons and Prado (2019), skewness by Fernandez-Perez et al. (2018), value as the long-term reversal by Asness et al. (2013), and open interests by Hong and Yogo (2012), and so forth. All these predictors are based on commodity-specific characteristics. In this paper, we introduce a new commodity return predictor, network momentum. Rather than focusing only on a commodity's own characteristics, we use the historical performance of all its connected commodities. Hence our analysis expands the scope of searching for commodity return predictors.

[3]Another related strand of literature focuses on developing asset pricing models to explain commodity returns. Yang (2013) introduces a two-factor model with the average market factor and basis factor. Szymanowska et al. (2014) show that the basis factor contains strong pricing power for the spot premia while two basis factors from spreading returns explain term premia well. Bakshi et al. (2019) introduce a three-factor model containing the average market factor, carry factor, and momentum factor, which outperforms the single-factor model. Boons and Prado (2019) propose different versions of two-factor models using the average market factor (AVG) and basis momentum. Sakkas and Tessaromatis (2020) suggest that the six-factor model including AVG, momentum, basis, basis-momentum, hedging pressure, and value factors has better cross-sectional pricing performance than previous factors models.

2.2 | Lead–lag relation and financial network

The lead–lag relation has a long tradition in asset pricing. However, the more recent origin of the lead–lag relation in the cross-section of stock returns stems from Cohen and Frazzini (2008). They suggest that firms are economically linked through the "customer–supplier" relation. Therefore, due to limited investor attention and the underreaction of news, supplier firms' stock returns can be predicted by historical stock returns of their major customers, or customer momentum.

Since their seminal work, a large number of follow-up studies consider different forms of economic links. Menzly and Ozbas (2010) show that due to investor specialization and the resulting informational segmentation of markets, the gradual information diffusion from economically related industries is pervasive and affects price formation. J. Cao et al. (2016) find the return predictability across alliance partners, and suggest that this lead–lag relation may be caused by investor inattention and limits to arbitrage. Jiang et al. (2016) show that a firm's R&D activities can predict the stock returns of the firm's industry peers. When a subset of companies in the industry has substantial R&D growth, industry peers experience positive abnormal returns and abnormal operating performance. This abnormal return cannot be explained by exogenous industry shocks. Lee et al. (2019) construct a technology-related network and find that the income of technology-related enterprises has a strong ability to predict the future earnings of focus enterprises. Parsons et al. (2020) document the lead–lag effect between co-headquartered areas but in different industries. These studies suggest that various forms of economic links can be used to predict stock return and generate price continuation patterns. However, evidence about the cross-return predictability implied from economic linkage is limited in asset classes beyond the equity markets. One exception is Chang et al. (2022). They show that the global trade network contains strong predictive information for sovereign CDS returns.

In commodity markets, Casassus et al. (2013) apply the correlation term structure model into three representative commodities groups with production, substitution, and complementary relationships. They show that commodities with economic linkage have long-term price comovement. However, these "lead–lag" effects are limited to specific economic relationships. Direct evidence about lead–lag relations in the cross-section of commodity returns remains lacking. Our paper fills this important literature gap.

Our paper is related to a recent and parallel work by Han and Kong (2022). They also rely on lasso regression to explore the lead–lag relation in commodity markets, though mainly from the time-series perspective. Besides the apparent different focuses on cross-section versus time-series perspectives, our paper differs from theirs in several additional and important aspects. First, they directly use lag returns of other commodities to predict commodity returns in and out-of-sample through the lasso regression and construct timing strategies. In contrast, we use the adaptive lasso regression to estimate the commodity network and then construct a network momentum measure. Therefore, we emphasize the importance of both the time-varying network structure and past performance. Second, we focus on not only return spillover but also volatility spillover using the VAR variance decomposition approach. Third and most importantly, we carefully explore the underlying driving mechanism and provide evidence that the underreaction of news, shown in the literature, cannot explain our network momentum effect. Instead, the overreaction driven by speculative demand and extrapolative beliefs plays a critical role in understanding the commodity network momentum profitability, arguably the first in the literature. In short, our paper and theirs contribute to understanding information spillover and commodity return predictability in different ways.

Besides these studies on economic links, a different strand of the literature focuses on employing econometric methods to characterize the return and volatility networks of different financial assets and hence assess the cross-asset information spillover effects (Baele, 2005; Ng, 2000; Yang & Zhou, 2017, among others). In general, two categories of approaches are widely used in the literature. One stream of studies applies the forecast error variance decomposition approach using the VAR model. Diebold and Yilmaz (2009) introduce the VAR variance decomposition approach and use it to measure volatility spillover. Diebold and Yilmaz (2012) extend the previous method and introduce a directional volatility spillover effect to build the network, which is used in our analysis. Diebold and Yılmaz (2014) apply this technique to examine the correlation of individual stocks, tracking the average and time-varying correlations of stock returns in major US financial institutions, including during the 2007–2008 financial crisis. Baruník and Křehlík (2018) propose a new framework for measuring connectedness among financial variables by using the VAR variance decomposition approach. They present the mechanism of cross-sectional correlations that impact the financial network spillover. The above approach is also used to investigate the commodity futures volatility spillover network by Xiao et al. (2020), Diebold et al. (2017), and Yang et al. (2021). Despite the rich evidence about commodity networks, whether commodity networks can be used to improve cross-sectional commodity return predictability remains unclear.

Another set of studies consider variable selection methods when detecting the information spillover effect. One example is the adaptive lasso regression introduced by Zou (2006). The idea is to predict each asset's return using the lag return of other assets. To avoid potential multicollinearity, the lasso approach shrinks the unpowerful predictor coefficients to zero and ensures sparsity. The adaptive lasso extends the original lasso to solve the problem that the L1 penalty term of lasso regression may lead to least-squares deviation. A quadratic penalty is performed and it is proved that the adaptive lasso has the oracle property. Guo et al. (2021, 2022) apply the adaptive lasso regression in the cryptocurrency market to build a time-varying cryptocurrency network system.

In our analysis, due to the lack of explicit and easy-to-obtain economic networks (such as customer–supplier relations in equity markets) in commodity markets, we, therefore, adopt the above two approaches, that is, VAR variance decomposition and adaptive lasso to estimate dynamic and directional networks in commodity markets and then use them to construct our commodity network momentum measures.

2.3 | Market underreaction and overreaction

The lead–lag return relation is typically explained through the market underreaction of news and the limited attention of investors. Hong and Stein (1999) build a theoretical model considering two types of agents with bounded rationality composed of "news-watchers" and "momentum traders" to explain market underreaction and overreaction. Frazzini (2006) shows that the tendency of investors to take losses and realize gains when facing the news leads to underreaction, which can explain the predictability of momentum. Recently a few studies attribute investor underreaction to limited attention. For instance, Barber and Odean (2008) confirm that individual investors are net buyers of high-profile stocks (e.g., news stocks, stocks with high abnormal volumes, and stocks with high extreme returns) due to attention constraints. Da et al. (2011) use the Google search volume (GSV) as a measure of investor attention, as stocks more attractive to individual investors usually also attract higher internet search volume. Cohen and Frazzini (2008) use the mutual funds holding for both supplier and customer company stocks to measure investor attention and show that the predictive relation is stronger for low-attention stocks, consistent with the limited attention story. Huang et al. (2022) document that information discreteness (ID) strongly affects the magnitude of the lead–lag effect. They use a proxy of ID following Da et al. (2014) and find that the lead–lag effect in prior studies enhances when lead firms face continuous information in small amounts.

Besides the underreaction mechanism, we recognize that the momentum effect can also be driven by overreaction, as Hong and Stein (1999) suggest. Hence, it may also play a role in the lead–lag return. Investors' behavior bias can trigger market overreaction. Scheinkman and Xiong (2003) show that investors tend to sell assets to other agents who have more optimistic beliefs, which leads to severe speculative bubbles in the market. They propose a continuous-time equilibrium model of bubbles that generates higher prices, higher volumes, excessive volatility, and predictable returns. Cooper et al. (2004) find that momentum profits are only significantly positive in good market states, implying the explanatory power of market overreaction. Chui et al. (2010) use the individualism index and find that momentum profit is higher in a strong individualism country, which is related to overconfidence and self-attribution bias. Chen et al. (2020) study the impact of attention spillovers on stock price and trading volume. They find that investors' attributing high returns to their skills will encourage investors' overconfidence and attribute the bias amplification to stock prices. Investors tend to trade more after gaining positive investing experience and focus on stocks adjacent to their ticker symbol. Barber and Odean (2001) show that male investors are more likely to be overconfident than female investors reflected in higher trading volume and turnover. Daniel et al. (2001) verify that there is a speculative bubble caused by irrational investors' behavior in the market.

Our empirical evidence shows that existing explanations based on market underreaction and limited attention cannot successfully explain our network momentum effect. Therefore, our analysis adds to the lead–lag and cross-momentum literature, which was almost exclusively dominated by the market underreaction explanation, by showing that overreaction may also play an important role.

2.4 | Extrapolation

In this paper, we try to fill the gap between investor overreaction and the predictive power of network momentum using the theory of extrapolation. Investors who have strong extrapolation bias tend to overweight recent past returns on their return expectations. Greenwood and Shleifer (2014) provide important evidence that investor expectations for future stock prices tend to be extrapolative. Barberis et al. (2015) and Hirshleifer et al. (2015) build theoretical models to understand asset pricing implications of extrapolative beliefs. Cassella and Gulen (2018) propose a novel nonlinear regression method to quantify the degree of extrapolative weighting in investor beliefs, that is, DOX, and show that DOX can be used to enhance market return predictability of price-scaled variables. Using data from a crowdsourcing platform for ranking stocks, Da et al. (2021) provide evidence that investors extrapolate from stock's recent past returns.

Recent research also provides strong evidence that extrapolation bias may trigger investor overreaction, and generate price bubbles. Barberis et al. (2018) present an extrapolation-based theoretical model of bubbles. Liao et al. (2022) show that the interaction of disposition effect and extrapolation can generate stock price bubbles. They also rely on account-level trading data to construct a new measure of DOX, which we adopt in this paper.

Our paper provides new evidence that investors may not only extrapolate from the asset's historical performance but also extrapolate from the past performances of connected assets. The cross-extrapolation is critical for understanding the commodity network momentum effect we documented.

3 | DATA AND VARIABLES

3.1 | Data source

We collect commodity futures prices, open interests, and volume data from the Bloomberg database. Our sample consists of 32 commodity futures in the major futures markets in the United States from 1970 to 2019. We exclude commodities that cease to trade. We also collect trading position data from the Commodity Futures Trading Commission (CFTC) website, with sample periods from 1986 to 2019. The specific futures name, abbreviations, sector categories, and the starting and ending periods are shown in Supporting Information Table A.1. To ensure meaningful empirical analysis in portfolio sorting with reasonably large cross-sectional observations, we start our empirical analysis from 1980 to 2019.

3.2 | Commodity return and other characteristics

One important feature of commodity futures prices is that multiple contracts are available at the same time, and hence the price series are discontinuous. To conduct meaningful empirical analysis, we follow the literature and construct continuous price series. We choose the first-nearby contract for each commodity given its liquidity. We hold it until 15 days before the settlement day and roll over to the next nearby contract, following Han et al. (2016). Rolling over to the next contract without adjustment could lead to a large contango/backwardation bias, therefore, we adjust the price series forward by multiplying the new price by the old to new contract price ratio on the rollover day. In this sense, we can obtain continuous price series for empirical analysis.[4] Following the literature, such as Gorton et al. (2013), we calculate daily and monthly commodity excess return based on a fully collateralized position, namely, $R_{t+1,T} = \frac{F_{t+1,T} - F_{t,T}}{F_{t,T}}$, where $F_{t+1,T}$ is futures price at time t with maturity T. We also calculate daily commodity return volatility using sample standard deviation of the past 22 days returns. We also calculate other commodity characteristics following the literature. Supporting Information Table A.2 presents the construction of main variables in the empirical analysis.

3.3 | Commodity network and network momentum

In this section, we describe the construction of our main variable: commodity network momentum. We first introduce two methods to extract commodity networks. Then we introduce the construction of our key variable of interest, that is, commodity network momentum.

[4]In the robustness check, we also show that our results remain to hold with other conjunction methods and nearby contract returns are used.

3.3.1 | Return spillover network based on adaptive lasso

Following Zou (2006), we construct the return spillover network in commodity markets using the adaptive lasso regression. Lasso regression differs from the conventional ordinary least-squares (OLS) regression by including the L1 penalty term and it helps shrink the insignificant coefficients to zero to facilitate the variable selection. However, Zou (2006) shows that the conventional lasso does not have the oracle property and instead introduces the adaptive lasso to reduce the least-square deviation. The objective function is expressed as

$$b^* = arg\,min\{||r_{i,t+1} - \alpha_i - \sum_{j\neq i} b_{i,j} r_{j,t}||^2 + \lambda_i \sum_{j\neq i} \hat{\omega}_{i,j}|b_{i,j}|\}. \quad (1)$$

Specifically, we regress the daily return of each commodity on all other commodity daily returns with 1 day lag and retrieve the adaptive lasso regression coefficient b^*. The first term on the right-hand side of the equation is the conventional OLS estimator, and the second term is the weighted-L1-penalty term. The weight of the adaptive lasso $\hat{\omega}_{i,j} = 1/|b_{i,j}^{\hat{OLS}}|$ is set as the reciprocal of the absolute value of OLS regression coefficients $b_{i,j}^{\hat{OLS}}$. This adjustment allows a smoother L1 penalty term and leads to less loss of coefficient validity. Following the literature, we take the value of parameter λ as 0.5, and set a rolling window of 250 days. The regression coefficient b^* is then used as the network connectedness coefficient.

3.3.2 | Volatility spillover network based on VAR decomposition

Besides the return spillover, we also consider volatility spillover using the VAR model variance decomposition approach by Diebold and Yilmaz (2012). For a $VAR(p)$ model of order p, the generalized forecast error variance decomposition $\theta_{ij}^g(H)$ is

$$\theta_{ij}^g(H) = \frac{\sigma_{ii}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma A_h' e_j\right)}, \quad (2)$$

where Σ is the covariance matrix of the forecast error vector, σ_{ii} is the variance of the forecast error term of the ith equation, e_i is the ith element of the selection vector 1, otherwise 0, A_h is the coefficient matrix of the h-step moving average expression of the model. Since the generalized method leads to $\sum_{j=1}^{N} \theta_{ij}^g(H) \neq 1$, we use the following formula to normalize the proportion of each entry:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^{N} \theta_{ij}^g(H)}. \quad (3)$$

Following Diebold and Yilmaz (2012), we can calculate the directional variance spillover of market i from other markets j:

$$S_i^g(H) = \frac{\sum_{j=1\, j\neq i}^{N} \tilde{\theta}_{ji}^g(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ji}^g(H)} \times 100, \quad (4)$$

where $S_i^g(H)$ represents the network connectedness. Following Diebold and Yilmaz (2009) and Diebold et al. (2017), we use $VAR(3)$ with a horizon of 12 days forecast error variance decomposition in the main empirical analysis. We use the full-sample estimation to construct a total volatility spillover connectedness network (Diebold–Yilmaz table, abbreviated as DY table below) shown in Supporting Information Table IA.1. We observe a strong cross-commodity spillover effect, as the information spillover for each commodity accounts for about 80% of the total variance of volatility. Moreover, we also use the 250-day rolling-window estimation to calculate the dynamic and directional spillover network in daily frequency. We then use the connectedness to construct network momentum in Section 3.3.3.

3.3.3 | Network momentum

In this section, we formally construct our key variable of interest: network momentum. Specifically, we combine the network connectedness with the 3-month momentum (past return) of each commodity. We obtain the monthly network by taking the within-month average of the daily network. Then we construct the new variable, network momentum, for each focal commodity by taking the weighted average of the momentum of its connected commodities (abbreviated as *NM*)

$$NM_{i,t} = \sum_{j \neq i}^{n} \omega_{j,t} \ MOM_{j,t}, \tag{5}$$

where $\omega_{j,t}$ represents the monthly network coefficient, $MOM_{i,t}$ represents the momentum of commodity j. In the main empirical test, we use 3-month momentum to represent quarterly price shocks.[5] Intuitively, the new variable defines the magnitude of connected commodities' past price shock for the focal commodity. The historical performances of those commodities with a higher degree of connectedness are assigned a higher weight when constructing the network momentum measure. We consider two measures of network momentum based on the two econometric methods. *NMAL* is defined as the network momentum where the weight is based on network connectedness from the adaptive lasso regression, and *NMDY* is defined as the network momentum where the weight is calculated using network connectedness from the VAR variance decomposition approach.

Panel A of Table 1 provides summary statistics for the main variables used in the empirical analysis. Panel B of Table 1 provides the correlation for these variables. We show that the correlations between network momentum and existing commodity characteristics are low for both two measures, with correlation coefficients generally below 0.30. Therefore, the low correlation implies that network momentum may contain incremental information beyond existing commodity characteristics in the literature.

3.3.4 | Network centrality

A natural consideration is whether network-specific information rather than network momentum may drive our potential empirical findings. Therefore, we consider a major characteristic of a network, namely, network centrality. Network centrality helps identify which commodities are more important in the network compared with others. Following the literature, such as Rodrigues (2019), we consider two measures of centrality: betweenness centrality (BC) and eigenvector centrality (EC). BC refers to the number of network nodes that appear between other nodes as the shortest path, which is used to measure the importance of the node to the optimal path of the network. The BC formula is as follows:

$$BC_i = \sum_{m,n} \frac{d_{mn}^*}{d_{mn}}, \tag{6}$$

where d_{mn}^* is the number of optimal paths between nodes m and n across node i. And d_{mn} represents the whole paths between nodes m and n. Alternatively, EC not only depends on the centrality degree of the node but also considers the degree of its neighbors, which is used to comprehensively measure network nodes. The expression for EC is

$$EC_i = w \sum_{j=1}^{n} a_{ij} x_j, \tag{7}$$

where a_{ij} is the network coefficient from i to j, x_j is the importance index (BC) of neighbor j, ω is the adjustment factor to ensure that ECs add up to one. These two additional network variables serve as important control variables in our following empirical analysis. Hence it allows us to differentiate the predictive power of network momentum from the information of the network itself. Panel B of Table 1 also shows that network momentum has a low correlation with these network centrality measures, supporting that network momentum contains important information not simply due to the network itself.

[5]Results generally hold true when alternative formation periods are considered.

TABLE 1 Descriptive statistics of main variables.

Variables	(1) Observations	(2) Mean	(3) Std	(4) Minimum	(5) 25%	(6) 50%	(7) 75%	(8) Maximum	(9) Skewness	(10) Kurtosis
Panel A: Descriptive statistics										
NMAL	8427	−0.01	0.21	−0.87	−0.08	−0.00	0.06	0.93	0.12	3.64
NMDY	8427	0.01	0.08	−0.24	−0.04	0.00	0.06	0.25	0.20	0.20
TS	8427	−0.01	0.03	−0.11	−0.02	−0.01	0.00	0.11	0.44	2.43
MOM	8427	0.00	0.02	−0.06	−0.01	0.00	0.02	0.07	0.14	−0.05
HHP	8427	0.13	0.19	−0.31	0.00	0.11	0.25	0.67	0.49	0.00
SHP	8427	0.24	0.29	−0.53	0.03	0.25	0.46	0.82	−0.26	−0.60
BM	8427	−0.01	0.06	−0.23	−0.03	−0.01	0.01	0.24	0.16	2.61
SKEW	8427	0.01	0.69	−1.91	−0.44	0.02	0.44	1.92	0.00	−0.10
VALUE	8427	−0.10	0.40	−1.18	−0.35	−0.09	0.17	0.86	−0.18	−0.27
ΔOI	8427	−0.02	1.05	−37.70	−0.18	−0.03	0.16	11.48	0.48	5.28
EC	8427	0.15	0.10	0.00	0.08	0.13	0.19	0.52	1.08	1.23
BC	8427	0.12	0.11	0.00	0.04	0.09	0.18	0.48	1.15	0.72

	NMAL	*NMDY*	*TS*	*MOM*	*HHP*	*SHP*	*BM*	*SKEW*	*VALUE*	*OI*	*EC*	*BC*
Panel B: Correlation												
NMAL	1.00											
NMDY	0.16	1.00										
TS	0.03	0.07	1.00									
MOM	−0.03	0.29	0.34	1.00								
HHP	0.00	0.06	0.09	0.29	1.00							
SHP	−0.02	0.05	0.15	0.42	0.74	1.00						
BM	0.01	0.03	0.27	0.12	0.01	−0.04	1.00					
SKEW	0.01	0.03	−0.04	0.01	−0.14	−0.09	0.03	1.00				
VALUE	0.01	−0.15	−0.19	−0.46	−0.16	−0.31	0.12	0.12	1.00			
ΔOI	0.01	0.09	−0.05	−0.03	−0.03	−0.02	−0.01	0.01	0.02	1.00		
EC	−0.01	0.04	0.02	0.07	−0.01	−0.04	−0.00	−0.04	−0.06	−0.01	1.00	
BC	0.02	0.01	0.02	0.03	0.02	−0.00	−0.02	0.01	−0.01	−0.00	0.01	1.00

Note: This table provides descriptive statistics of the main variables in the empirical analysis. Panel A of this table presents descriptive statistics. Panel B presents pairwise correlations. All variables in the table are winsorized at the 1%–99% level.

Abbreviations: BC, betweenness centrality; BM, basis momentum; EC, eigenvector centrality; HHP, hedging pressure for hedgers; MOM, momentum; NMAL, network momentum based on adaptive lasso; NMDY, network momentum based on Diebold–Yilmaz; delta OI, change in open interest; SHP, hedging pressure for speculators; SKEW, skewness; TS, term structure; VALUE, value.

4 | EMPIRICAL RESULTS

4.1 | Visualizing commodity network

In this section, we report our main empirical findings. Before we move on to the cross-sectional return predictability analysis, we first illustrate the commodity networks. Following Diebold et al. (2017), we use the network graph to visualize the network connectedness of commodity futures and check whether the financial networks extracted using econometric methods are consistent with the potential economic networks for commodities.

Figures 1 and 2 provide the full-sample *volatility* spillover network plot following the VAR variance decomposition and the rolling-window monthly sample *return* spillover network plot following the adaptive lasso, respectively. The line linking two commodities represents the connectedness (correlation) and the darkness of the line represents the strength of the connectedness. The distance of nodes represents the closeness of the two commodities associated with each other. The closer the relative position is, the more homogeneous the associated commodity futures are. The arrows of lines reflect the direction of the spillover effect. In addition, we use different node colors to distinguish different commodity sectors.

Our findings about commodity networks can be summarized as follows. First, we observe a strong information spillover effect in commodity markets. Except for some commodities, the overall degree of connectedness is high. Second, commodities within the same sector are clustered, confirming the networks extracted from the econometric methods accurately describe the real-world economic network in the commodity markets. Third, some commodities are more in isolation (such as hogs [LH] and orange juice [JO]), which tend to be the end product in the industry, while others are more closely related (such as live cattle [LC], lead [LL], copper [HG], natural gas [NG], etc.). Commodities with close economic links also have close positions in the plots (such as Brent Crude Oil [CO] and Crude Oil [CL]). Fourth, the snapshots of the network at different times indicate a strong time-varying of commodity networks. Therefore, relying on a static network, such as ex-ante specified supply-chain relation, will overlook this important feature. Hence the approaches we employed lead to the timely and accurate description of connectedness in commodity markets. Overall, our analysis support that there is a strong information spillover effect in commodity markets, and these connections are consistent with economic linkages. The strong connectedness among different commodities builds the foundation for the network momentum effect.

4.2 | Portfolio sorting and factor-spanning tests

We then move on to our main empirical analysis regarding the cross-sectional return predictability. Throughout the empirical analysis, we focus on the commodity network momentum measure constructed using the adaptive lasso regression (NMAL).[6]

We use the conventional univariate portfolio sorting approach. At the beginning of each month, we allocate all commodities into five portfolios according to their network momentum signals. Portfolio 1 contains commodities with the lowest network momentum, that is, commodities whose connected commodities perform poorly in the past few months. Portfolio 5 contains the highest network momentum commodities, namely, commodities whose connected pairs perform very well in the past. We then take the long–short return spread, which reflects a zero-cost long–short strategy by buying high-network momentum commodities and selling low-network momentum commodities. We then rebalance our portfolio every month.

Table 2 reports portfolio sorting results. To understand the persistence of return patterns over time, we not only consider holding the portfolio for 1 month but also 3, 6, and 12 months. At the 1-month horizon, we observe a clear increasing pattern of average returns from portfolio 1 to portfolio 5, supporting the positive return predictive power of network momentum. We also find that the long–short portfolio generates a positive and statistically significant return spread of 11.7% per year. These findings support the predictive relation between network momentum and 1-month ahead commodity returns. Therefore, our analysis shows that the historical performance of connected commodities contains strong predictive power for the future returns of the focal commodity at least in the short horizon.

Then we check the persistence of predictability by extending the portfolio holding periods. However, different from the short-horizon results, we find that the positive relation loses its significance in the 3-month and turns negative in the 6- and 12-month horizons. These results indicate that the predictive power embedded in the network momentum concentrates on the short horizon. This observation is important, as existing studies about economic links and cross-return predictability such as Cohen and Frazzini (2008) mainly attribute the source of return predictability to investor underreaction and slow information diffusion. The reversal pattern we observe distinguishes from the underreaction pattern shown in the existing studies. Therefore, the new finding motivates us to formally examine the underlying driving mechanisms for the network momentum effect in the following sections.

[6]In the Supporting Information, Tables IA.2 and IA.3, we replicate our main empirical analysis using the variance decomposition-based network momentum (i.e., NMDY) as a robustness check. Our main results remain qualitatively unaffected.

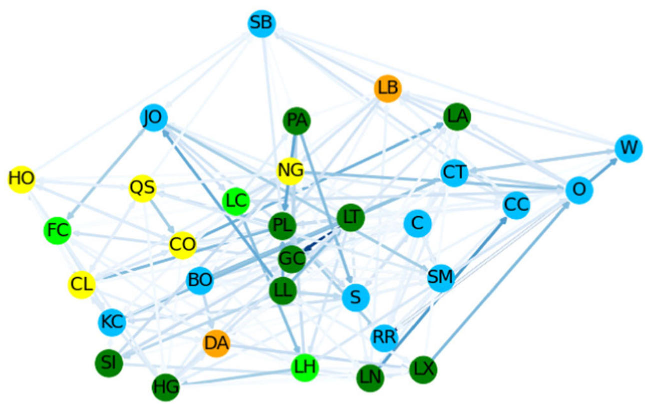

FIGURE 1 Full-sample volatility spillover network graph. This figure visualizes the full-sample volatility spillover network using VAR variance decomposition. Each node represents a single commodity and its color shows the sector of commodities (blue represents agriculture, dark green represents metal, light green represents livestock, yellow represents energy, and orange represents additional production). The connecting lines with arrows indicate the directional connectedness between commodities and the darkness of lines shows the magnitude of connectedness. VAR, vector autoregressive. BO, Soybean Oil; C, Corn; CC, Cocoa; CL, Crude Oil; CO, Brent Crude Oil; CT, Cotton; DA, Milk; FC, Feeder Cattle; GC, Gold; HG, Copper; HO, Heating Oil; JO, Orange Juice; KC, Coffee; LA, Aluminum; LB, Lumber; LC, Live Cattle; LH, Hogs; LL, Lead; LN, Nickel; LT, Tin; LX, Zinc; NG, Natural Gas; O, Oats; PA, Palladium; PL, Platinum; S, Soybean; SB, Sugar; SI, Silver; SM, Soybean Meal; RR, Rough Rice; QS, Gas Oil; VAR, vector autoregressive; W, Wheat.

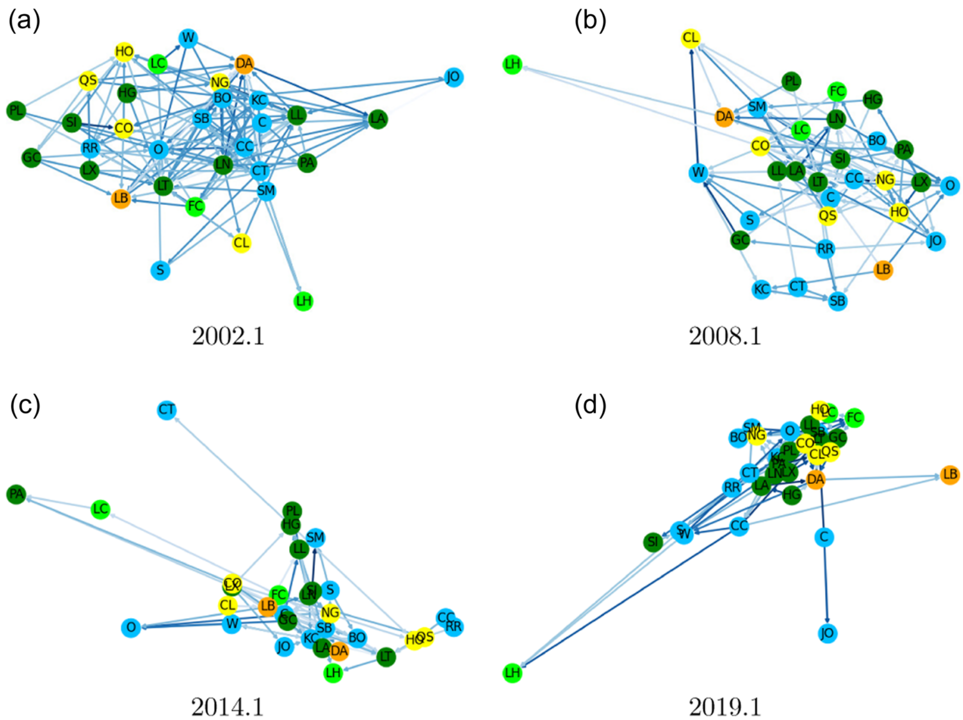

FIGURE 2 Snapshot of return spillover network graph. These figures visualize the snapshot of rolling-window monthly return spillover network using adaptive lasso on four time points: January 2002, January 2008, January 2014, and January 2019 for illustrative purposes. Each node represents a single commodity and its color shows the sector of commodities (blue represents agriculture, dark green represents metal, light green represents livestock, yellow represents energy, and orange represents additional production). The connecting lines with arrows indicate the directional connectedness between commodities and the darkness of lines shows the magnitude of connectedness. BO, Soybean Oil; C, Corn; CC, Cocoa; CL, Crude Oil; CO, Brent Crude Oil; CT, Cotton; DA, Milk; FC, Feeder Cattle; GC, Gold; HG, Copper; HO, Heating Oil; JO, Orange Juice; KC, Coffee; LA, Aluminum; LB, Lumber; LC, Live Cattle; LH, Hogs; LL, Lead; LN, Nickel; LT, Tin; LX, Zinc; NG, Natural Gas; O, Oats; PA, Palladium; PL, Platinum; S, Soybean; SB, Sugar; SI, Silver; SM, Soybean Meal; RR, Rough Rice; QS, Gas Oil; VAR, vector autoregressive; W, Wheat.

TABLE 2 Portfolio sorting for NMAL.

Horizon	*P1*	*P2*	*P3*	*P4*	*P5*	*L/S*
$h = 1$	−0.055*	0.016	0.017	0.012	0.063**	0.117***
	(−1.93)	(0.67)	(0.68)	(0.48)	(2.03)	(3.60)
$h = 3$	−0.034	0.030	0.027	0.021	0.017	0.051
	(−1.21)	(1.14)	(1.08)	(0.82)	(0.58)	(1.58)
$h = 6$	0.003	0.022	0.041*	0.017	−0.012	−0.015
	(0.10)	(0.84)	(1.66)	(0.65)	(−0.41)	(−0.47)
$h = 12$	0.041	0.030	0.035	0.000	−0.003	−0.044
	(1.38)	(1.19)	(1.50)	(0.01)	(−0.10)	(−1.36)

Note: This table reports the average returns of portfolios sorted by network momentum (NMAL) from low ($P1$) to high ($P5$), and L/S refers to the long–short $P5$–$P1$ portfolio. We consider holding horizons (h) from 1 to 12 months. The numbers in brackets are the Newey–West h.a.c. t statistics, *, **, and *** indicate 10%, 5%, and 1% statistical significance levels, respectively. All returns are annualized.

TABLE 3 Factors spanning test for NMAL.

α	β_{AVG}	β_{TS}	β_{MOM}	β_{SHP}	β_{HHP}	β_{BM}	*Adj.* R^2
0.074**	0.942	−0.060	0.359				0.022
(2.21)	(0.98)	(−0.12)	(0.54)				
0.088**	1.063	0.487	0.498	−2.827***	0.986		0.031
(2.30)	(0.93)	(0.78)	(0.51)	(−2.74)	(0.97)		
0.069**	0.951					0.660	0.013
(1.98)	(1.01)					(1.12)	

Note: This table reports the time-series factor-spanning tests. We regress long–short network momentum portfolio returns using NMAL on three sets of mutifactor models: (i) three-factor model (AVG, TS, and MOM) from Bakshi et al. (2019), (ii) five-factor model (AVG, TS, MOM, SHP, and HHP) augment the three-factor model with two hedging pressure factors, and (iii) two-factor model (AVG and BM) from Boons and Prado (2019). The numbers in brackets are the Newey–West h.a.c. t statistics. *, **, and *** indicate 10%, 5%, and 1% statistical significance levels, respectively. *Adj.* R^2 presents the adjusted R^2 for regression. All returns are annualized.

Abbreviations: AVG, average; BM, basis momentum; HHP, hedging pressure for hedgers; MOM, momentum; NMAL, network momentumbased on adaptive lasso; SHP, hedging pressure for speculators; TS, term structure.

Another important issue is that the documented long–short return spread may represent risk premia. Namely, the positive network momentum–return relation may reflect exposures to systematic risk factors. Therefore, we also check whether existing commodity market risk factors in the literature can successfully account for the network momentum effect. We conduct the conventional time-series factor-spanning tests. Specifically, we regress the long–short network momentum portfolio returns on a set of tradable factors contemporaneously, including the average commodity market factor, term structure, momentum, hedging pressure, and basis-momentum factors. We consider the popular two-factor (average factor and basis-momentum factor), three-factor (average, term structure, and momentum factors), and five-factor (average, term structure, momentum, and hedging pressure by hedgers and speculators factors) models in the literature. If the network momentum effect can be attributed to some risk factor exposures, we should expect the intercept (alpha or abnormal return) to be statistically insignificant while the factor regression coefficients should be statistically significant.

Table 3 reports the time-series factor-spanning regression results. Consistent with our prediction, we show that the abnormal return is consistently positive and significant. Therefore, the predictive power of network momentum cannot be fully attributed to exposures to existing commodity market factors. We also find that the factor loadings are generally insignificant except for the hedging pressure factor by the speculator, which has negative loadings. Overall, our findings suggest that the predictive power of network momentum cannot be fully attributed to risk premia. Therefore, we proceed to behavioral-based explanations in the following sections.

4.3 | Fama–MacBeth regressions

Our results so far present strong empirical evidence about the network momentum effect. However, one may wonder whether the effect can be attributed to existing commodity characteristics. Therefore, we consider the predictive relation between network momentum and commodity return using the conventional Fama and MacBeth (1973) cross-sectional regression approach. We regress 1-month ahead of individual commodity returns on network momentum signal and control for other commodity characteristics. We consider several prevalent commodity return predictors in the literature, including term structure (*TS*), momentum (*MOM*), hedging pressure for hedgers (*HHP*), hedging pressure for speculators (*SHP*), basis momentum (*BM*), value (*VALUE*), and open interest change (ΔOI). Moreover, to capture the network feature and ensure that it is indeed network momentum not network itself matters, we also control for two measures of network centrality (EC, BC). The cross-sectional predictive regression specifications are as follows:

$$R_{i,t+1} = \alpha_i + \beta_{i1} NMAL_{it} + \gamma' Z_{it} + \epsilon_{it}, \tag{8}$$

where $NMAL_{it}$ is network momentum calculated using the adaptive lasso approach, Z_{it} is a vector of other commodity characteristics used as control variables, including term structure (TS_{it}), momentum (MOM_{it}), hedging pressure by hedgers (HHP_{it}), hedging pressure by speculators (SHP_{it}), basis momentum (BM_{it}), skewness ($SKEW_{it}$), value ($VALUE_{it}$), open interests (ΔOI_{it}), and two versions of network centrality, eigenvector centrality (EC_{it}) and betweenness centrality (BC_{it}).

We run cross-sectional regression each month and then calculate the time-series average value of $\beta_{i,k}$ for each period as the coefficient of the Fama–MacBeth cross-sectional regression. We use Newey–West standard error to calculate t statistics. The main results of the regression are shown in Table 4.

Consistent with the portfolio sorting results above, we find that network momentum positively and significantly predicts future commodity returns across all specifications. The predictive relation is not only statistically significant but also economically meaningful. A one standard deviation increase in network momentum is associated with a 0.24 standard deviation increase in the next month's commodity returns. Controlling for existing commodity characteristics does not affect our findings. The predictive power of the network momentum signal remains strong if we add control variables one by one or all together. Therefore, our results support the *incremental* predictive information in the network momentum beyond existing commodity characteristics.[7]

5 | UNDERSTANDING COMMODITY NETWORK MOMENTUM

5.1 | Two competing hypotheses

Our results so far provide strong evidence that network momentum contains incremental predictive power for future commodity returns. This predictive power can hardly be explained by exposure to existing risk factors. Therefore, these findings indicate a potential behavioral-based explanation. To dig deeper into the underlying driving mechanisms, we consider the following two competing hypotheses. First, according to existing studies about economic links, such as Cohen and Frazzini (2008), Menzly and Ozbas (2010), and Lee et al. (2019), investor's underreaction to news about economically connected assets due to limited attention could generate this predictive return pattern. In our case, when news arrives on a focal commodity's connected commodities, investors may overlook the news and hence lead to a delayed response, due to the limited attention constraint. As a result, the gradual incorporation of news from the network could lead to the network momentum pattern. A testable implication is the predictive relation should extend to longer horizons and gradually vanish. We also expect the predictive relation to be stronger for commodities attracting less attention. Therefore, we have the first hypothesis:

Hypothesis A: *The predictive relation is driven by investor limited attention and market underreaction.*

[7]In unreported analysis, we add network momentum to each existing characteristic and check whether adding network momentum improves predictive performance. We observe consistent improvements in adjusted R^2 when network momentum is included, supporting the incremental predictive power of network momentum beyond existing characteristics.

TABLE 4 Fama–MacBeth cross-sectional regression for NMAL.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
NMAL	0.237***	0.210**	0.253***	0.255***	0.181**	0.234**	0.279***	0.258***	0.290***	0.223**	0.274**
	(2.63)	(2.24)	(2.70)	(2.56)	(1.99)	(2.45)	(2.64)	(2.74)	(2.90)	(2.24)	(2.21)
TS		0.354	0.218	0.128	0.359	0.094	−0.106	0.169	−0.009	0.179	−0.865
		(0.82)	(0.50)	(0.28)	(0.79)	(0.21)	(0.52)	(−0.25)	(−0.02)	(0.40)	(−1.43)
MOM		1.556**	1.573**	1.944***	1.511*	1.882**	1.279*	1.507*	1.951**	1.768**	2.471**
		(2.03)	(2.02)	(2.62)	(1.88)	(2.32)	(1.74)	(1.93)	(2.41)	(2.20)	(2.00)
HHP			0.124**	0.131*	0.150**	0.085	0.145**	0.123**	0.116*	0.104*	0.108
			(2.09)	(1.68)	(2.52)	(1.38)	(2.30)	(2.03)	(1.90)	(1.69)	(1.04)
SHP				0.011							−0.027
				(0.18)							(−0.34)
BM					0.479**						0.794***
					(2.10)						(2.64)
SKEW						−0.070**					−0.048
						(−2.40)					(−1.20)
VALUE							−0.031				−0.045
							(−1.03)				(−1.10)
ΔOI								0.000			0.000
								(0.55)			(0.17)
EC									0.222*		0.138
									(1.87)		(1.03)
BC										−0.029	0.048
										(−0.30)	(0.41)
Constant	0.025	0.028	0.010	−0.005	0.009	0.012	0.007	0.010	−0.020	0.014	−0.008
	(1.12)	(1.46)	(0.56)	(−0.20)	(0.48)	(0.62)	(0.34)	(0.52)	(−0.87)	(0.68)	(−0.20)
Observations	382	382	382	382	382	382	382	382	382	382	382
Adj. R^2	0.037	0.107	0.115	0.120	0.137	0.123	0.147	0.113	0.123	0.118	0.182

Note: This table presents the Fama and MacBeth (1973) cross-sectional regression. We regress time $t+1$ commodity returns on time t network momentum signal (NMAL) and a set of commodity characteristics as control variables. These variables include basis, momentum, skewness, value, open interests, eigenvector centrality, and betweenness centrality. The regression coefficients are the time-series average of cross-sectional regression coefficients. The numbers in brackets are the Newey–West h.a.c. t statistics. *, **, and *** indicate 10%, 5%, and 1% statistical significance levels, respectively. *Adj.* R^2 presents the adjusted R^2 for regression. All returns are annualized.

Abbreviations: BC, betweenness centrality; BM, basis momentum; EC, eigenvector centrality; HHP, hedging pressure for hedgers; MOM, momentum; NMAL, network momentum based on adaptive lasso; delta OI, change in open interest; SHP, hedging pressure for speculators; SKEW, skewness; TS, term structure; VALUE, value.

However, we recognize that limited attention and underreaction may not be the sole mechanism behind the lead–lag relation. Other behavioral biases, such as overconfidence, lottery demand, or extrapolation bias, may lead investors to overreact to the network signals. Specifically, investors may overreact to news or extrapolate from the historical performance not only in the focal commodity but also in connected commodities. As a result, their trading activities tend to generate price pressure and lead to the return continuation as captured by the network momentum effect. Therefore, we expect the effect should experience a relatively quick reversal due to overreaction. Moreover, the predictive relation tends to be stronger when the speculative demand is high and when the propensity to extrapolate is high. Therefore, we form the following alternative hypothesis:

Hypothesis B: *The predictive relation is driven by investor speculative demand, extrapolation, and overreaction.*

We recognize that other alternative explanations may also exist. However, throughout the paper, we mainly focus on these two hypotheses. We resort to the following empirical analysis to formally understand which hypothesis provides the most plausible explanation for the network momentum effect.

5.2 | Longer holding periods and underreaction coefficients

To differentiate these two competing hypotheses, we first rely on the predictive results over different horizons. Intuitively, if the lead–lag relation is driven by the underreaction, we expect the predictive relation to be persistent for a relatively long period and then gradually diminish. In contrast, if the overreaction matters more, we should observe a clear reversal pattern, that is, the positive predictive relation should change sign when the horizon extends. Our portfolio sorting results in Table 2 have already demonstrated the insignificant positive and then negative relations when holding periods extend beyond 1 month. Consistent with the portfolio sorting results, Fama–MacBeth regression results in panel A of Table 5 confirm this finding. These results collectively support that our findings about the network momentum effect in commodity markets are unlikely driven by the conventional explanation based on the underreaction of news.

Figure 3 plots the cumulative returns of the network momentum portfolios over time. The figure shows that the predictive positive relation between network momentum and future commodity returns is short-lived, and the long-term portfolio spread returns are generally lower than spread returns holding only 1 month, which cannot be explained by conventional slow information diffusion explanation for the lead–lag relation.[8]

To further confirm the role of overreaction, we follow Cohen and Frazzini (2008) and construct a measurement of the underreaction coefficient. Define RET_1 as portfolio returns based on network momentum for a 1-month horizon, and $CAR_{1,h}$ as cumulative portfolio return from month 1 to month h.[9] Cohen and Frazzini (2008) introduce the underreaction coefficient measure (URC) as follows: $URC = RET_1/(CAR_{1,h} + RET_1)$. We recognize, however, when $CAR_{1,h}$ is negative and its absolute value is close to RET_1, hence URC tends to be infinity, which means that the URC changes in nonlinear formation in the condition of overreaction.[10] Therefore, in our empirical implementation, we reciprocate its construction method to avoid variable discontinuity. Namely, we define the reciprocal underreaction coefficient URC (RURC) for holding the h period as

$$RURC_h = \frac{RET_1 + CAR_{1,h}}{RET_1}. \tag{9}$$

Therefore, when the RURC is less than 1 or even negative, it indicates the market overreaction during the holding periods; when RURC is greater than 1, it indicates the market underreaction during the holding periods.

Our results in panel B of Table 5 provide the reciprocal underreaction coefficients. Consistent with the above portfolio sorting and regression analysis results for longer horizons, we find that the RURC remains less than 1. This finding supports that overreaction (Hypothesis B) rather than underreaction (Hypothesis A) mainly drives the lead–lag relation in commodity markets. Therefore, the traditional slow information diffusion explanation does not explain our findings. Therefore, we proceed for other possible explanations consistent with overreaction.

5.3 | Investor attention and speculative demand

Since our results are consistent with market overreaction rather than market underreaction, it is reasonable to expect that the conventional limited attention story does not help explain our findings. Nevertheless, we are still interested in whether the network momentum effect interacts with proxies of investor attention. Moreover, recent studies, such as

[8]A similar pattern of cumulative returns can be observed in Supporting Information Figure IA.1 when network momentum (NMDY) based on the variance decomposition approach is used.

[9]We follow Cohen and Frazzini (2008) and use the raw return rather than the abnormal return as in conventional event study literature.

[10]In Cohen and Frazzini's (2008) paper, their customer momentum is mainly caused by underreaction, the probability of large negative values in $CAR_{1,h}$ is low.

TABLE 5 Underreaction test for NMAL.

Horizon	*NMAL*	*TS*	*MOM*	*HHP*	*Constant*	*Adj.* R^2
Panel A: Fama–MacBeth regression in the different holding periods						
$h = 1$	0.253***	0.019	1.593**	0.105*	0.012	0.397
	(2.70)	(0.04)	(2.09)	(1.85)	(0.50)	
$h = 3$	0.109	1.000**	0.811	0.092	0.022	0.386
	(1.02)	(1.98)	(0.95)	(1.59)	(1.15)	
$h = 6$	0.031	1.434***	−0.796	0.113**	0.012	0.287
	(0.39)	(2.87)	(−1.04)	(2.09)	(0.56)	
$h = 12$	−0.090	−0.727	−0.835	0.046	−0.002	−0.129
	(−1.04)	(−1.55)	(−1.10)	(0.82)	(−0.08)	
Panel B: Underreaction coefficient						
Horizon	RET_1	$CAR_{1,h}$	$RURC_h$			
$h = 1$	0.117***					
	(3.60)					
$h = 3$		−0.060	0.489			
		(−1.35)	(−1.35)			
$h = 6$		−0.128***	−0.095***			
		(−2.73)	(−2.73)			
$h = 12$		−0.156***	−0.330***			
		(−3.49)	(−3.49)			

Note: This table presents the underreaction test. Panel A reports the results of Fama–MacBeth regressions with the different holding periods. Panel B provides the reciprocal underreaction coefficient motivated by Cohen and Frazzini (2008). The coefficients of $CAR_{1,h}$ are cumulative portfolio return from $t + 1$ to $t + h$. $RURC_h = (RET_1 + CAR_{1,h})/RET_1$. The numbers in brackets are the Newey–West h.a.c. t statistics for null hypothesis (in particular, $r = 1$ for $RURC_h$ in Panel B). *, **, and *** indicate 10%, 5%, and 1% statistical significance levels, respectively. All returns are annualized.

Abbreviations: HHP, hedging pressure for hedgers; MOM, momentum; NMAL, network momentum adaptive lasso; TS, term structure.

Bali et al. (2021) and Barber et al. (2022), also show that irrational traders tend to hold assets with salient features which attract attention. Therefore, we are interested in whether the results are consistent with speculative demand.

We consider several different attention proxies. One prominent measure of investor attention is the Google Trend Search Volume Index (GSV) as used by Da et al. (2011) and subsequent studies.[11] Therefore, we check how the predictive relation varies across different commodities with different degrees of internet search volume.[12] We also consider three additional attention proxies, extreme return (MAX), skewness (SKEW), and abnormal turnover (ATR), as considered by Barber and Odean (2008) and Bali et al. (2011). Besides their roles as attention proxies, they also reflect the lottery preference and the attractiveness of speculative demand. These measures have also been used by Asness et al. (2020) and Liu et al. (2019).

We resort to the double-sorting approach. We first sort commodities according to their values of attention proxies into high and low groups. Then within each group, we further sort commodities into three portfolios according to the network momentum signals. We then form long–short network momentum portfolios for each of the low- and high-attention groups. Table 6 reports the double-sorting results. Panel A reports results about GSV. We find that the long–short network momentum portfolio return spread is indeed stronger in the high-attention group relative to the low-attention group. This finding again supports that the existing limited attention

[11]Google Trends data are from http://www.google.com/trends.

[12]Since commodity futures do not have a general representative keyword like stock code, we use two kinds of keywords to retrieve the index, [exchange abbreviation + commodity name] and [commodity name + price] as the keyword to search (such as "COMEX Silver" and "Silver Price") to ensure that the search is related to commodity futures traders. Finally, we obtained GSV data for 32 commodities from 2004 to 2019.

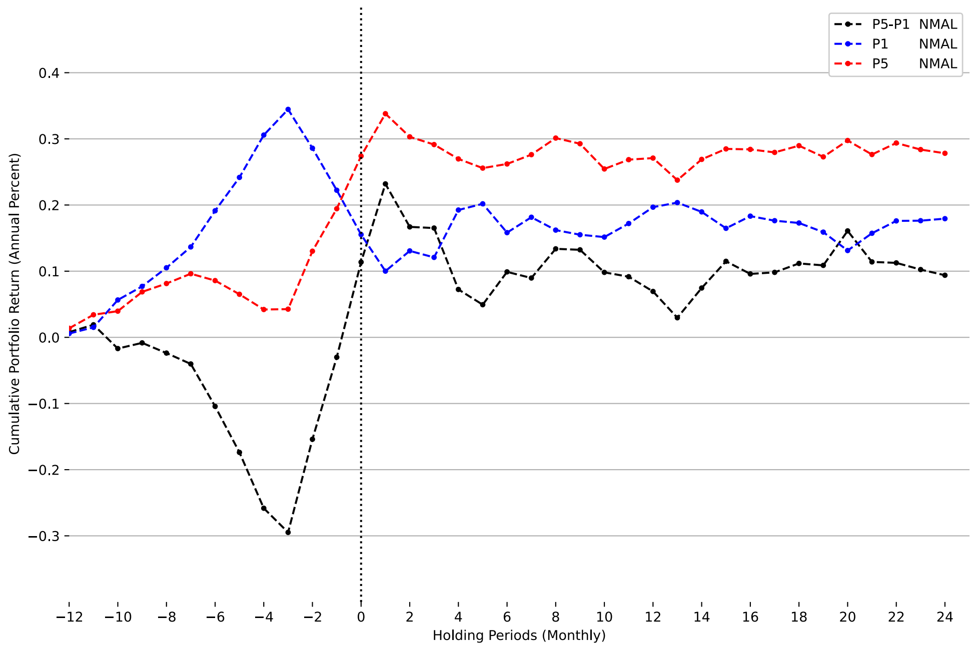

FIGURE 3 Portfolio cumulative returns of NMAL portfolios over time. This figure shows the average cumulative returns of portfolios formed on network momentum signal using NMAL. Commodities are sorted into five portfolios based on network momentum signals in period 0, portfolio returns of $P1$ (low signal value portfolio), $P5$ (high signal value portfolio), and $P5–P1$ (long–short portfolio return spreads) over time are shown in this figure. NMAL, network momentum adaptive lasso.

explanation fails to account for our finding, as we observe above. However, the return spread between high and low GSV groups is not statistically significant. Panels B–D report results using alternative attention proxies, including abnormal turnover, extreme return (MAX), and skewness. Consistent with GSV findings, we show that the network momentum long–short return spread is stronger for high-attention commodities across all measures. Moreover, we find that the return spreads between high and low-attention groups are statistically significant when extreme return and skewness are considered. Since these measures are commonly used measures for lottery preference and speculative demand, our findings also support that these attention-grabbing commodities are more likely to extract the excessive speculative demand of irrational traders. As a result, those commodities earn higher returns in the short horizon given the price pressure-driven return continuation but then experience a reversal when horizons are extended.

5.4 | Limits to arbitrage

Another interesting implication is that limits to arbitrage should play a role given the mispricing feature of network momentum. The idea of limits to arbitrage dating back to Shleifer and Vishny (1997), namely, betting against irrational traders is costly and risky. Gromb and Vayanos (2010) show that market frictions may deploy arbitrage capital. Regardless of under- or overreactions, deviations from intrinsic prices are not quickly corrected, as market frictions impede rational arbitrage activities. Hence, we expect the network momentum effect to be stronger when arbitrage is more difficult. We construct two prevalent limits to arbitrage proxies at the individual commodity level: illiquidity (ILR) proposed by Amihud (2002) and idiosyncratic volatility (IVOL) used by Stambaugh et al. (2015).

Panels E and F in Table 6 report results about limits to arbitrage. In line with our prediction, we find that the network momentum–return relation is stronger among commodities that are more illiquid to trade and which have higher idiosyncratic volatility. The return spreads in the high limits to the arbitrage group as well as the difference between high and low groups are statistically significant. Therefore, our findings support that the limit-to-arbitrage explanation plays an important role in understanding the predictive relation.

TABLE 6 Attention, speculation, and limited-to-arbitrage.

Group	P1	P3	L/S	P1	P3	L/S
	Panel A: Google search volume			*Panel B: Abnormal turnover*		
Low	0.011	0.018	0.007	0.050	0.084*	0.034
	(0.22)	(0.42)	(0.16)	(1.31)	(1.83)	(0.62)
High	−0.032	0.009	0.042	−0.033	0.022	0.056
	(−0.70)	(0.17)	(0.89)	(−0.83)	(0.55)	(1.10)
H/L	−0.043	−0.009	0.035	−0.084*	−0.066	0.018
	(−0.90)	(−0.19)	(0.53)	(−1.75)	(−1.21)	(0.25)
	Panel C: Extreme returns			*Panel D: Skewness*		
Low	0.033	0.021	−0.011	0.021	0.032	0.011
	(1.34)	(0.97)	(−0.47)	(0.78)	(1.12)	(0.37)
High	−0.034	0.066*	0.099***	−0.028	0.061	0.089***
	(−1.07)	(1.78)	(2.63)	(−0.99)	(1.91)	(2.56)
H/L	−0.066**	0.044	0.111***	−0.049*	0.029	0.078*
	(−2.12)	(1.27)	(2.43)	(−1.65)	(0.84)	(1.73)
	Panel E: Idiosyncratic volatility			*Panel F: Illiquidity*		
Low	0.006	0.002	0.008	−0.000	−0.024	−0.024
	(−0.28)	(0.08)	(0.34)	(−0.00)	(−0.77)	(−0.71)
High	0.018	0.109***	0.091**	0.019	0.110***	0.091***
	(0.47)	(2.58)	(2.16)	(0.65)	(3.37)	(2.52)
H/L	0.023	0.107***	0.084*	0.019	0.134***	0.115**
	(0.69)	(2.63)	(1.75)	(0.61)	(3.50)	(2.47)

Note: This table presents double-sorted portfolio results for attention, speculation, and limited-to-arbitrage measures. We first sort commodities according to their attention, speculation, or limit-to-arbitrage measures into high and low groups and then within each group we sort commodities into three portfolios according to the network momentum (NMAL) signals. We also report the long–short (*L/S*, *P*3–*P*1) return spread for network momentum portfolios and the difference between high- and low-attention (or speculation and limits to arbitrage) groups (*H/L*). The numbers in brackets are the Newey–West h.a.c. *t* statistics. *, **, and *** indicate 10%, 5%, and 1% statistical significance levels, respectively. All returns are annualized.

5.5 | Extrapolation and cross-extrapolation

Our empirical results so far show that the predictive relation is consistent with overreaction and it is stronger when attention, speculative demand, and arbitrage constraints are high. These findings support the existence of mispricing as we documented. However, all these mechanism analyses are based on information about focal commodities. Therefore, it is still unclear why the *network* momentum in particular generates the predictive return pattern. In this section, we consider the issue from a new perspective: extrapolation. Recent studies such as Greenwood and Shleifer (2014), Barberis et al. (2018), and Cassella and Gulen (2018) among others highlight the importance of extrapolative bias in driving asset prices. We conjecture that extrapolation may play an important role in understanding the network momentum effect. The intuition is as follows: Irrational investors may extrapolate not only from the commodity's own historical performance but may also extrapolate from its connected commodities. This argument leads to two sets of testable implications. First, not only the focal commodity's attention and speculative demand matter, but connected commodities' respective proxies may also play an important role. Second and more directly, if investors indeed extrapolate from connected commodities, we should expect the predictive relation to be stronger when the propensity to extrapolate is high.

To test the first implication, we construct network-attention proxies.

$$NVR_{it} = \sum_{j \neq i = 1}^{n} VR_{jt} * \lambda_{j,t}, \tag{10}$$

where VR is the proxy for investor attention and speculative demand. $\lambda_{i,jt}$ represents the weights of connected commodity j in the network of the focal commodity i. The measure is similar to network momentum, except for replacing momentum with attention proxies.

In addition, following Huang et al. (2022), we also use ID to test the extrapolative attention effect. Specifically, we calculate ID by

$$ID_{i,t} = sign(CR_{i,t}) \times (\%neg_{i,t} - \%pos_{i,t}), \tag{11}$$

where $sign(CR_{i,t})$ is the sign of cumulative return for commodity i in the last 3 months. $\%pos_{i,t}$ and $\%neg_{i,t}$ are the percentage number of days during the past 3 months with positive and negative returns. The low ID indicates when a commodity faces continuous information in small amounts, which may not fully attract investors' attention relative to conspicuous and discrete information. We consider the cross-commodity ID using equation (10).

Table 7 reports the double-sorting portfolio results using network-attention proxies. Consistent with our findings in Table 6, we find that the network momentum long–short portfolios are again consistently more profitable when the values of attention proxies are high. Significant return spreads are observed when ID, extreme returns, and skewness are considered. Therefore, our findings support that the lottery and speculative features of connected commodities also inspire irrational traders to hold respective commodities and generate the predictive return pattern.

To examine the second and more direct implication for extrapolation, we formally construct a measure of the time-varying DOX motivated by Liao et al. (2022) using trading position information.[13] We measure DOX as the weighted average past return based on investors' buys and sells. Moreover, we classify the DOX using positions of different categories of investors (Commercial position, non-commercial position, and non-reportable position) from CFTC COT reports.

$$DOXB_{i,t} = \frac{\sum_{j=t-\tau}^{t} (Buy_{i,j} * PastRet_{i,j})}{\sum_{j=t-\tau}^{t} Buy_{i,j}}, \tag{12}$$

$$DOXS_{i,t} = \frac{\sum_{j=t-\tau}^{t} (Sell_{i,j} * PastRet_{i,j})}{\sum_{j=t-\tau}^{t} Sell_{i,t}}, \tag{13}$$

where $DOXB_{i,t}$ and $DOXS_{i,t}$ are the DOX of commodity i in period t on the buyer and seller side, respectively. τ represents the extrapolative windows. $Buy_{i,t}$ and $Sell_{i,t}$ is the long or short position the commercial/non-commercial/non-reportable investors hold.[14] We not only construct extrapolation at the individual commodity level but also construct network extrapolation following the weighted average approach mentioned above.

Table 8 reports the extrapolation findings. Following Liao et al. (2022), we primarily focus on the extrapolation on the buy side. We find that the network momentum portfolio return spreads are generally stronger when extrapolation is high. We also find that the return spreads are statistically significant when extrapolation is high (Panel A). However, the difference between the high and low extrapolation groups is insignificant. When we move to network extrapolation (Panel B), we observe stronger results. We observe clear differential performance for different types of investors. For commercial traders who primarily trade for hedging purposes, we do not find a significant difference between high and low extrapolation groups. In contrast, we find that the return spread differences between high and low extrapolation groups are statistically significant when non-reportable traders (small and retail investors) and non-commercial traders (large institutions mainly trade for speculation purposes). These findings provide more direct evidence that commodity investors indeed extrapolate from connected commodities. The results are relatively weaker when the sell-side

[13]A survey-based DOX measure is introduced by Cassella and Gulen (2018). Due to the lack of long enough commodity survey forecast data, we instead construct the extrapolation measure based on trading information, analog to Liao et al. (2022).

[14]Following Liao et al. (2022), we use $\tau = 11$, i.e. the past 12 months in the empirical test.

TABLE 7 Network attention.

Group	P1	P3	L/S	P1	P3	L/S
	Panel A: Google search volume			*Panel B: Information discreteness*		
Low	0.014	0.027	0.013	0.012	0.021	0.009
	(0.32)	(0.63)	(0.32)	(0.44)	(0.71)	(0.28)
High	−0.008	0.035	0.043	−0.003	0.085***	0.088***
	(−0.20)	(0.76)	(1.06)	(−0.11)	(2.55)	(2.60)
H/L	-0.022	0.008	0.029	−0.015	0.064*	0.079*
	(−0.55)	(0.18)	(0.50)	(−0.53)	(1.74)	(1.75)
	Panel C: Abnormal turnover			*Panel D: Extreme returns*		
Low	0.028	0.040	0.011	0.026	0.045	0.019
	(0.76)	(0.94)	(0.21)	(0.93)	(1.57)	(0.59)
High	−0.038	0.047	0.086	−0.032	0.065*	0.097***
	(−0.95)	(1.02)	(1.57)	(−1.14)	(1.95)	(2.79)
H/L	−0.076*	−0.016	0.060	−0.058*	0.021	0.078*
	(−1.65)	(−0.30)	(0.84)	(−1.87)	(0.58)	(1.67)
Panel E: Skewness						
Low	0.026	0.013	−0.013			
	(0.95)	(0.45)	(−0.41)			
High	−0.003	0.067**	0.070**			
	(−0.11)	(2.23)	(2.31)			
H/L	−0.029	0.054*	0.083**			
	(−0.98)	(1.68)	(2.00)			

Note: This table presents double-sorted portfolio results for network-attention measures. Network-attention measures are constructed in a similar way to network momentum using the weighted average of attention measures for connected commodities of a focal commodity. We first sort commodities according to their network-attention measures into high and low groups and then within each group we sort commodities into three portfolios according to the network momentum (NMAL) signals. We also report the long–short (*P*3–*P*1) return spread for network momentum portfolios and the difference between high- and low-network-attention groups. The numbers in brackets are the Newey–West h.a.c. *t* statistics. *, **, and *** indicate 10%, 5%, and 1% statistical significance levels, respectively. All returns are annualized.

extrapolation is considered. Nevertheless, the overall results remain true. In short, our analyses support that extrapolation from connected commodities plays a critical role in understanding the network momentum effect in commodity markets.

6 | ROBUSTNESS CHECKS AND FURTHER ANALYSES

In this section, we conduct comprehensive robustness checks. For space consideration, these results are presented in the Supporting Information. First, we replicate the main portfolio and regression analyses using network momentum calculated by VAR variance decomposition (NMDY) in Supporting Information Tables IA.2 and IA.3. Consistent with our main findings using the adaptive lasso (NMAL), NMDY still positively and significantly predicts future commodity returns. Therefore, our findings are not restricted to a specific network approach.[15]

Second, we consider alternative rollover and conjunction methods for commodity futures. In the main analysis, we focus on switching to the next nearby contract 15 days before the current front-end contract expires with adjusting for the contango/backwardation bias. In the robustness checks, we consider different cases including holding the front-end

[15]In unreported analysis, we also construct the commodity network following two additional specifications: that is, return spillover using VAR variance decomposition and volatility spillover using an adaptive lasso. Our main results about network momentum remain qualitatively unaffected. Hence our findings are robust to different network measures.

TABLE 8 DOX and Network DOX

Variables	Non-reportable position *P1*	*P3*	*L/S*	Non-commercial position *P1*	*P3*	*L/S*	Commercial position *P1*	*P3*	*L/S*
Panel A: Double sorts for DOXB and NMAL									
Low	−0.031	−0.004	0.027	−0.034	−0.001	0.033	−0.049*	0.006	0.055*
	(−1.09)	(−0.14)	(0.85)	(−1.20)	(−0.02)	(1.02)	(−1.78)	(0.20)	(1.73)
High	0.008	0.076**	0.068*	0.007	0.074**	0.067*	0.014	0.079**	0.065*
	(0.25)	(2.14)	(1.66)	(0.23)	(2.09)	(1.71)	(0.45)	(2.30)	(1.70)
H/L	0.039	0.080**	0.041	0.041	0.074*	0.034	0.062*	0.073*	0.011
	(1.15)	(2.07)	(0.85)	(1.20)	(1.92)	(0.72)	(1.90)	(1.92)	(0.24)
Panel B: Double sorts for Network DOXB and NMAL									
Low	0.005	0.021	0.017	0.011	0.013	0.002	−0.012	0.040	0.052*
	(0.18)	(0.71)	(0.56)	(0.39)	(0.41)	(0.07)	(−0.43)	(1.32)	(1.75)
High	−0.021	0.069**	0.090***	−0.019	0.076**	0.095***	−0.002	0.076**	0.079**
	(−0.79)	(2.13)	(2.91)	(−0.76)	(2.40)	(3.07)	(−0.09)	(2.32)	(2.46)
H/L	−0.026	0.047	0.073*	−0.030	0.063	0.093**	0.010	0.037	0.027
	(−0.97)	(1.34)	(1.77)	(−1.11)	(1.80)	(2.28)	(0.33)	(1.02)	(0.64)
Panel C: Double sorts for DOXS and NMAL									
Low	−0.035	0.014	0.049	−0.037	0.008	0.045	−0.047*	0.006	0.052
	(−1.24)	(0.45)	(1.47)	(−1.28)	(0.25)	(1.30)	(−1.69)	(0.19)	(1.63)
High	0.016	0.064*	0.049	0.021	0.056*	0.035	0.003	0.072**	0.069*
	(0.51)	(1.89)	(1.30)	(0.68)	(1.67)	(0.90)	(0.09)	(2.04)	(1.77)
H/L	0.050	0.050	0.000	0.058*	0.049	−0.009	0.050	0.066*	0.017
	(1.53)	(1.34)	(0.00)	(1.70)	(1.24)	(−0.19)	(1.48)	(1.69)	(0.35)
Panel D: Double sorts for Network DOXS and NMAL									
Low	−0.003	0.013	0.016	−0.034	0.012	0.046	−0.008	0.017	0.025
	(−0.11)	(0.43)	(0.52)	(−1.21)	(0.44)	(1.56)	(−0.29)	(0.57)	(0.83)
High	−0.003	0.071**	0.074**	0.021	0.075**	0.054	−0.010	0.085***	0.095***
	(−0.10)	(2.14)	(2.28)	(0.79)	(2.26)	(1.63)	(−0.39)	(2.61)	(3.05)
H/L	0.002	0.058	0.056	0.055*	0.062*	0.007	−0.001	0.067*	0.067
	(0.07)	(1.56)	(1.29)	(1.91)	(1.75)	(0.17)	(−0.02)	(1.89)	(1.59)

Note: This table presents double-sorted portfolio results for degree of extrapolation (DOX) and network DOX. Network DOX is constructed in a similar way to network momentum using the weighted average of DOX measures for connected commodities of a focal commodity. We first sort commodities according to their DOX (or network DOX) measures into high and low groups and then within each group we sort commodities into three portfolios according to the network momentum (NMAL) signals. We also report the long–short (*P3*–*P1*, *L/S*) return spread for network momentum portfolios and the difference between high and low DOX (or network DOX) groups (*H/L*). We consider DOX (and network DOX) constructed from three groups of investors in commodity markets: non-reportable, non-commercial, and commercial traders. Panel A and Panel B report results using the DOX constructed from buy side (DOXB and network DOXB). Panel C and Panel D report results using the DOX constructed from sell side (DOXS and network DOXS). The numbers in brackets are the Newey–West h.a.c. t statistics. *, **, and *** indicate 10%, 5%, and 1% statistical significance levels, respectively. All returns are annualized.

contract to the end of maturity, switching to the next nearby contract 1 month before the maturity, and without adjusting for contango/backwardation bias. We also consider other contracts, including the second and the third nearby contracts. The results shown in Supporting Information Table IA.4 are consistent with the main empirical finding. Therefore, our findings are robust to different contracts and conjunction methods.

Moreover, we consider several alternative network momentum formation approaches. Our results in Supporting Information Table IA.5 show that using cumulative returns over the past 12 months, the average return over the past 12 months, and using only the top 3 and top 5 most connected commodities when constructing network momentum still generate positive and significant return spread. In contrast, if we focus only on the past 1-month return, we observe positive while insignificant return spreads in the long–short network momentum portfolios. This finding is different from the equity market lead–lag relation, such as Cohen and Frazzini (2008), which primarily focuses on underreaction and slow information diffusion, but it is consistent with our main findings regarding overreaction and extrapolation. Namely, irrational investors need to observe the historical performance for at least a few months to extrapolate for future performance. Nevertheless, our main results remain qualitatively unaffected.

Furthermore, we consider the sub-sample performances. Supporting Information Table IA.6 shows that the network momentum portfolio performs well both in the first and second half of the sample, and it also performs well in the post-financialization period. However, we recognize that the portfolio returns turn negative during the financial crisis period, which may be partially driven by the well-documented momentum crash. Using a balanced panel for all commodities starting from the same date does not change our main findings.

We further consider the performance of our network momentum strategy during the recession and non-recession periods using the NBER recession dummy.[16] We find that our results hold in general for both recession and non-recession periods, though the effect is more significant in the non-recession period.[17] In general, the new strategy performs well across different subsample periods.

We also conduct out-of-sample tests. To notice, the portfolio sorting we used in the main analysis is out-of-sample by construction, as we only use up to time t information to form a portfolio. The network momentum measure is also constructed in a rolling-window way, hence effectively avoiding the potential look-ahead bias concern. The Fama–MacBeth regressions in the main analysis use the full sample to estimate coefficients. In Supporting Information Table IA.7, we recursively estimate regression coefficients using an expanding window with an initial window size of 120 months (approximately one-third of the full-sample length). The model using network momentum generates a positive and statistically significant out-of-sample R^2 of 0.212%. Hence our results support the predictive power of network momentum out-of-sample.

Another concern is whether the network momentum profits can be interpreted as compensations for disaster risk. Existing studies, such as Barrsos and Santa-Clara (2015), show that momentum experiences crash. Hence disaster risk, which captures higher-order moments, may play a role. Moreover, several studies, such as Demirer et al. (2018) and Zhang (2021), show that disaster risk affects commodity returns. However, it is unclear whether disaster risk explains our network momentum strategy in commodity markets. We examine the issue using a news-based disaster risk measure, that is, the news-implied volatility (NVIX) introduced by Manela and Moreira (2017). The measure captures the rare disaster concern using textual analysis.[18] We consider both time-series spanning tests and cross-sectional Fama–MacBeth regressions.[19]

Supporting Information Table IA.8 shows that while regression coefficients of disaster risk and its components are consistently positive, they are statistically insignificant, except for securities market disaster risk, which is marginally significant. The intercepts are positive and highly significant. The adjusted R^2 is low or negative, indicating that disaster

[16]Existing studies, such as Levine et al. (2018) and Cao et al. (2022), consider the impact of economic states on commodity prices.

[17]In unreported analysis, we observe more connected commodities in the recession while the connection becomes more sparse in the non-recession period. The weakening performance of network momentum in the recession period is consistent with the increased connectedness in the bad time. Ang and Chen (2002) show that equity portfolio returns have higher comovements in the bad time. During the recession, a large amount of commodities experience price declines. The strong comovement among different commodities makes the extracted network more connected, which may distort the true underlying economic network among different commodities, for example, through the input-output relation. Since the network momentum measure is the weighted average of connected commodity historical returns, the strong comovement during the recession may lead to overweighting those economically unrelated commodities while underweighting those truly economically linked ones. Hence the network momentum strategy performance becomes weaker.

[18]The measure is downloaded from the author's website (https://asafmanela.github.io/data/). In addition to the total disaster risk index, there are six disaster risk components: government, intermediation, natural disaster, securities market, war, and unclassified.

[19]First, we conduct time-series spanning regression by regressing our network momentum long–short portfolio return spread on disaster risk contemporaneously. If disaster risk is an important determinant of our network momentum, we should find a significant regression coefficient. Second, we also consider the cross-sectional test. If disaster risk is a priced factor in network momentum, then the disaster risk beta should explain the cross-sectional variations of commodity returns and the predictive power of the network momentum signal should decline, when disaster risk beta is included. We conduct the conventional two-stage Fama–MacBeth regressions, as used in asset pricing tests. In the first stage, we run time-series regressions of individual commodity returns on an average commodity market factor (AVG) and the disaster risk factor and then retrieve the disaster risk beta for each individual commodity. In the second stage, we run cross-sectional regressions by regressing commodity returns on disaster risk betas. We include network momentum and other characteristics in the regression.

risk does not explain many time-series variations in the network momentum portfolio returns. Supporting Information Table IA.9 shows that the NVIX beta has a negative price of risk, consistent with the state variable property that high disaster risk periods are bad times, hence commodities with high disaster beta offer a hedge and earn lower returns. The price of risk is marginally significant. Instead, disaster risk components do not deliver a significant price of risk with a consistent sign. More importantly, network momentum remains positive and significant, even controlling for disaster risk betas. In short, the network momentum effect in commodity markets is unlikely driven by disaster risk.

Finally, we also consider the feasibility of the strategy by removing extremely illiquid commodities and taking into consideration of transaction costs.[20] Supporting Information Table IA.10 shows that our main results remain valid when extremely illiquid commodities are removed and when transaction costs are considered.

In summary, our comprehensive robustness checks confirm that the predictive power of network momentum for future commodity returns remains strong across different specifications.

7 | CONCLUSION

This paper investigates the lead–lag relation in the cross-section of commodity returns. We employ two methods to estimate dynamic and directional commodity networks: the adaptive lasso and variance decomposition. We find that the generated commodity networks are generally consistent with economic linkages of different commodities, confirming the usefulness of these approaches to characterize information spillover effects in commodity markets. Most importantly, we construct a new commodity return predictor: commodity network momentum, which reflects the weighted average of past returns of connected commodities for the focal commodity. Using both portfolio sorting and Fama–MacBeth regression analysis, we provide strong evidence that network momentum positively and significantly predicts future commodity returns. We also show that the predictive power cannot be explained by existing commodity risk factors nor can it be subsumed by existing commodity characteristics. These findings support the incremental predictive power of the new predictor we proposed.

We further explore the potential underlying economic mechanism through which network momentum may affect future returns. Different from existing studies about lead–lag relation, mainly in the equity market, we find that the predictive relation is consistent with investor overreaction rather than underreaction. Namely, the positive predictive relation does not persist for a longer period as the slow information diffusion hypothesis suggests. Instead, the predictive relation experiences a quick reversal. These findings indicate a potentially alternative mechanism for the lead–lag relation. We find that the predictive relation is stronger for commodities that attract higher investor attention, with lottery-like properties, and with higher arbitrage constraints. We further show that investors may extrapolate from not only the commodity's historical performance but also the historical performance of connected commodities. Our results suggest that cross-asset extrapolation is critical for understanding commodity network momentum.

We then conduct comprehensive robustness checks. Our main findings remain strong when alternative network measures, different conjunction methods, subsample periods, out-of-sample tests, and trading feasibility are considered. Our results cannot be attributed to disaster risk.

Overall, this paper provides novel empirical evidence about the existence of strong cross-asset return predictability in commodity markets and its underlying economic mechanism. The dominance of investor overreaction as well as the role of cross-asset extrapolation in commodity markets offer new insight that the prevalent view of slow information diffusion may not be the sole driving force for the lead–lag relation in the cross-section of asset returns.

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[20]We construct commodity level illiquidity measure using the measure proposed by Amihud (2002) and we remove the top 20% of extremely illiquid commodities. Moreover, we follow Sakkas and Tessaromatis (2020) and consider transaction costs. Commodity market trades have half spreads between 3.1 and 4.4 basis points. We conservatively assume 4.4 basis points as a half spread, which indicates the total annual rollover transaction cost for the long-only commodity portfolio is 105.6 basis points ($12 \times 2 \times 4.4$). For a long–short combination, transaction costs will be doubled to 211.2 basis points.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study have been obtained from several sources. The commodity futures pricing data are from Bloomberg. The data require a license fee. The commodity futures trading position data have been obtained from the weekly commitment of trader (COT) reports from the Commodity Futures Trading Commission (CFTC) website.

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[Commodity futures pricing data]; Not publicly available; data set can be acquired paying a data license fee at Bloomberg.

[Commodity futures trading position data]; Publicly available; data set can be obtained from the weekly COT reports from the CFTC website.

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