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 characteristics. Unlike existing lead-lag studies, the predictive relation is consistent with overreaction rather than underreaction. We provide evidence that the predictive relation is stronger for more attention-grabbing commodities. Extrapolation from connected commodities contributes to this relation. Overall, our paper highlights the role of information spillover in commodity return predictability.

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Keywords: Commodity futures, network momentum, lead-lag relation, investor attention, extrapolation

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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 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, and patent networks, etc. The rich evidence of the lead-lag relation or cross-asset momentum (or cross-momentum hereafter) suggests that the link between 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 co-movement, 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 co-movements. Therefore, we expect the relationship between network and return predictability may also hold in commodity markets. However, 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 further show that the positive network momentum-return relation remains strong when various existing commodity characteristics as well as network properties are controlled. A one standard deviation increase in network momentum is associated with a 0.21 standard deviation increase in the next month's returns when the adaptive lasso-based measure is used. In short, our findings support that network momentum contains incremental return predictive power for commodity returns.

We next 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 underreaction of news 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 institutional differences of equity and commodity markets may help to reconcile the observed differential effects. First, unlike equity markets where retail investors are important, the commodity markets are dominated by institutions.[1] Compared with retail investors, institutional investors are more sophisticated, therefore, they are more likely to have better capacity to process information. Hence, the underreaction of news due to overlooking information is less likely to be happened in commodity markets. Instead, institutional investors may tend to over-interpret news and hence could lead to overreaction. Second, unlike equity markets, which stocks have clear fundamentals from financial statement, commodity price formation is more complicated. While their prices are affected by demand and supply, there are 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. Therefore, they tend to overreact to news. Third, while it is true that commodity futures markets allow the ease of short selling, the markets also make margin trading and leverage easier. Therefore, when good news arrival, investors may use margin trading (and hence leverage) to amplify their bets, which could also lead to overreaction. In short, the different underreaction and overreaction of these equity and commodity markets could be driven by 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 searching volume, extreme 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.

[1] For instance, see the GameStop stock frenzy due to 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.

(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 extract 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 also 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 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 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, sub-sample periods, transaction costs, and extreme illiquidity are taken into consideration. Hence our findings are robust across different specifications.

The overall contribution of our paper is three-fold. First, we add to the commodity asset pricing literature by introducing a novel 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 highlighting one potential way to quantify the economic value of using the information spillover effect in practice. Third, our paper is also a natural extension of the fast-growing literature on economic links and the cross-asset momentum effect, especially in stock markets. We provide arguably the first empirical investigation 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 in commodity markets, we instead rely on econometric tools to quantify the commodity network. Most importantly, our analysis shows that conventional investor underreaction and 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 carried 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 existing studies.

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 to 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 et al. (1975) propose that in order 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

[3] Another related strand of literature focuses on developing asset pricing models to explain commodity returns. Yang (2013) introduce 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 AVG 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 have better cross-sectional performance than previous factors models.

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) etc. 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.

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. 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 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, respectively. They show that commodities with economic linkage have long-term price co-movement. 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.

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 (Ng (2000), Baele (2005), Yang and Zhou (2017), etc.). 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 vector autoregressive model (VAR). 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, that is, the weighting of the penalty term is performed once, and it is proved that the adaptive lasso has the oracle property. Guo et al. (2021a) and Guo et al. (2021b) 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, i.e., 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 by 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, and stocks with high abnormal volumes, 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 strongly affects the magnitude of the lead-lag effect. They use a proxy of information discreteness (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 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 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) build an equilibrium model to reconcile the investors' extrapolative beliefs. Hirshleifer et al. (2015) describe the extrapolation bias from the perspective of policy implications. Cassella and Gulen (2018) propose a novel non-linear regression method to quantify the degree of extrapolative weighting in investor beliefs, i.e. degree of extrapolation (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 trading account-level data to construct a new measure of DOX, which we adopt in this paper.

Our paper provides new evidence that investors 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. To avoid the survivorship bias, we exclude commodities that cease to trade. We also collect trading position data from the Commercial Futures Trading Commission (CFTC) website, with the sample periods from 1986 to 2019. The specific futures name, abbreviations, sector categories, and the starting and ending periods are shown in Appendix 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, we, therefore, adjust the price series forward by multiplying the new price by the old to new contract price ratio on the roll-over 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. 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, i.e., commodity network momentum.

[4]In the robustness check, we also show that our results remain 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 OLS regression by including the L1 penalty term and it helps to 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:

$$b^* = arg\ min\{||r^s_{i,t+1} - \alpha_i - \sum_{j\neq i} b_{i,j} r^s_{j,t}||^2 + \lambda_i \sum_{j\neq i} \hat{\omega}_{i,j} |b_{i,j}|\} \tag{1}$$

Specifically, we regress the daily return of each commodity on all other commodity daily returns with one 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 $\hat{\omega}_{i,j} = 1/|b^{\hat{OLS}}_{i,j}|$ is set as the reciprocal of the absolute value of OLS regression coefficients $b^{\hat{OLS}}_{i,j}$. 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 vector autoregressive model (VAR) variance decomposition approach by Diebold and Yilmaz (2012). For a VAR(p) model of order p, the forecast error variance decomposition $\theta^g_{ij}(H)$ is:

$$\theta^g_{ij}(H) = \frac{\sigma^{-1}_{ii} \sum_{h=0}^{H-1} (e'_i A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e'_i A_h \Sigma A'_h e_j)} \tag{2}$$

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 $\sum_{j=1}^{N} \theta^g_{ij}(H) \neq 1$, we use the following formula to normalize the proportion of each entry:

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

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

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

where $S^{g}_{\cdot\, i}(H)$ represents the network connectedness. Following Diebold and Yilmaz (2009), we use VAR 3-step-forecast error variance decomposition applying the VAR(12) model 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 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 form network momentum in the next section.

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. (Abbreviate 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 three-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 to identify which commodities are more important in the network compared to others. Following the literature, we consider two measures of centrality: betweenness centrality and eigenvector centrality. Betweenness centrality (BC) refers to the number of network nodes that appear between other nodes as the shortest path, which is used to measure the criticality 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, Eigenvector centrality

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

(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 weight, x_j is the importance index of neighbor j. 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.

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 Spring Network Plot 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.

Figure 1 and Figure 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 connection (correlation) and the darkness of the line represents the strength of the connection. 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 LH (hogs), and JO (orange juice)), which tend to be the end product in the industry. while others are more closely related (such as LC (live cattle), LL (lead), HG (copper), NG (natural gas), etc.). Commodities with close economic links also have close positions in the plots (such as CO (Brent Crude Oil) and CL (Crude Oil)). Fourth, the snapshots of network at different times indicates a strong time-varying of commodity network. Therefore, relying on static network, such as ex-ante specified supply-chain relation, will overlook this important feature. Hence the approaches we employed lead to 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, i.e., 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

[6] In the internet appendix, Table **??** to Table **??**, 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.

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-month 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.

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 to 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. We, therefore, 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. We, therefore, 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 0.21 standard deviation increase in the next month's commodity returns. Controlling for existing commodity characteristics does not affect our findings. The predictive power of network momentum signal remains strong if we add control variables one by one or altogether. Therefore, our results support the *incremental* predictive information in the network momentum beyond existing commodity characteristics.

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, due to the limited attention constraint, investors may overlook the news and hence lead to delayed response. 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 to attract less attention. Therefore, we have the first hypothesis:

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

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 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 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, i.e., 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 one month. Consistent with the portfolio sorting results, Fama-Macbeth regression results in panel A of Table 5 confirms 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 one month, which cannot be explained by conventional slow information diffusion explanation for the lead-lag relation.

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.[7] 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. [8] 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

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

[8] In Cohen's paper, their customer momentum is mainly caused by underreaction, the probability of large negative values in $CAR_{1,t}$ is low.

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. We, therefore, 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 to 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 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 Searching Volume Index (GSV) as used by Da et al. (2011) and subsequent studies [9]. We, therefore, check how the predictive relation varies across different commodities with different degrees of internet searching volume.[10] We also consider three additional attention proxies, extreme return (MAX), skewness (SKEW), and abnormal turnover (ATR). Besides their roles as attention proxies, they also reflect the attractiveness of speculative demand. These three measures have also been used by Asness et al. (2020) and Liu et al. (2019).

[9] Google Trends data is from http://www.google.com/trends

[10] Since commodity futures species 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 Google search volume data for 32 commodity futures varieties from 2004 to 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 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. Panel B to Panel 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) shows that market frictions may deploy arbitrage capital. Regardless of under- or over-reactions, 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).

Panel E and Panel 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 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.

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), 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. Irrational investors may extrapolate not only from the commodity's historical performance but, more importantly, 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 including investor attention and speculative demand. $\lambda_{i,jt}$ represents the weights of commodity j in the network coefficient where the i commodity is located. The measure is similar to network momentum, except for replacing momentum with attention proxies.

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

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

where $sign(CR_{i,t})$ is the sign of cumulative return for commodity i in the last three months. $\%pos_{i,t}$ and $\%neg_{i,t}$ are the percentage number of days during the past three 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 similarly consider the cross-commodity ID by 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. The significant return spreads are observed when information discreteness, 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 degree of extrapolation (DOX) motivated by Liao et al. (2022) using trading position information. We measure DOX as the weighted average past return based on investors' buys and sells. We classify the DOX using different sources of investors' positions (Commercial position, non-commercial position, and non-reportable position) from CFTC COT reports.

$$DOXB_{i,t} = \frac{\sum_{T=t-\tau}^{t-1}(Buy_{i,t} * PastRet_t)}{\sum_{T=t-\tau}^{t-1} Buy_{i,t}} \tag{11}$$

$$DOXS_{i,t} = \frac{\sum_{T=t-\tau}^{t-1}(Sell_{i,t} * PastRet_t)}{\sum_{T=t-\tau}^{t-1} Sell_{i,t}} \tag{12}$$

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.[11] 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 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

In this section, we conduct comprehensive robustness checks. Firstly, we replicate the main empirical analysis using network momentum calculated by VAR variance decomposition (NMDY). For space consideration, these results are presented in Table IA.2 to Table IA.8 of the Internet Appendix. Consistent with our main findings using the adaptive lasso (NMAL), NMDY still positively and significantly predicts future commodity returns. Therefore, our

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

findings are not restricted to a specific network approach.

Second, we consider alternative roll-over 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 contract to the end of maturity, switching to the next nearby contract one 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 Table IA.9 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 Table IA.10 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 one-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. Table IA.11 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. In general, the new strategy performs well across different sub-sample periods.

Finally, we also consider the feasibility of the strategy by removing extremely illiquid commodities and taking into consideration of transaction costs.[12] Table IA.12 shows that our main results remain to hold 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 direction commodity networks: the adaptive lasso and variance decomposition. We find 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 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.

[12]We construct commodity level illiquidity measure using the measure proposed by Amihud (2002) and we remove the top 20 percent 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 (12x2x4.4). For a long-short combination, transaction costs will be double to 211.2 basis points

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 more attention-grabbing commodities: commodities with higher internet searching volume, abnormal turnover, extreme returns, and return skewness. Collectively, these findings are consistent with the lottery preference and speculative demand of irrational traders. We also show that the predictive relation is stronger when arbitrage is more difficult, supporting that limits to arbitrage also play an important role. 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, sub-sample periods, and trading feasibility are considered.

Overall, this paper provides novel empirical evidence about the existence of strong cross-asset return predictability in commodity markets. 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.

References

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1):31–56.

Asness, C., Frazzini, A., Gormsen, N. J., and Pedersen, L. H. (2020). Betting against correlation: Testing theories of the low-risk effect. *Journal of Financial Economics*, 135(3):629–652.

Asness, C. S., Moskowitz, T. J., and Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance*, 68(3):929–985.

Baele, L. (2005). Volatility spillover effects in european equity markets. *Journal of Financial and Quantitative Analysis*, 40(2):373–401.

Bakshi, G., Gao, X., and Rossi, A. G. (2019). Understanding the sources of risk underlying the cross section of commodity returns. *Management Science*, 65(2):619–641.

Bali, T. G., Hirshileifer, D., Peng, L., and Tang, Y. (2021). Attention, social interaction, and investor attraction to lottery stocks. Technical report, National Bureau of Economic Research.

Barber, B. M., Huang, X., Odean, T., and Schwarz, C. (2022). Attention-Induced Trading and Returns: Evidence from Robinhood Users. *Journal of Finance*, 77(6):3141–3190.

Barber, B. M. and Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics*, 116(1):261–292.

Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, 21(2):785–818.

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2015). X-capm: An extrapolative capital asset pricing model. *Journal of Financial Economics*, 115(1):1–24.

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2018). Extrapolation and bubbles. *Journal of Financial Economics*, 129(2):203–227.

Baruník, J. and Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, 16(2):271–296.

Boons, M. and Prado, M. P. (2019). Basis-momentum. *Journal of Finance*, 74(1):239–279.

Brennan, M. J. (1976). The supply of storage. In *The Economics of Futures Trading*, pages 100–107. Springer.

Cao, J., Chordia, T., and Lin, C. (2016). Alliances and return predictability. *Journal of Financial and Quantitative Analysis*, 51(5):1689–1717.

Casassus, J., Liu, P., and Tang, K. (2013). Economic linkages, relative scarcity, and commodity futures returns. *The Review of Financial Studies*, 26(5):1324–1362.

Cassella, S. and Gulen, H. (2018). Extrapolation bias and the predictability of stock returns by price-scaled variables. *The Review of Financial Studies*, 31(11):4345–4397.

Chang, J. J., Du, H., Lou, D., and Polk, C. (2022). Ripples into waves: Trade networks, economic activity, and asset prices. *Journal of Financial Economics*, 145(1):217–238.

Chen, X., An, L., Wang, Z., and Yu, J. (2020). Attention spillover in asset pricing. *Available at SSRN 3716918*.

Cheng, I.-H. and Xiong, W. (2014). Financialization of commodity markets. *Annu. Rev. Financ. Econ.*, 6(1):419–441.

Chui, A. C., Titman, S., and Wei, K. J. (2010). Individualism and momentum around the world. *Journal of Finance*, 65(1):361–392.

Cohen, L. and Frazzini, A. (2008). Economic links and predictable returns. *Journal of Finance*, 63(4):1977–2011.

Cooper, M. J., Gutierrez Jr, R. C., and Hameed, A. (2004). Market states and momentum. *Journal of Finance*, 59(3):1345–1365.

Cootner, P. H. (1960). Returns to speculators: Telser versus keynes. *Journal of Political Economy*, 68(4):396–404.

Da, Z., Engelberg, J., and Gao, P. (2011). In search of attention. *Journal of Finance*, 66(5):1461–1499.

Da, Z., Gurun, U. G., and Warachka, M. (2014). Frog in the pan: Continuous information and momentum. *The Review of Financial Studies*, 27(7):2171–2218.

Da, Z., Huang, X., and Jin, L. J. (2021). Extrapolative beliefs in the cross-section: What can we learn from the crowds? *Journal of Financial Economics*, 140(1):175–196.

Daniel, K. D., Hirshleifer, D., and Subrahmanyam, A. (2001). Overconfidence, arbitrage, and equilibrium asset pricing. *Journal of Finance*, 56(3):921–965.

Diebold, F. X., Liu, L., and Yilmaz, K. (2017). Commodity connectedness. Technical report, National Bureau of Economic Research.

Diebold, F. X. and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal*, 119(534):158–171.

Diebold, F. X. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1):57–66.

Diebold, F. X. and Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3):607–636.

Fernandez-Perez, A., Frijns, B., Fuertes, A.-M., and Miffre, J. (2018). The skewness of commodity futures returns. *Journal of Banking & Finance*, 86:143–158.

Frazzini, A. (2006). The disposition effect and underreaction to news. *Journal of Finance*, 61(4):2017–2046.

Gorton, G. B., Hayashi, F., and Rouwenhorst, K. G. (2013). The Fundamentals of Commodity Futures Returns. *Review of Finance*, 17(1):35–105.

Greenwood, R. and Shleifer, A. (2014). Expectations of returns and expected returns. *The Review of Financial Studies*, 27(3):714–746.

Gromb, D. and Vayanos, D. (2010). Limits of arbitrage. *Annual Review of Financial Economics*, 2(1):251–275.

Guo, L., Härdle, W. K., and Tao, Y. (2021a). A time-varying network for cryptocurrencies. *ArXiv Preprint ArXiv*.

Guo, L., Sang, B., Tu, J., and Wang, Y. (2021b). Cross-cryptocurrency return predictability. *Available at SSRN*.

Han, Y., Hu, T., and Yang, J. (2016). Are there exploitable trends in commodity futures prices? *Journal of Banking & Finance*, 70:214–234.

Hicks, J. R. et al. (1975). Value and capital: An inquiry into some fundamental principles of economic theory. *OUP Catalogue*.

Hirshleifer, D., Li, J., and Yu, J. (2015). Asset pricing in production economies with extrapolative expectations. *Journal of Monetary Economics*, 76:87–106.

Hong, H. and Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, 54(6):2143–2184.

Hong, H. and Yogo, M. (2012). What does futures market interest tell us about the macroeconomy and asset prices? *Journal of Financial Economics*, 105(3):473–490.

Huang, S., Lee, C. M., Song, Y., and Xiang, H. (2022). A frog in every pan: Information discreteness and the lead-lag returns puzzle. *Journal of Financial Economics*, 145(2):83–102.

Jiang, Y., Qian, Y., and Yao, T. (2016). R&d spillover and predictable returns. *Review of Finance*, 20(5):1769–1797.

Kaldor, N. (1939). Welfare propositions of economics and interpersonal comparisons of utility. *Economic Journal*, pages 549–552.

Kaldor, N. (1976). Speculation and economic stability. In *The Economics of Futures Trading*, pages 111–123. Springer.

Keynes, J. M. (1930). Treatise on money: Pure theory of money vol. i.

Lee, C. M., Sun, S. T., Wang, R., and Zhang, R. (2019). Technological links and predictable returns. *Journal of Financial Economics*, 132(3):76–96.

Liao, J., Peng, C., and Zhu, N. (2022). Extrapolative bubbles and trading volume. *The Review of Financial Studies*, 35(4):1682–1722.

Liu, J., Stambaugh, R. F., and Yuan, Y. (2019). Size and value in china. *Journal of Financial Economics*, 134(1):48–69.

Menzly, L. and Ozbas, O. (2010). Market segmentation and cross-predictability of returns. *Journal of Finance*, 65(4):1555–1580.

Miffre, J. (2016). Long-short commodity investing: A review of the literature. *Journal of Commodity Markets*, 1(1):3–13.

Miffre, J. and Rallis, G. (2007). Momentum strategies in commodity futures markets. *Journal of Banking & Finance*, 31(6):1863–1886.

Ng, A. (2000). Volatility spillover effects from japan and the us to the pacific–basin. *Journal of international money and finance*, 19(2):207–233.

Parsons, C. A., Sabbatucci, R., and Titman, S. (2020). Geographic lead-lag effects. *The Review of Financial Studies*, 33(10):4721–4770.

Sakkas, A. and Tessaromatis, N. (2020). Factor based commodity investing. *Journal of Banking & Finance*, 115:105807.

Scheinkman, J. A. and Xiong, W. (2003). Overconfidence and speculative bubbles. *Journal of Political Economy*, 111(6):1183–1220.

Shleifer, A. and Vishny, R. W. (1997). The Limits of Arbitrage. *Journal of Finance*, 52(1):35–55.

Stambaugh, R. F., Yu, J., and Yuan, Y. (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *Journal of Finance*, 70(5):1903–1948.

Szymanowska, M., De Roon, F., Nijman, T., and Van Den Goorbergh, R. (2014). An anatomy of commodity futures risk premia. *The Journal of Finance*, 69(1):453–482.

Working, H. (1949). The theory of price of storage. *American Economic Review*, 39(6):1254–1262.

Xiao, B., Yu, H., Fang, L., and Ding, S. (2020). Estimating the connectedness of commodity futures using a network approach. *Journal of Futures Markets*, 40(4):598–616.

Yang, F. (2013). Investment shocks and the commodity basis spread. *Journal of Financial Economics*, 110(1):164–184.

Yang, J., Li, Z., and Miao, H. (2021). Volatility spillovers in commodity futures markets: A network approach. *Journal of Futures Markets*, 41(12):1959–1987.

Yang, Z. and Zhou, Y. (2017). Quantitative easing and volatility spillovers across countries and asset classes. *Management Science*, 63(2):333–354.

Zou, H. (2006). The adaptive lasso and its oracle properties. *Journal of the American Statistical Association*, 101(476):1418–1429.

8 Tables and Figures

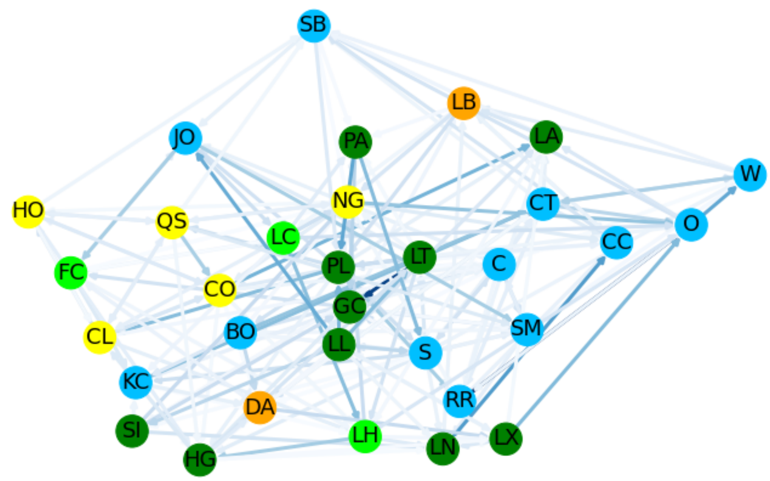
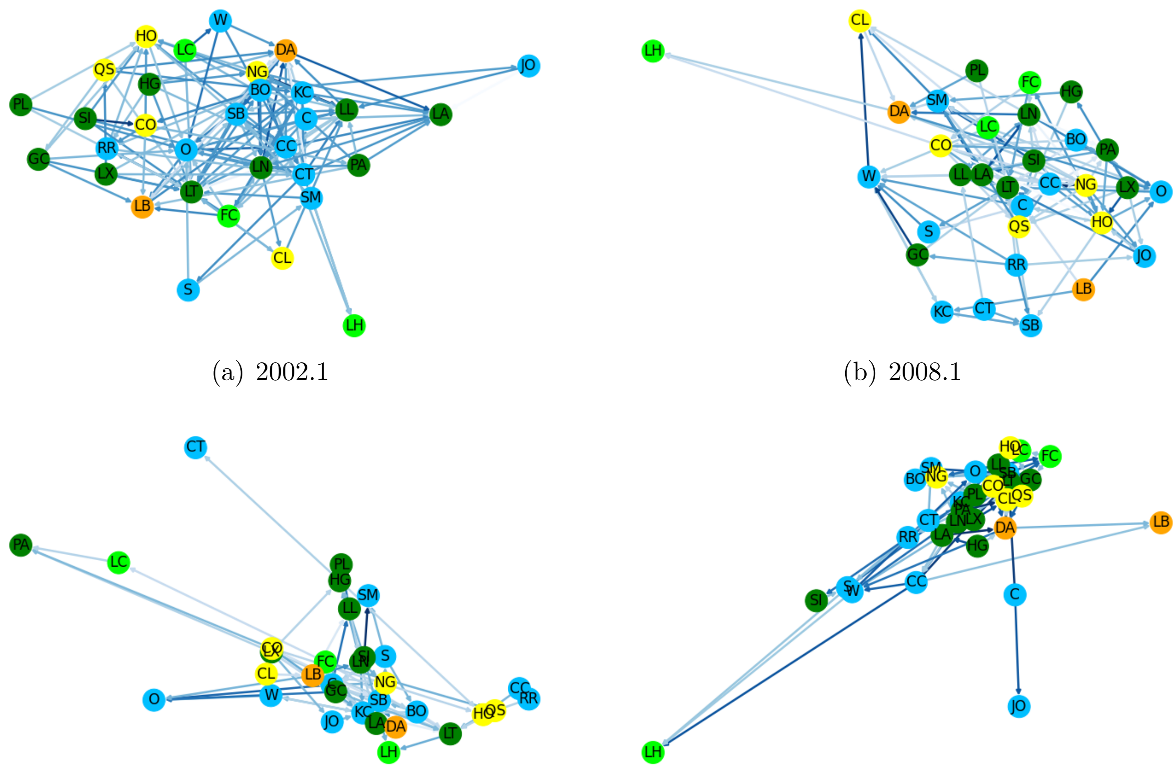


Figure 1: All-Sample Volatility Spillover Network Plot

Note: This figure visualizes the all-sample volatility spillover network. Each node represents single commodity and its color shows the category of commodities (Blue represents agriculture, green represents metal, lime represents livestock, yellow represents energy, and orange represents addtional production). The connecting lines indicate direct connectedness between each commodities and the darkness of lines shows the magnitude of connectedness.



(a) 2002.1 (b) 2008.1

(c) 2014.1 (d) 2019.1

Figure 2: Monthly-Sample Return Spillover Network Plot

Note: These figures visualize the monthly-sample return spillover network. Each node represents single commodity and its color shows the category of commodities (Blue represents agriculture, green represents metal, lime represents livestock, yellow represents energy, and orange represents additional production). The connecting lines indicate direct connectedness between each commodities and the darkness of lines shows the magnitude of connectedness.

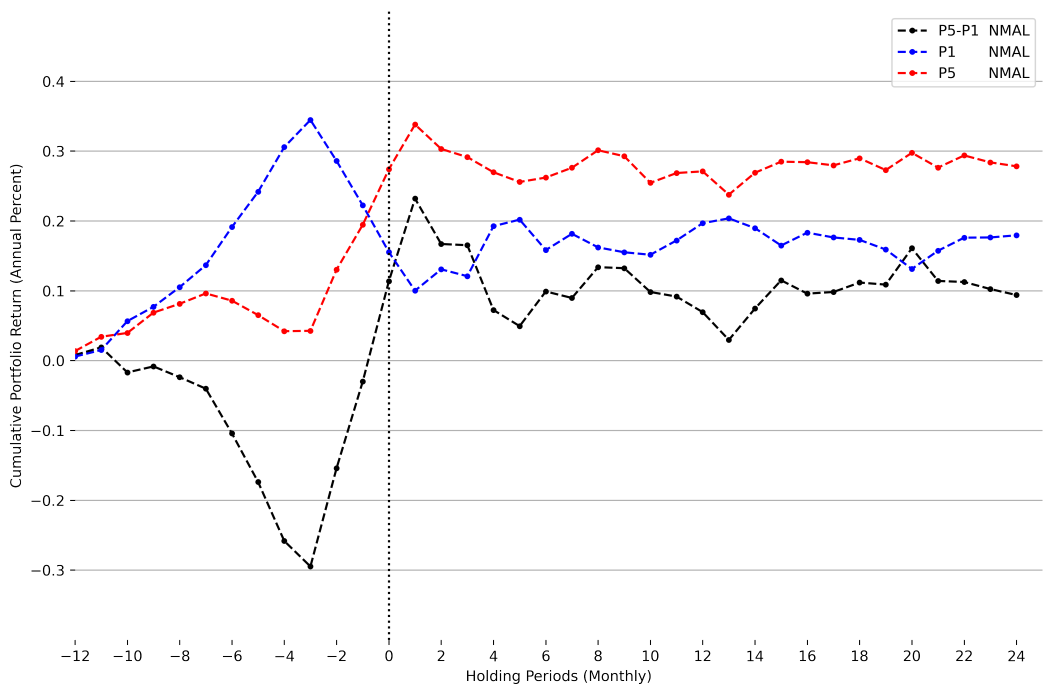


Figure 3: Portfolio Cumulative Return of NMAL Over Time

Note: This figure shows the portfolio average cumulative return formed on the NMAL. Commodities are sorted into five groups based on network momentum signals in period 0, the group return of P1, P5, and P5-P1 over time are shown in this figure.

Table 1: Descriptive Statistics of Key Variables

Panel A: Descriptive Statistics

VARIABLES	(1) Count	(2) Mean	(3) Std	(4) Min	(5) 25%	(6) 50%	(7) 75%	(8) Max	(9) Skew.	(10) Kurt.
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

Panel B: Correlation

	NMAL	NMDY	TS	MOM	HHP	SHP	BM	SKEW	VALUE	OI	EC	BC
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: Panel A of this table presents descriptive statistics for the main variables used in the empirical analysis. Panel B presents the correlation between these variables. All variables in the table are winsorized at the 1%-99% level throughout the table.

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)
Period	466	466	466	466	466	466

Note: This table shows portfolio returns based on NMAL. h is the holding horizon for each portfolio.The number of brackets shows the Newey–West h.a.c. t-statistic, *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. All returns are in annual percent.

Table 3: Factors Spanning Test for NMAL

	α	β_{AVG}	β_{TS}	β_{MOM}	β_{SHP}	β_{HHP}	β_{BM}	$adj.R^2$
R_{NMAL}	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 shows the spanning tests to explain if portfolio returns based on network momentum(NMAL) provides an alpha relative to the known factors model. Factor return R_{NMAL} regressed on the beta from three kinds of muti-factor models: (i) Three factors model(AVG, TS, MOM) from Bakshi et al. (2019). (ii) Five factors model(AVG, TS, MOM, SHP, HHP) from Szymanowska et al. (2014). (iii) Two factors model(AVG, BM) from Boons and Prado (2019). The number of brackets shows the Newey–West h.a.c. t-statistic. *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. $adj.R^2$ presents the adjusted R^2 for regression. All returns are in annual percent.

Table 4: Fama-Macbeth Cross-sectional Regression for NMAL

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$NMAL$	0.210**	0.253***	0.255***	0.181**	0.234**	0.279***	0.258***	0.290***	0.223**	0.274**
	(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)
Const	0.028	0.010	-0.005	0.009	0.012	0.007	0.010	-0.020	0.014	-0.008
	(1.46)	(0.56)	(-0.20)	(0.48)	(0.62)	(0.34)	(0.52)	(-0.87)	(0.68)	(-0.20)
Sample Period	382	382	382	382	382	382	382	382	382	382
Adj R^2	0.307	0.397	0.425	0.539	0.418	0.428	0.380	0.408	0.404	0.643

Note: This table presents the Fama-Macbeth cross-sectional regression following Fama and MacBeth (1973). The results show the average coefficient where monthly portfolio return based on NMAL is regressed on the value of commodity characteristics in the previous month. We propose the baseline two-factor model(1), three-factor model(2), augmented four-factor model(3)-(9), and model(10) controlling all commodity characteristics. The number of brackets shows the Newey–West h.a.c. t-statistic. *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. $adj.R^2$ presents the adjusted R^2 for regression. All returns are in annual percent.

Table 5: Underreaction Test for NMAL

Panel A: Fama-Macbeth regression in the different holding periods						
Horizon	$NMAL$	TS	MOM	HHP	Const	Adj. R^2
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 to clarify whether the portfolio returns based on network momentum is caused by market underreaction. Panel A shows the result of Fama-Macbeth regression in the different holding periods. Panel B shows 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 number of brackets shows the Newey–West h.a.c. t-statistic 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 in annual percent.

Table 6: Attention, Speculation and Limited-to-Arbitrage

Group	P1	P3	L/S	P1	P3	L/S
	Panel A: Google Searching index			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 the bivariate portfolio sorting results for attention, speculation and limited-to-arbitrage index. We first sort commodities according to their network attention, speculation, or limit-to-arbitrage index into high and low groups and then sorting commodities into 3 groups based on NMAL signal. We also present the spread returns into H/L group and L/S group. The number of brackets shows the Newey–West h.a.c. t-statistic. *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. All returns are in annual percent.

Table 7: Network Attention

Group	P1	P3	L/S	P1	P3	L/S
	Panel A: Google Searching index			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 the bivariate portfolio sorting results for network attention index. We first sort commodities according to their network attention or speculation index into high and low groups and then sorting commodities into 3 groups based on NMAL signal. We also present the spread returns into H/L group and L/S group. The number of brackets shows the Newey–West h.a.c. t-statistic. *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. All returns are in annual percent.

Table 8: DOX and Network DOX

VARIABLE	P1	P3	L/S	P1	P3	L/S	P1	P3	L/S
	Non-reportable position			Non-commercial position			Commercial position		
Panel A: 2 × 3 Double sort 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: 2 × 3 Double sort 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: 2 × 3 Double sort 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: 2 × 3 Double sort 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 shows the double sorting results for (network) degree of extrapolation (DOX) related to NMAL. We first sort commodities according to time-varying DOX (set $\tau = 12$) into high and low groups and then sorting commodities according to NMAL signal. We also present the spread returns in H/L and L/S groups. DOXB and DOXS represent for long-side and short-side positions, respectively. The number of brackets shows the Newey–West h.a.c. t-statistic. *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. All returns are in annual percent.

A Appendix

Table A.1: Basic Information for Commodity Futures

Abbreviation	Name	Category	Data Start Time	Data End Time
C	Corn	agriculture	1/1/70	10/31/19
CC	Cocoa	agriculture	1/1/70	10/31/19
KC	Coffee	agriculture	8/16/72	10/31/19
CT	Cotton	agriculture	1/1/70	10/31/19
O	Oats	agriculture	1/3/72	10/31/19
JO	Orange juice	agriculture	1/1/70	10/31/19
S	Soybean	agriculture	1/1/70	10/31/19
SM	Soybean Meal	agriculture	1/1/70	10/31/19
BO	Soybean Oil	agriculture	1/1/70	10/31/19
SB	Sugar	agriculture	1/1/70	10/31/19
W	wheat	agriculture	1/1/70	10/31/19
RR	Rough Rice	agriculture	12/1/88	10/31/19
FC	Feeder Cattle	livestock	12/1/71	10/31/19
LH	Hogs	livestock	6/1/86	10/31/19
LC	Live Cattle	livestock	1/1/70	10/31/19
LA	Aluminum	metal	7/1/97	10/31/19
HG	Copper	metal	12/1/88	10/31/19
GC	Gold	metal	1/1/75	10/31/19
LL	Lead	metal	7/1/97	10/31/19
LN	Nickel	metal	7/1/97	10/31/19
PA	Palladium	metal	10/1/86	10/31/19
PL	Platinum	metal	5/1/86	10/31/19
SI	Silver	metal	1/1/75	10/31/19
LT	Tin	metal	7/1/97	10/31/19
LX	Zinc	metal	7/1/97	10/31/19
CO	Brent Crude Oil	energy	6/1/88	10/31/19
CL	Crude Oil	energy	4/1/83	10/31/19
QS	Gas Oil	energy	7/1/89	10/31/19
NG	Natural Gas	energy	4/1/90	10/31/19
HO	Heating Oil	energy	2/2/87	10/31/19
DA	Milk	additional production	1/1/96	10/31/19
LB	Lumber	additional production	8/1/86	10/31/19

Table A.2: Commodity Future Predictors and Limited-to-Arbitrage Index

Variable	Abb.	Construction Method	Formula
		Panel A: Commodity Future Predictors	
Term Structure	TS	The logarithmic price spread between the first front month and the second front month	$yield_r = \ln f_{i,t}^{first} - \ln f_{i,t}^{second}$
Momentum	MOM	Cumulative return over the past 12 months	$mom_{i,t} = \prod_{t=T-12}^{T-1}(1 + r_{i,t}) - 1$
Hedging Pressure for Hedgers	HHP	The ratio of hedgers' long-short open interest (short-long) over total open interest of hedgers	$HHP_{it} = \frac{1}{12}\sum_{j=0}^{11}\frac{S_{H,it-1}-L_{H,it-1}}{S_{H,it-1}+L_{H,it-1}}$
Hedging Pressure for Speculators	SHP	The ratio of Speculators' long-short open interest (long-short) over total open interest of Speculators	$SHP_{it} = \frac{1}{12}\sum_{j=0}^{11}\frac{L_{S,it-1}-S_{S,it-1}}{S_{S,it-1}+L_{S,it-1}}$
Basis Momentum	BM	The spread of momentum between the first front contract and the second front contract	$BM_{it} = mom_{it}^{T_1} - mom_{it}^{T_2}$
Value	VALUE	The average price over the past 5.5 years to 4.5 years (D days) divided the current price	$VALUE_{it} = \ln[(\frac{1}{D}\sum_{d=1}^{D} f_{i,d})/f_{i,d}]$
Skewness	SKEW	Skewness of returns over the past 12 months(252 days)	$SKEW_{it} = \sum_{t=1}^{252}(r_{i,t} - \mu_i)^3/252\sigma_i^2$
Open Interest	ΔOI	The spread of open interest between the current month's and the previous month's	$\Delta OI_{it} = OI_{it} - OI_{it-1}$
		Panel B: Attention, Speculation and Limited-to-Arbitrage Index	
Maximum	MAX	The largest 5 daily return averages over the past 21 trading days	$MAX_{it} = \sum_{i=1}^{22} max_{it}^5$
Abnormal Turnover	ATR	Turnover rate in the past 21 days divide turnover rate in the past 252 days	$ATR_{it} = TR_{it}^1/TR_{it}^{12}$
Illiquidity	ILR	The ratio of absolute value for 12-month moving average of monthly return over the monthly dollar volume	$ILR_{it} = \frac{1}{12}\sum_{t-11}^{t}\frac{\lvert r_{i,t}\rvert}{\$Volume_{it}}$
Idiosyncratic Volatility	IVOL	12-month rolling volatility of the residual terms of three-factor model (AVG, TS, MOM) from Bakshi et al. (2019)	$IVOL_{it} = \frac{\sigma_{it}^2(\mathbf{E}_i)}{\lvert\mu_{it}(\mathbf{E}_i)\rvert}$
Information discreteness	ID	Sign of cumulative return times the spread between percentage of days with positive and negative returns during past three months	$ID_{i,t} = sign(CR_{i,t}) \times (\%neg_{i,t} - \%pos_{i,t})$
		Panel C: Centrality Variables	
Betweenness Centrality	BC	The ratio of the shortest path network nodes appear between other nodes.	$BC_i = \sum_{m,n} d_{mn}^*/d_{mn}$
Eigenvector Centrality	EC	Network weighted importance index of node	$EC_i = w\sum_{j=1}^{n} a_{ij}x_j$
		Panel D: Extrapolation	
Degree of Extrapolation in buy side	DOXB	The weighted average past return based on investors' buys	$DOXB_{i,t} = \frac{\sum_{T=t-\tau}^{t-1}(Buy_{i,t} * PastRet_t)}{\sum_{T=t-\tau}^{t-1} Buy_{i,t}}$
Degree of Extrapolation in sell side	DOXS	The weighted average past return based on investors' sells	$DOXS_{i,t} = \frac{\sum_{T=t-\tau}^{t-1}(Sell_{i,t} * PastRet_t)}{\sum_{T=t-\tau}^{t-1} Sell_{i,t}}$

Internet Appendix to

Commodity Network and Predictable Returns

(not for publication)

This appendix presents supplementary results not included in the main body of the paper.

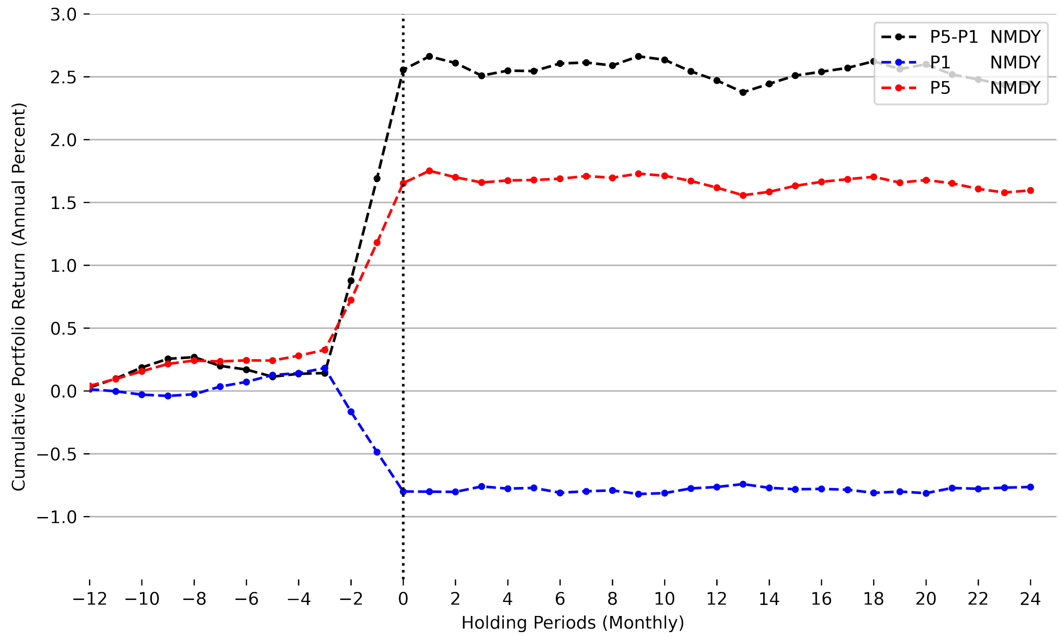


Figure IA.1: Portfolio Cumulative Return of NMDY

Note: This figure shows the portfolio average cumulative return formed on the NMDY. In period 0 commodities are sorted into five groups based on network momentum signals, the group returns of P1, P5 and P5-P1 over time are shown into this figure.

Table IA.1: All-sample DY Table

	C	CC	KC	CT	O	JO	S	SM	BO	SB	W	RR	FC	LH	LC	LA	HG	GC	LL	LN	PA	PL	SI	LT	LX	CO	CL	QS	HO	NG	DA	LB	From
C	16.40	0.43	1.35	3.96	2.02	1.45	8.22	8.82	1.16	1.71	3.73	0.71	0.12	0.19	0.20	1.65	4.05	5.80	4.04	0.30	1.32	6.57	1.47	3.44	2.32	5.17	5.48	3.79	1.56	1.58	0.16	0.83	83.60
CC	2.95	28.89	1.02	5.66	0.43	0.40	0.71	1.27	1.61	1.59	0.36	7.34	0.30	3.08	0.39	2.05	2.33	0.34	3.10	6.57	3.38	4.88	0.28	3.91	0.52	2.13	0.80	1.50	0.55	6.40	1.64	3.62	71.11
KC	1.29	1.92	22.11	3.67	2.10	0.33	5.94	0.97	5.58	0.65	0.59	1.04	7.73	2.30	7.77	3.60	3.70	7.23	1.05	0.10	0.66	1.05	4.07	2.29	0.97	2.59	2.73	0.83	0.40	1.38	2.71	0.66	77.89
CT	4.42	3.17	3.69	28.83	2.11	0.58	6.25	2.19	5.40	2.72	4.95	0.78	2.54	0.93	1.49	0.69	1.87	0.99	2.02	2.14	3.07	2.61	1.44	4.42	1.84	1.58	0.95	0.36	0.27	0.31	3.95	1.43	71.17
O	3.51	2.70	1.03	7.14	28.34	0.67	2.37	1.04	2.49	1.23	1.37	5.30	2.46	4.77	5.18	0.63	0.42	2.10	1.47	0.44	0.20	3.32	0.43	3.88	3.97	1.02	1.73	1.39	2.43	3.76	1.69	1.49	71.66
JO	4.53	1.05	0.36	0.83	1.02	26.80	1.00	0.99	1.28	4.69	0.52	2.80	3.80	1.06	2.92	0.91	2.36	2.97	4.00	1.24	2.07	7.36	1.61	7.75	1.14	2.71	3.13	3.21	2.38	0.09	0.34	3.08	73.20
S	8.11	2.34	2.00	1.67	1.24	3.13	18.80	11.55	5.97	0.81	1.87	1.48	0.13	0.35	0.39	0.66	3.36	5.78	4.78	0.77	4.70	4.94	1.56	3.82	0.98	1.81	2.12	2.86	0.85	0.70	0.25	0.21	81.20
SM	10.16	1.52	0.52	0.38	0.31	6.71	13.04	20.08	0.70	0.06	1.57	1.65	1.26	0.75	0.19	0.41	2.62	8.44	3.82	0.30	3.90	3.67	1.25	1.65	1.24	2.65	3.03	5.18	1.50	0.75	0.38	0.31	79.92
BO	5.09	0.82	2.97	2.94	2.29	1.27	14.59	4.76	16.45	3.98	2.80	0.83	0.61	0.58	2.24	2.90	2.80	2.39	2.13	0.17	3.55	5.52	0.51	4.17	0.62	2.02	2.12	1.90	1.23	2.82	0.84	2.11	83.55
SB	1.03	3.95	2.29	5.32	3.67	2.41	1.25	0.99	0.82	26.79	4.36	1.15	1.77	1.68	2.74	5.50	1.02	0.61	0.32	2.30	0.88	2.97	1.78	0.94	0.62	3.42	2.12	3.84	6.72	5.29	0.65	0.78	73.21
W	8.32	0.70	1.28	6.57	10.20	0.96	5.24	8.56	0.51	1.48	19.04	1.70	1.15	0.75	0.42	2.00	1.47	0.30	3.08	3.96	0.12	1.11	2.04	3.43	3.99	3.58	3.88	1.36	1.49	0.10	0.46	0.77	80.96
RR	5.94	2.73	1.95	5.67	8.03	2.50	3.68	3.81	1.00	2.70	3.22	22.57	1.11	1.09	1.44	1.86	1.24	0.46	1.01	0.54	3.41	7.42	2.24	0.83	0.99	1.15	0.91	0.75	0.82	5.92	1.75	1.24	77.43
FC	0.61	0.09	0.64	3.17	1.81	5.57	1.18	5.15	0.23	1.11	0.69	1.25	26.33	1.38	22.99	0.86	0.80	1.06	2.52	0.48	0.82	0.36	0.59	1.03	1.52	1.96	1.82	1.30	1.37	2.80	4.93	3.61	73.67
LH	0.53	1.36	14.68	0.48	0.75	0.59	1.71	0.41	1.38	1.48	0.11	0.61	4.16	27.02	5.04	5.23	3.65	2.39	2.87	2.23	0.51	0.38	0.71	3.78	2.01	4.76	5.80	0.41	1.46	2.60	0.10	0.83	72.98
LC	0.86	1.97	1.26	3.43	1.06	7.11	0.51	3.01	0.25	0.69	0.84	2.84	20.79	1.99	28.98	0.62	0.10	0.50	2.25	0.23	0.85	1.39	0.63	2.53	0.76	1.66	1.61	1.42	1.34	2.23	2.30	4.00	71.02
LA	1.74	0.88	1.04	8.25	4.45	0.50	1.46	0.61	0.45	0.63	2.88	4.83	0.37	0.30	0.09	23.61	2.97	0.72	6.18	3.06	0.65	11.88	1.49	0.49	3.97	4.69	1.86	3.70	2.56	0.99	1.06	1.67	76.39
HG	1.16	0.95	0.51	0.72	0.28	2.11	5.21	1.89	2.87	2.08	0.30	1.90	0.38	5.53	0.45	0.91	20.10	2.59	7.31	1.72	0.69	6.19	2.02	3.33	2.74	5.89	5.65	4.51	4.50	3.08	0.18	2.25	79.90
GC	1.19	0.98	2.94	0.96	1.20	0.38	5.35	1.87	3.01	3.24	0.39	0.30	0.82	1.37	1.09	0.52	4.83	20.01	2.55	0.90	4.49	8.19	7.38	12.95	0.48	2.29	2.49	3.89	2.19	0.20	1.21	0.31	79.99
LL	3.73	0.43	1.10	0.15	2.33	2.36	5.43	3.53	0.98	0.96	2.17	3.37	1.22	0.60	0.44	2.95	2.69	0.96	25.76	2.03	1.34	6.30	0.57	1.48	11.49	1.24	1.75	3.68	2.37	4.67	1.01	0.91	74.24
LN	3.69	4.40	0.35	1.45	0.21	2.78	9.08	6.50	3.61	0.93	1.35	2.01	1.26	6.21	1.49	2.37	4.72	1.43	5.51	24.27	0.86	2.11	3.85	0.32	4.84	0.53	0.43	0.22	0.15	1.07	0.73	1.25	75.73
PA	3.85	0.21	1.03	0.78	0.92	0.27	1.02	0.39	0.69	8.62	1.97	2.39	1.34	0.76	4.28	1.50	0.63	1.67	1.80	1.37	16.16	13.48	0.72	6.72	1.42	1.84	1.50	3.70	2.16	8.73	2.67	5.41	83.84
PL	7.91	0.14	0.49	0.25	0.43	0.48	2.45	1.84	0.64	6.97	1.98	1.48	0.26	0.17	0.81	1.60	0.46	1.76	8.19	1.36	9.72	28.81	1.77	4.86	1.25	0.90	1.45	1.47	0.17	5.58	0.28	4.07	71.19
SI	0.62	0.48	0.50	0.49	1.57	1.61	5.74	2.42	3.83	1.23	0.73	0.55	1.38	0.22	0.93	0.37	3.17	9.80	8.11	1.96	3.97	3.25	15.93	15.76	0.77	1.30	1.14	3.08	1.16	2.82	1.50	3.61	84.07
LT	1.21	2.33	0.22	1.68	1.65	1.09	4.71	1.22	3.30	2.61	0.84	1.89	1.22	0.76	1.98	1.66	6.27	6.58	10.16	0.83	1.27	5.90	1.41	29.26	1.98	1.05	1.13	2.13	0.83	2.17	0.28	0.39	70.74
LX	2.60	0.20	0.71	0.46	2.54	1.26	3.63	1.45	1.30	0.17	1.28	2.21	0.27	4.41	0.69	3.48	8.36	0.77	12.32	4.19	0.40	3.05	0.66	0.36	25.98	2.98	3.47	2.03	2.28	1.59	4.27	0.62	74.02
CO	3.56	0.14	1.04	1.03	0.89	0.19	3.32	1.80	0.59	1.67	1.31	0.62	3.51	0.25	3.85	0.98	3.32	0.83	1.33	0.84	1.86	7.32	0.35	1.13	0.58	16.86	11.82	11.68	8.84	6.07	0.96	1.45	83.14
CL	3.63	0.29	1.73	0.86	1.23	0.25	3.59	1.98	0.45	1.27	0.89	0.87	2.92	1.01	3.11	0.72	4.61	1.60	1.72	0.66	1.79	7.30	0.44	1.34	0.68	15.93	13.38	10.63	7.82	4.97	1.00	1.32	86.62
QS	1.68	0.31	1.11	0.46	0.95	0.41	2.97	1.10	1.17	1.62	0.75	0.77	1.90	0.55	3.40	0.90	2.06	0.87	0.87	1.76	1.71	5.44	0.42	3.23	0.52	14.34	10.45	16.38	13.65	5.94	0.65	1.67	83.62
HO	0.57	0.36	1.12	0.29	1.74	0.45	1.84	0.34	1.08	1.54	0.34	0.84	1.85	0.97	2.98	0.37	2.73	0.39	0.77	2.23	0.90	3.95	0.23	4.10	0.71	13.74	10.69	15.91	16.57	7.12	0.66	2.61	83.43
NG	0.61	0.54	2.34	0.28	0.73	0.27	1.97	1.38	4.17	0.47	0.89	0.50	4.21	9.57	5.35	2.69	0.32	1.04	0.18	1.36	0.98	0.93	5.32	5.08	0.47	2.21	2.05	4.39	3.34	31.49	0.85	4.02	68.51
DA	4.05	2.36	7.41	5.25	0.42	0.77	6.19	1.35	6.89	0.58	1.22	0.23	3.68	2.13	3.68	2.96	4.63	2.33	1.37	0.50	2.17	1.62	1.50	1.47	1.36	6.02	3.74	2.25	1.96	0.93	18.68	0.31	81.32
LB	0.60	4.30	1.46	2.40	1.99	0.36	0.21	0.36	0.68	0.59	2.78	2.40	0.37	0.72	0.32	5.05	0.20	2.83	1.18	4.54	0.94	1.99	2.60	2.15	2.56	1.45	0.52	0.89	0.97	4.25	1.16	47.17	52.83
To	99.74	44.02	60.12	76.67	60.56	49.22	129.88	83.54	64.09	60.07	49.05	56.63	74.85	56.42	88.37	58.59	83.80	77.53	108.01	51.06	63.19	142.44	51.33	112.66	59.35	114.61	98.39	104.25	79.32	96.93	40.64	56.85	76.63

Note: This table presents the all-sample DY table based upon VAR-decomposition method following Diebold and Yilmaz (2012), the sample periods is from 1975-01 to 2019-12. The last column "From" is the spillover from total commodities to the focal commodity. The last vertical index "To" is the spillover from the focal commodity to total commodities. The bottom right coefficient is about "Net" spillover measured as the sum of "From" subtract from the sum of "To". All coefficients of this table are set in percent.

Table IA.2: Portfolio Sorting for NMDY

Horizon	P1	P2	P3	P4	P5	L/S
h=1	-0.002	-0.018	-0.023	0.041	0.086***	0.088**
	(-0.06)	(-0.67)	(-0.90)	(1.52)	(2.58)	(2.27)
h=3	0.043	0.026	0.010	-0.008	0.005	-0.038
	(1.45)	(0.99)	(0.39)	(-0.29)	(0.15)	(-1.05)
h=6	-0.011	0.018	-0.009	0.054	0.031	0.042
	(-0.38)	(0.67)	(-0.34)	(2.04)	(1.00)	(1.13)
h=12	0.038	0.033	0.015	0.017	-0.031	-0.070*
	(1.24)	(1.22)	(0.57)	(0.60)	(-1.03)	(-1.82)
Period	466	466	466	466	466	466

Note: This table shows portfolio sorting returns based on NMDY for different holding horizon. The number of brackets shows the Newey–West h.a.c. t-statistic, *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. All returns are in annual percent.

Table IA.3: Factors Spanning Test for NMDY

	α	β_{AVG}	β_{TS}	β_{MOM}	β_{SHP}	β_{HHP}	β_{BM}	$adj.R^2$
R_{NMDY}	0.082*	2.312	-0.499	0.201				0.012
	(1.82)	(1.61)	(-0.63)	(0.21)				
	0.073	2.130**	-0.070	-0.001	-0.809	-0.750		0.010
	(1.58)	(2.05)	(-0.10)	(-0.00)	(-0.92)	(-0.90)		
	0.072	2.305**					-0.026	0.029
	(1.50)	(2.11)					(-0.05)	

Note: This table shows the spanning tests to explain if factor portfolio based on network momentum(NMDY) provides an alpha relative to known factors model. Factor return R_{NMDY} regressed on the beta from three kinds of muti-factor models: regressed on the beta from three kinds of muti-factor models: (i) Three factors model(AVG, TS, MOM) from Bakshi et al. (2019). (ii) Five factors model(AVG, TS, MOM, SHP, HHP) from Szymanowska et al. (2014). (iii) Two factors model(AVG, BM) from Boons and Prado (2019). The number of brackets shows the Newey–West h.a.c. t-statistic. *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. $adj.R^2$ presents the adjusted R^2 for regression. All returns are in annual percent.

Table IA.4: Fama-Macbeth Cross-sectional Regression for NMDY

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$NMDY$	0.613**	0.542**	0.526**	0.470*	0.478*	0.505*	0.505**	0.525**	0.553**	0.640*
	(2.45)	(2.19)	(1.98)	(1.88)	(1.88)	(1.89)	(2.05)	(2.05)	(2.21)	(1.88)
TS	0.186	0.019	-0.024	0.044	-0.060	0.113	-0.053	-0.040	0.016	-0.266
	(0.42)	(0.04)	(0.06)	(0.10)	(-0.13)	(0.25)	(-0.12)	(-0.09)	(0.03)	(-0.57)
MOM	1.567**	1.593**	1.807**	0.129**	2.073**	2.933***	1.618**	1.950**	1.650**	2.045**
	(2.07)	(2.09)	(2.23)	(2.27)	(2.56)	(3.39)	(2.08)	(2.46)	(2.10)	(1.99)
HHP		0.105*	0.155	1.514*	0.066	0.131**	0.098*	0.089	0.107*	0.145
		(1.85)	(1.88)	(1.92)	(1.11)	(2.26)	(1.68)	(1.49)	(1.84)	(1.26)
SHP			0.020							-0.071
			(-0.28)							(-0.73)
BM				0.442*						0.473
				(1.86)						(1.67)
$SKEW$					-0.074**					-0.075**
					(-2.45)					(-2.22)
$VALUE$						0.133***				-0.009
						(2.68)				(-0.25)
ΔOI							0.000			-0.000
							(0.31)			(-0.25)
EC								0.219*		0.102
								(1.85)		(0.86)
BC									-0.015	-0.036
									(-0.16)	(-0.23)
Const	0.031	0.012	-0.004	0.011	0.015	0.009	0.013	-0.023	0.010	-0.024
	(1.25)	(0.50)	(-0.14)	(0.44)	(0.59)	(0.34)	(0.56)	(-0.80)	(0.39)	(-0.60)
Sample Periods	382	382	382	382	382	382	382	382	382	382
Adj R^2	0.204	0.306	0.364	0.458	0.427	0.381	0.288	0.375	0.329	0.359

Note: This table presents the Fama-Macbeth cross-sectional regression following Fama and MacBeth (1973). The results show the average coefficient where monthly portfolio return based on NMDY is regressed on the value of commodity characteristics in the previous month. We propose the baseline two-factor model(1), three-factor model(2), augmented four-factor model(3)-(9), and model(10) controlling all commodity characteristics. The number of brackets shows the Newey–West h.a.c. t-statistic. *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. $adj.R^2$ presents the adjusted R^2 for regression. All returns are in annual percent.

Table IA.5: Underreaction Test for NMDY

Panel A: Fama-Macbeth regression in the different holding periods						
Horizon	$NMDY$	TS	MOM	HHP	Const	Adj. R^2
h = 1	0.542**	0.218	1.573**	0.124**	0.010	0.306
	(2.19)	(0.50)	(2.02)	(2.09)	(0.58)	
h = 3	-0.361	1.170***	0.512	0.097	0.041	0.072
	(-1.47)	(2.56)	(0.63)	(1.63)	(1.63)	
h = 6	-0.122	1.445***	-0.669	0.107	0.001	0.196
	(-0.52)	(2.90)	(-0.87)	(1.97)	(0.20)	
h = 12	-0.266	-0.359	-0.473	0.050	0.017	-0.038
	(-1.06)	(-0.74)	(-0.63)	(0.87)	(0.91)	

Panel B: Underreaction Coefficient			
Horizon	RET_1	$CAR_{1,h}$	$RURC_h$
h = 1	0.088**		
	(2.27)		
h = 3		-0.110**	-0.250**
		(-2.20)	(-2.20)
h = 6		-0.036	0.591
		(-0.68)	(-0.68)
h = 12		-0.146***	-0.650***
		(-2.87)	(-2.87)

Note: This table presents the underreaction test to clarify whether the portfolio returns based on network momentum(NMDY) is caused by market underreaction. Panel A shows the coefficient of Fama-Macbeth regression in the different holding periods. Panel B shows the underreaction coefficient modified 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 number of brackets shows the Newey–West h.a.c. t-statistic 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 in annual percent.

Table IA.6: Attention, Speculation and Limited-to-Arbitrage for NMDY

Group	P1	P3	L/S	P1	P3	L/S
	Panel A: Google Searching index			Panel B: Abnormal Turnover		
Low	0.035	0.032	-0.003	0.030	0.081*	0.051
	(0.77)	(0.64)	(-0.05)	(0.83)	(1.87)	(1.03)
High	-0.036	0.014	0.051	-0.020	0.058	0.078
	(-0.81)	(0.24)	(0.87)	(-0.580	(1.22)	(1.45)
H/L	-0.071	-0.017	0.053	-0.062	-0.014	0.048
	(-1.49)	(-0.37)	(0.81)	(-1.47)	(-0.25)	(0.71)
	Panel C: Extreme Returns			Panel D: Skewness		
Low	0.041	0.031	-0.010	0.036	0.093**	0.057
	(1.51)	(1.14)	(-0.31)	(1.04)	(2.50)	(1.31)
High	0.069	0.144**	0.075	-0.034	0.060	0.094*
	(1.19)	(2.34)	(1.00)	(-1.01)	(1.32)	(1.89)
H/L	0.036	0.123**	0.088	-0.069*	-0.032	0.037
	(0.62)	(1.98)	(1.10)	(-1.80)	(-0.62)	(0.60)
	Panel E: Idiosyncratic Volatility			Panel F: Illiquidity		
Low	-0.027	0.055	0.083*	-0.006	0.078	0.084*
	(-0.86)	(1.43)	(1.77)	(-0.18)	(1.68)	(1.67)
High	0.025	0.118	0.093	0.076*	0.115	0.039
	(0.45)	(1.66)	(1.11)	(1.79)	(2.39)	(0.68)
H/L	0.068	0.085	0.017	0.121***	0.054	-0.067
	(1.22)	(1.21)	(0.19)	(2.63)	(0.95)	(-0.94)

Note: This table presents the bivariate portfolio sorting results for network attention index. We first sort commodities according to their attention, speculation and limited-to-arbitrage index into high and low groups and then sorting commodities according to network momentum signal.Then we sort commodities into 3 groups based on NMDY signal. We also present the spread returns into H/L group and L/S group. The number of brackets shows the Newey–West h.a.c. t-statistic. *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. All returns are in annual percent.

Table IA.7: Network Attention for NMDY

Group	P1	P3	L/S	P1	P3	L/S
	Panel A: Google Searching index			Panel B: Information Discreteness		
Low	0.054	0.037	-0.018	0.007	0.042	0.035
	(1.36)	(0.87)	(-0.44)	(0.27)	(1.33)	(1.03)
High	-0.023	0.036	0.059	0.000	0.051*	0.051
	(-0.50)	(0.70)	(1.08)	(0.01)	(1.68)	(1.55)
H/L	-0.077**	-0.001	0.076	-0.007	0.009	0.016
	(-2.02)	(-0.02)	(1.29)	(-0.23)	(0.28)	(0.37)
	Panel C: Abnormal Turnover			Panel D: Extreme Return		
Low	0.030	0.081*	0.051	0.031	0.041	0.010
	(0.83)	(1.87)	(1.03)	(1.24)	(1.59)	(0.36)
High	-0.020	0.058	0.078	-0.026	0.059*	0.085**
	(-0.58)	(1.22)	(1.45)	(-0.86)	(1.66)	(2.32)
H/L	-0.062	-0.014	0.048	-0.057*	0.018	0.075*
	(-1.47)	(-0.25)	(0.71)	(-1.82)	(0.53)	(1.80)
	Panel E: Skewness					
Low	0.006	0.032	0.026			
	(0.18)	(0.84)	(0.57)			
High	-0.022	0.062	0.083*			
	(-0.62)	(1.41)	(1.72)			
H/L	-0.028	0.030	0.058			
	(-0.69)	(0.58)	(0.93)			

Note: This table presents the bivariate portfolio sorting results for network attention index. We first sort commodities according to their network attention or speculation index into high and low groups and then sorting commodities according to network momentum signal. Then we sort commodities into 3 groups based on NMDY signal. We also present the spread returns into H/L group and L/S group. The number of brackets shows the Newey–West h.a.c. t-statistic. *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. All returns are in annual percent.

Table IA.8: DOX and Network DOX for NMDY

Group	P1	P3	L/S	P1	P3	L/S	P1	P3	L/S
	Non-reportable position			Non-commercial position			Commercial position		
Panel A: 2 × 3 double sort for DOXB and NMDY									
Low	-0.015	0.007	0.022	-0.023	0.015	0.038	-0.014	0.007	0.021
	(-0.54)	(0.23)	(0.63)	(-0.80)	(0.51)	(1.11)	(-0.49)	(0.26)	(0.63)
High	0.016	0.064*	0.048	0.005	0.071*	0.066	0.027	0.089**	0.062
	(0.51)	(1.77)	(1.27)	(0.17)	(1.89)	(1.63)	(0.94)	(2.43)	(1.59)
H/L	0.031	0.057	0.026	0.028	0.056	0.028	0.041	0.082**	0.040
	(0.88)	(1.35)	(0.51)	(0.83)	(1.32)	(0.53)	(1.16)	(2.01)	(0.79)
Panel B: 2 × 3 double sort for network DOXB and NMDY									
Low	0.034	0.016	-0.018	0.023	0.031	0.008	0.030	0.015	-0.015
	(1.19)	(0.56)	(-0.56)	(0.82)	(1.08)	(0.26)	(1.12)	(0.56)	(-0.47)
High	-0.018	0.073**	0.091***	-0.014	0.061	0.075**	-0.007	0.075**	0.083**
	(-0.63)	(2.09)	(2.66)	(-0.49)	(1.76)	(2.14)	(-0.25)	(2.17)	(2.38)
H/L	-0.052	0.057	0.109**	-0.037	0.030	0.067	-0.037	0.060	0.097
	(-1.61)	(1.50)	(2.34)	(-1.16)	(0.80)	(1.40)	(-1.14)	(1.64)	(2.13)
Panel C: 2 × 3 double sort for DOXS and NMDY									
Low	-0.020	0.009	0.029	0.007	0.008	0.001	-0.010	0.010	0.021
	(-0.70)	(0.31)	(0.86)	(0.25)	(0.28)	(0.03)	(-0.38)	(0.34)	(0.61)
High	0.020	0.068*	0.049	0.006	0.076**	0.070*	0.019	0.072**	0.053
	(0.68)	(1.91)	(1.29)	(0.20)	(2.10)	(1.77)	(0.64)	(1.96)	(1.38)
H/L	0.040	0.059	0.019	-0.002	0.068*	0.069	0.030	0.061	0.032
	(1.15)	(1.48)	(0.39)	(-0.05)	(1.65)	(1.33)	(0.85)	(1.48)	(0.63)
Panel D: 2 × 3 double sort for network DOXS and NMDY									
Low	0.030	0.009	-0.021	0.027	0.006	-0.022	0.036	0.030	-0.006
	(1.11)	(0.31)	(-0.69)	(0.99)	(0.20)	(-0.67)	(1.34)	(1.07)	(-0.19)
High	-0.002	0.076**	0.078**	-0.003	0.061*	0.064*	-0.027	0.064*	0.091***
	(-0.08)	(2.12)	(2.27)	(-0.10)	(1.79)	(1.84)	(-0.97)	(1.83)	(2.65)
H/L	-0.033	0.067*	0.100**	-0.030	0.055	0.085*	-0.064**	0.034	0.097**
	(-0.97)	(1.75)	(2.13)	(-0.92)	(1.53)	(1.84)	(-2.02)	(0.88)	(2.11)

Note: This table shows the double sorting results for degree of extrapolation (DOX) related to NMDY. We first sort commodities according to time-varying DOX (set $\tau = 12$) into high and low groups and then sorting commodities according to NMDY. We also present the spread returns in H/L and L/S groups. DOXB and DOXS repesent for long-side and short-side position, respectively. The number of brackets shows the Newey–West h.a.c. t-statistic. *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. All returns are in annual percent.

Table IA.9: Robustness Checks: Other Conjunction Methods and Nearby Contracts

Horizon	P1	P2	P3	P4	P5	L/S
Panel A: Adjusted at expiration						
h=1	-0.011	0.015	0.052*	0.026	0.066*	0.077*
	(-0.36)	(0.49)	(1.67)	(0.95)	(1.85)	(1.90)
Panel B: Adjusted 30 days before expiration						
h=1	-0.014	0.015	0.024	0.025	0.07**	0.084**
	(-0.45)	(0.53)	(0.92)	(0.96)	(1.98)	(2.07)
Panel C: Unadjusted when expiration						
h=1	0.007	0.052**	0.053**	0.060**	0.106***	0.099***
	(0.23)	(2.01)	(1.97)	(2.22)	(3.23)	(2.82)
Panel D: The second-nearby contract						
h=1	-0.038	-0.012	0.045*	0.021	0.092***	0.130***
	(-1.31)	(-0.46)	(1.72)	(0.78)	(2.88)	(3.78)
Panel E: The tired-nearby contract						
h=1	-0.037	0.054*	0.047	0.028	0.08***	0.117***
	(-1.39)	(1.93)	(1.63)	(1.03)	(2.66)	(3.64)

Note: This table presents the portfolio sorting results for network momentum (NMAL) by five kinds of conjunction methods and nearby contracts price. The number of brackets shows the Newey–West h.a.c. t-statistic, *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. The subscript of variables indicate the holding periods relative to the portfolio sorting. All returns are in annual percent.

Table IA.10: Robustness Checks: Alternative Formation for Network Momentum

Horizon	P1	P2	P3	P4	P5	L/S
Panel A: Cumulative 12-months momentum						
h=1	-0.027	0.009	0.024	0.057**	0.046	0.073**
	(-0.90)	(0.38)	(1.02)	(2.12)	(1.57)	(2.20)
Panel B: Average 12-months momentum						
h=1	-0.021	0.007	0.019	0.058**	0.043	0.064**
	(-0.71)	(0.31)	(0.80)	(2.22)	(1.53)	(1.99)
Panel C: Past one month return						
h=1	-0.019	0.016	0.016	0.027	0.015	0.034
	(-0.67)	(0.63)	(0.64)	(1.06)	(0.50)	(1.07)
Panel D: Top3 network coefficient						
h=1	-0.048*	-0.002	0.024	0.034	0.048	0.096***
	(-1.76)	(-0.08)	(0.89)	(1.38)	(1.54)	(3.06)
Panel E: Top5 network coefficient						
h=1	-0.051*	0.017	0.011	0.048*	0.032	0.084***
	(-1.87)	(0.68)	(0.43)	(1.91)	(1.06)	(2.69)

Note: This table presents five kinds of alternative formation for network momentum. Panel A to Panel C modifies the methods of momentum, and Panel D and Panel E modifies the network coefficient. This table shows portfolio returns based on these network momentum over time. Where in the brackets are T-test values, *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. The subscript of variables indicate the holding periods relative to the portfolio sorting. All returns are in annual percent.

Table IA.11: Robustness Checks:Sub-sample Periods

Horizon	P1	P2	P3	P4	P5	L/S
Panel A: Sub-sample in first-half periods from 1981 to 2001						
h=1	-0.113***	0.009	-0.018	0.005	0.052	0.166***
	(-3.05)	(0.28)	(-0.53)	(0.15)	(1.13)	(3.21)
Panel B: Sub-sample in second-half periods from 2001 to 2019						
h=1	0.004	0.040	0.074*	0.010	0.106**	0.102**
	(0.09)	(0.91)	(1.79)	(0.25)	(2.33)	(2.50)
Panel C: Sub-sample after financialization of commodity markets from 2004 to 2019						
h=1	-0.014	0.019	0.062	-0.019	0.088*	0.102**
	(-0.28)	(0.40)	(1.37)	(-0.39)	(1.77)	(2.39)
Panel D: Sub-sample during financial crisis from 2007 to 2010						
h=1	0.366**	0.216	0.167	0.063	0.202	-0.164
	(2.40)	(0.94)	(1.36)	(0.44)	(1.19)	(-1.39)

Note: This table presents the result for portfolio sort in sub-sample periods. Panel A and Panel B show the portfolio sort results for the half-periods sub-sample. Panel C shows the post-financialization performance of portfolio sort following Cheng and Xiong (2014). Panel D shows portfolio sort result during the financial crisis. The number of brackets shows the Newey–West h.a.c. t-statistic, *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. The subscript of variables indicates the holding periods relative to the portfolio sorting. All returns are in annual percent.

Table IA.12: Robustness Checks: Feasibility

Horizon	P1	P2	P3	P4	P5	L/S
Panel A: Removing extremely illiquid commodities						
h=1	-0.068**	0.024	-0.013	0.033	0.049	0.118***
	(-2.32)	(0.94)	(-0.47)	(1.11)	(1.57)	(3.43)
h=3	-0.121**	0.036	0.024	0.063	0.082	0.203***
	(-2.37)	(0.78)	(0.51)	(1.21)	(1.53)	(3.38)
h=6	-0.011	0.026	0.089	0.126	-0.009	0.003
	(-0.15)	(0.37)	(1.27)	(1.63)	(-0.12)	(0.03)
h=12	0.189	0.203**	0.176*	0.134	-0.004	-0.193
	(1.59)	(1.96)	(1.68)	(1.21)	(-0.03)	(-1.61)
Panel B: Considering transaction cost						
h=1	-0.055*	0.016	0.017	0.012	0.063**	0.117***
	(-1.93)	(0.67)	(0.68)	(0.48)	(2.02)	(3.59)
h=3	-0.032	0.026	0.026	0.022	0.014	0.046
	(-1.20)	(1.05)	(1.07)	(0.88)	(0.51)	(1.49)
h=6	0.006	0.018	0.036	0.018	-0.011	-0.017
	(0.22)	(0.70)	(1.52)	(0.73)	(-0.40)	(-0.58)
h=12	0.035	0.028	0.029	-0.000	-0.004	-0.041
	(1.21)	(1.13)	(1.29)	(-0.00)	(-0.16)	(-1.30)

Note: This table tests whether the portfolio sorting strategy can generate tradeable predictive return considering the illiquidity risk and transaction cost. Panel A of the table presents the result for portfolio sort when removing extremely illiquid commodities. According to Amihud (2002), We calculate the illiquidity measurement $ILR_{it} = \frac{1}{12}\sum_{t-11}^{t} \frac{|r_{i,t}|}{\$Volume_{it}}$ and sort the commodities based on ILR and remove the top 20% commodities out of the sorting test. Panel B of the table shows the portfolio sorting test considering the transaction cost. According to Sakkas and Tessaromatis (2020), We assume the cost as a half spread of 4.4 basis points, and the total annual rollover transaction cost for the long-only commodity portfolio is 105.6 basis points (12x2x4.4). For a long-short combination, transaction costs will double to 211.2 basis points. The number of brackets shows the Newey–West h.a.c. t-statistic, *, ** and *** indicate 10%, 5% and 1% statistical significance levels respectively. The subscript of variables indicates the holding periods relative to the portfolio sorting. All returns are in annual percent.