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Financialization and Commodity Markets Serial Dependence

Zhi Da,[a] Ke Tang,[b] Yubo Tao,[c] Liyan Yang[d,e,*]

[a] Department of Finance, Mendoza College of Business, University of Notre Dame, Notre Dame, Indiana 46556; [b] Institute of Economics, School of Social Sciences, Tsinghua University, Beijing 100084, China; [c] Department of Economics, Faculty of Social Sciences, and Asia-Pacific Academy of Economics and Management, University of Macau, Macau Special Administrative Region 999078, China; [d] Department of Finance, Joseph L. Rotman School of Management, University of Toronto, Toronto, Ontario M5S3E6, Canada; [e] Guanghua School of Management, Peking University, Peking 100871, China

*Corresponding author

Contact: zda@nd.edu, https://orcid.org/0000-0003-2815-1516 (ZD); ketang@tsinghua.edu.cn, https://orcid.org/0000-0003-4049-030X (KT); yubotao@um.edu.mo, https://orcid.org/0000-0002-1013-9984 (YT); liyan.yang@rotman.utoronto.ca, https://orcid.org/0000-0002-2599-1328 (LY)

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Abstract. Recent financialization in commodity markets makes it easier for institutional investors to trade a portfolio of commodities via various commodity-indexed products. We present several pieces of novel causal evidence that daily exposure to such index trading results in price overshoots and reversals, as reflected in negative daily return autocorrelations, only among commodities in that index. This is because index trading propagates nonfundamental noise to all indexed commodities. We present direct evidence for such noise propagation using commodity news sentiment data.

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Keywords: financialization • return autocorrelations • index trading • news sentiment • ETF arbitrage • price discovery

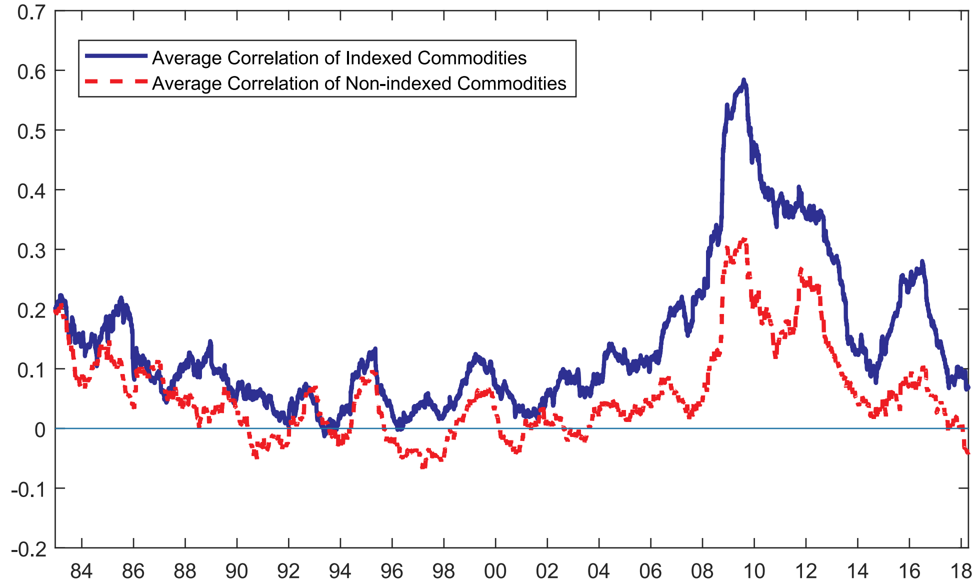
1. Introduction

The financialization of commodity markets has progressed over the past two decades. According to the Commodity Futures Trading Commission (CFTC), investment flows to various commodity indices increased from \$15 to \$200 billion from 2003 to 2008. Barclays estimates that commodity index investment rose to \$360 billion in the first quarter of 2022.[1] The rapid money inflow in commodity markets, especially in 2007 and 2008, has led to heated debate among researchers and policymakers about the influence of financialization on commodity price discovery and return dynamics.

Although theoretical papers such as Basak and Pavlova (2016) and Goldstein and Yang (2022) analyze the impact of financialization on commodity futures prices, it is still difficult to empirically identify the impact of financialization on commodity prices. For example, comovement among indexed commodities, as shown in Figure 1,[2] does not necessarily imply that financialization is the cause because indexed commodities could have been endogenously selected into an index precisely because they are exposed to the same fundamental shocks. Instead of focusing on slow-moving return comovements, we examine daily price overshoots and reversals, which are clear signs of nonfundamental shocks and price inefficiency. Our paper aims to provide novel causal evidence that exposure to commodity index trading (CIT) results in such short-term price inefficiency even at the index level.

Daily price overshoots and reversals result in negative daily return autocorrelations. Figure 2 shows a clear divergence in such return autocorrelations between the portfolios of indexed and nonindexed commodities. We draw the first-order autocorrelation coefficient of daily returns on commodity indices using a 10-year backward rolling window. We observe a slight increasing trend in the past 38 years in the daily autocorrelation of the equal-weighted nonindexed commodities (NIDX) portfolio returns. In sharp contrast, the daily autocorrelations in two popular commodity indices, S&P Goldman Sachs Commodity Index (GSCI) and the Bloomberg Commodity Index (BCOM), have steadily declined since 2004 when financialization began.[3] They entered negative territory around 2005 and became significantly negative

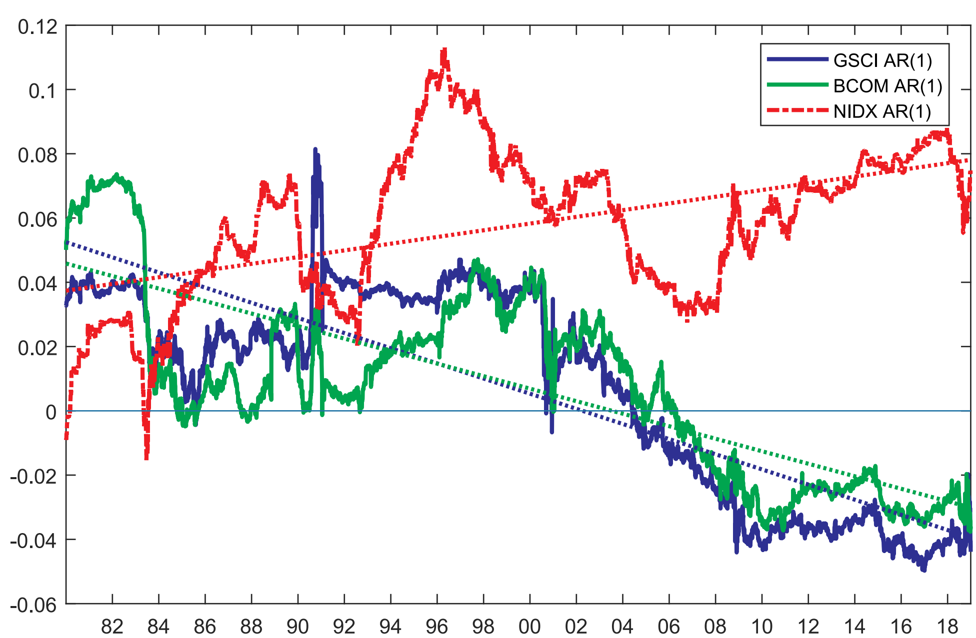
Figure 1. (Color online) Average Return Correlations of Indexed and Nonindex Commodities



Notes. This figure plots the average return correlations of commodities in the GSCI and BCOM indices (indexed commodities) and those not included in these indices (nonindexed commodities). We follow Tang and Xiong (2012) to compute these correlations. Specifically, we first calculate an equal-weighted index for each sector of indexed and nonindexed commodities, then the average correlation among five sector indices for an annual rolling window. Because there are no nonindexed commodities in energy and livestock sectors, we take heating oil and reformulated blendstock for oxygenated blending and lean hogs as nonindexed commodities because of their small weights in the index. The sample period is from 1980 to 2018.

in 2006. The negative (positive) daily autocorrelations on commodity indices (nonindexed commodities) are also economically significant. Trading strategies implementable in real time to take advantage of these autocorrelations generate substantial profits even after accounting for direct transaction costs, suggesting that the negative autocorrelation goes beyond the simple market microstructure noise.

Figure 2. (Color online) First-order Return Autocorrelations of Commodity Indices and Equal-Weighted Portfolio of Nonindexed Commodities



Notes. This figure plots the evolution of serial dependence in index returns from 1980 to 2018. Serial dependence is measured by first-order autocorrelation using a 10-year backward rolling window from index returns at the daily frequency. The indices are GSCI, BCOM, and an equal-weighted portfolio of nonindexed commodities (NIDX).

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We then construct daily measures of indexed commodities' exposure to index trading at the market, sector, and individual commodity levels and document strong negative relations between such measures and future daily return autocorrelations of indexed commodities. The fact that our analyses are conducted at daily frequency alleviates concerns that some slow-moving unobserved factors are driving such negative relations. In particular, we find that the negative daily autocorrelation among indexed commodities goes beyond one day and becomes stronger during the high index exposure period regardless of the exact measurement of index exposure. As a placebo test, we do not find any significant relation between autocorrelations and index exposure among nonindexed commodities.

We then present three pieces of causal evidence suggesting that index trading exposure drives negative index return autocorrelations. First, Figure 2 shows some divergence in return autocorrelations between the indexed and nonindexed commodity portfolios even before 2004 when financialization started. Although it is important to note that return autocorrelation was rarely negative for indexed commodities before 2004, the pre-2004 divergence does raise concerns that some unobserved factors, unrelated to index trading, could also contribute to the widening gap in autocorrelations between indexed and nonindexed commodities. To address this concern, we construct a better group of nonindex commodities by adopting the synthetic matching method proposed by Acemoglu et al. (2016). The gist of this methodology is to construct portfolios of nonindexed commodities that resemble indexed commodities as closely as possible in returns (and, therefore, also autocorrelations) pre-2004. In other words, the synthetic matching imposes the parallel pretrends assumption, after which we continue to reach the same conclusion, namely, index trading exposure negatively impacts the return autocorrelation of indexed commodities but has no effect on that of these mimicking nonindexed commodity portfolios.

Our second causal test takes advantage of the fact that the same indexed commodity can receive different weights in GSCI and BCOM. Following Greenwood (2008), each year, we focus on the five commodities that are most overweighted in BCOM relative to GSCI.[4] We verify that these overweighted commodities come from very different sectors and their identities change every year. We show that their daily return autocorrelations are significantly better predicted by their exposures to BCOM than those to GSCI even after controlling for their levels of liquidity and production that contribute to their overweights in the first place. The result suggests that index trading drives the negative return autocorrelation. It is important to note that the relative weight differences are determined at the beginning of the year and held constant throughout that year. Missing factors that indirectly correlate with overweighting at the beginning of the year are unlikely to drive the subsequent day-to-day relation between index trading and return autocorrelation.

Our third causal test zooms into a specific form of index trading, commodity index exchange-traded fund (ETF) arbitrage, which is unlikely driven by slow-moving fundamental factors. When the ETF is temporarily overpriced relative to its underlying commodity index, arbitrageurs sell shares in the ETF (create ETF shares) and buy the underlying indexed commodities, thus propagating the positive price pressure from the ETF to the underlying. As the positive price pressure reverts subsequently, we observe lower indexed commodity returns in the future. Following Brown et al. (2021), we employ commodity index ETF flows to proxy for such arbitrage activity. Consistent with the notion that index trading drives price overshoots and reversals or negative return autocorrelation, we find commodity index ETF creation (redemption) to predict negative (positive) returns on indexed commodities but not among nonindexed commodities. This finding also rules out a reverse causality concern that a predictable return reversal in the future causes index trading today—an informed index trader buys (sells) before a positive (negative) return reversal—the opposite to what we find with ETF arbitrageurs.

These three tests confirm that commodity index trading causes negative index return autocorrelations. But why? To help digest our empirical findings, we develop a stylized model of commodity index trading in the online appendix. In the model, index traders propagate both information and noise across commodities in the same index. With a significant presence of index traders, the impact of noise dominates, and the noise gives rise to correlated price overshoots and subsequent reversals among indexed commodities. The model, thus, corroborates the theoretical hypothesis proposed by Goldstein and Yang (2022, pp. 2615) that "growth in financialization first increases and then decreases price informativeness."

We are agnostic about the exact nature of the noise. The noise refers to any nonfundamental shocks that affect the trading demand of index traders. It could reflect price pressure propagated by index ETF arbitrage as in our third causal test. It could also come from the liquidity demand of the index traders and their clients. Indeed, we find index trading to be associated with more negative autocorrelations among the more illiquid indexed commodities. Finally, the noise may reflect the sentiment of the index traders and their clients (Baker and Wurgler 2006). Separating liquidity shocks from sentiment is challenging as they might be interconnected (Baker and Stein 2004). For example, correlated sentiment can result in correlated trading and liquidity shocks. Nevertheless, the sentiment channel allows a direct test of the noise propagation mechanism featured in the stylized model. To the extent we

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can measure "sentiment" on commodities, such measure should positively correlate with contemporaneous returns but negatively predict future returns among indexed commodities. Still, it should not predict returns on nonindexed commodities.

Empirically, we examine the news sentiment of articles covering individual commodities. To study the propagation of such sentiment across indexed commodities and alleviate the impact of sector-specific common fundamental shocks, we compute a "connected" index sentiment measure for each commodity. Taking an indexed commodity, corn, as an example, we compute its connected index sentiment by averaging the sentiment measures on other nongrain indexed commodities (e.g., energy, metals).

Consistent with the model prediction, we find that the connected index sentiment is positively related to the contemporaneous return of corn but predicts corn's next-day return negatively and significantly. Although the connected sentiment may still contain a fundamental component common to all commodities, the fact that such a positive correlation reverts on the next day confirms the existence and propagation of "nonfundamental" shocks. As index trading propagates such shocks across commodities in the same index, it results in synchronized price overshoots and reversals and negative return autocorrelations even at the index level. We confirm that the sentiment propagation results are much stronger during periods in which the commodity markets are more exposed to index trading, and the results are not driven by the global financial crisis in 2008–2009. As a placebo test, we repeat the same tests among nonindexed commodities but find no evidence for the propagation of such nonfundamental shocks.

Our study is closely related to two strands of literature. First, it contributes to the debates on the price impact of index investments in the commodity markets. Henderson et al. (2015) find that the hedging activities of issuers of commodity-linked notes can significantly influence commodity futures prices. Gilbert (2010) and Singleton (2013) show that index investments predict oil price movements. Ready and Ready (2022) find that order flows from index traders influence commodity prices. Chen et al. (2021) show that aggregate assets under the management of commodity trading advisors (CTAs) can predict the return correlations between CTAs and the stock market. Mou (2011) and Yan et al. (2019) find that index rebalancing causes futures prices to shift significantly. A very recent paper by Han and Kong (2020) employs a machine-learning approach to study the serial dependence of commodity futures returns and finds significant full-sample and out-of-sample predictability. Using a theoretical model, Basak and Pavlova (2016) show that excess correlation among commodities can arise if institutional investors care about outperforming a commodity index. Sockin and Xiong (2015) theoretically show that financial inflows and outflows (through index investing) to commodity markets can be misread as a signal of global economic growth if informational frictions exist in commodity futures markets. Consistent with this study, a recent empirical work by Brogaard et al. (2019) shows that inefficient commodity prices can distort the real decisions of a firm. However, Büyükşahin and Harris (2011) and Irwin and Sanders (2012) find little evidence that index position changes are linked to price movements in futures markets. Hamilton and Wu (2015) present mixed results.

In a review article, Cheng and Xiong (2014) call for direct tests of price impacts with clear identification strategies. Our study moves closer to meeting their challenge. By focusing on autocorrelations, our empirical setting allows us to identify the price impact of commodity index trading. In particular, prices of indexed commodities overshoot and reverse subsequently when reacting to nonfundamental shocks, whereas nonindexed commodities do not show such a reversal pattern. Our paper speaks to price inefficiency at high frequency (daily to weekly), whereas the existing literature mostly focuses on price inefficiency at a lower frequency (a persistent divergence between price and fundamental value). Empirically, low-frequency persistent mispricing is difficult to detect as it requires a precise measure of fundamental value. We contribute to the commodity literature by linking variations in index trading to price inefficiency in indexed commodities at the daily frequency. Price reversal at daily frequency is a clear sign of nonfundamental shocks and price inefficiency, and our analysis at daily frequency helps to rule out slow-moving trends as the main driving forces. The high-frequency price inefficiency is economically meaningful as it imposes costs on institutional investors who trade often and individual investors who invest in commodities through those institutions. On a more positive note, it also suggests that proactive investors can generate economically significant profits by providing liquidity to index traders on a systematic basis.

Second, our study also speaks to the existing literature that links indexing to side effects, mostly in equity markets, including the amplification of fundamental shocks (Hong et al. 2012), nonfundamental price changes (Chen et al. 2004), excessive comovement (Barberis et al. 2005; Greenwood 2005, 2008; Da and Shive 2018; Baltussen et al. 2019), a deterioration of firms' informational environment (Israeli et al. 2017), increased nonfundamental volatility in individual stocks (Ben-David et al. 2018), and the reduced welfare of retail investors (Bond and García 2022).

The remainder of the paper is organized as follows. Section 2 describes the data and variables used in this research. Section 3 delivers the stylized facts on the relation between index trading exposure and index return

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autocorrelation. Section 4 illustrates three pieces of causal evidence. Section 5 presents tests using news sentiment and return autocorrelations. Section 6 summarizes the results of robustness checks, and Section 7 concludes. Online appendices provide additional materials and analyses and a stylized theoretical model that formalizes our empirical hypotheses and findings.

2. Data and Variable Construction

In this section, we describe the commodities used in our analyses and introduce the two most popular commodity indices and their construction. We then describe how we measure the exposure of a commodity to index trading. A summary of our key variables and notations is provided in Online Appendix A.1.

2.1. Commodities and Commodity Indices

Commodity price data are obtained from Commodity Systems Inc. Following Kang et al. (2020), we compute the daily excess return for each commodity using the nearest-to-maturity (front-month) contract and roll positions on the seventh calendar day of the maturity month into the next-to-maturity contract.[5] The excess return r_{it} of commodity i on date t is calculated as

$$r_{it} = \frac{F_i(t,T) - F_i(t-1,T)}{F_i(t-1,T)}, \tag{1}$$

where $F_i(t,T)$ is the futures price on day t for a futures contract maturing on date T. To mitigate the effect of outliers, we winsorize 1% of the returns at the top and bottom 0.5 percentiles each.

Table 1 lists the 27 commodities we examine categorized into five sectors: energy, grains, livestock, metals, and softs. Futures listing exchanges and coverage periods are also provided for each commodity.

The recent financialization makes it easier for institutional investors to trade various commodity indices.

Table 1. Detailed List of Commodities for Analysis

Ticker	Name	Full name	Exchange	Inception	GSCI	BCOM	CIT	Indexed	Nonindexed
				Panel A: Energy					
CL	Crude oil	Crude Oil, WTI/Global Spot	NYMEX	1983/03/30	✓	✓		✓	
HO	Heating oil	ULSD NY Harbor	NYMEX	1978/11/14	✓	✓		✓	
NG	Natural gas	Natural Gas, Henry Hub	NYMEX	1990/04/04	✓	✓		✓	
RB	Gasoline	Gasoline, Blendstock	NYMEX	2005/10/03	✓	✓		✓	
				Panel B: Grains					
BO	Soybean oil	Soybean Oil/Crude	CBOT	1959/07/01		✓	✓	—	—
C-	Corn	Corn/No. 2 Yellow	CBOT	1959/07/01	✓	✓	✓	✓	
KW[a]	KC wheat	Wheat/No. 2 Hard Winter	CBOT	1970/01/05	✓	*	✓	—	—
MW	Minn wheat	Wheat/Spring 14% Protein	MGEX	1979/01/02					✓
O-	Oat	Oats/No. 2 White Heavy	CBOT	1959/07/01					✓
RR	Rough rice	Rough Rice #2	CBOT	1986/08/20					✓
S-	Soybean	Soybeans/No. 1 Yellow	CBOT	1959/07/01	✓	✓	✓	✓	
SM[a]	Soybean meal	Soybean Meal/48% Protein	CBOT	1959/01/07		*	*		✓
W-	Wheat	Wheat/No. 2 Soft Red	CBOT	1959/07/01	✓	✓	✓	✓	
				Panel C: Livestock					
FC	Feeder cattle	Cattle, Feeder/Average	CME	1971/11/30	✓		✓	—	—
LC	Live cattle	Cattle, Live/Choice Average	CME	1964/11/30	✓	✓	✓	✓	
LH	Lean hogs	Hogs, Lean/Average Iowa/S Minn	CME	1966/02/28	✓	✓	✓	✓	
				Panel D: Metals					
GC	Gold	Gold	NYMEX	1974/12/31	✓	✓		✓	
HG	Copper	Copper High Grade/Scrap No. 2 Wire	NYMEX	1959/01/07	✓	✓		✓	
PA	Palladium	Palladium	NYMEX	1977/01/03					✓
PL	Platinum	Platinum	NYMEX	1968/03/04					✓
SI	Silver	Silver 5,000 Troy Oz.	NYMEX	1963/06/12	✓	✓		✓	
				Panel E: Softs					
CC	Cocoa	Cocoa/Ivory Coast	ICE	1959/07/01	✓		✓	—	—
CT	Cotton	Cotton/1-1/16″	ICE	1959/07/01	✓	✓	✓	✓	
JO	Orange juice	Orange Juice, Frozen Concentrate	ICE	1967/02/01					✓
KC	Coffee	Coffee ‘C’/Colombian	ICE	1972/08/16	✓	✓	✓	✓	
LB	Lumber	Lumber/Spruce-Pine Fir 2x4	CME	1969/10/01					✓
SB	Sugar	Sugar #11/World Raw	ICE	1961/01/04	✓	✓	✓	✓	

Notes. This table provides a detailed list of the commodities studied in this paper and their basic information. The futures contracts of these commodities are all traded in the United States. The commodities that are included in both indices are classified as indexed commodities, whereas commodities not included in any indices are classified as nonindexed commodities.

[a]KW and SM are both included in BCOM from 2013. Because SM is included in BCOM from 2013, its position on index trading is reported in the CIT report since 2013. BO, KW, FC, and CC are neither indexed commodities nor nonindexed commodities according to our classification criteria.

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A commodity index functions similarly to an equity index, such as the S&P 500, in which its value is derived from the total value of a specified basket of commodities. Currently, the largest two indices by market share are the GSCI and BCOM. These two indices use different selection criteria and weighting schemes: the GSCI is weighted by the world production of each commodity, whereas the BCOM focuses on the relative amount of trading activity of a commodity. Importantly, the weights of both indices are set at the beginning of the year and do not vary during the year. Table 1 provides index membership information for each of the 27 commodities in our sample.

We collect daily price data on the GSCI and BCOM from Datastream and calculate their daily returns as $(P_t - P_{t-1})/P_{t-1}$. We also construct an equally weighted NIDX and calculate its daily returns by simply equally averaging daily returns across nonindexed commodities. Table 2 provides the summary statistics for the daily returns on individual commodities and the commodity indices during our sample period from 2006 to 2018.

Although the indexed commodities offer relatively low annual Sharpe ratios compared with that in the equity market, their return correlations with the equity and bond market before financialization are fairly low (Tang and Xiong 2012). As a result, institutional investors

Table 2. Descriptive Statistics of Commodities' Returns

Commodity	Observations	Mean, %	Standard deviation	Minimum	Maximum	$AR(1)$	Sharpe ratio
Panel A: Energy							
CL	3,979	−0.03	0.021	−0.074	0.072	−0.063	−0.222
HO	3,979	−0.01	0.019	−0.063	0.065	−0.039	−0.046
NG	3,979	−0.13	0.027	−0.083	0.096	−0.056	−0.780
RB	3,979	0.01	0.021	−0.072	0.067	−0.034	0.049
Panel B: Grains							
BO	3,991	0.00	0.014	−0.045	0.050	0.017	−0.016
C-	3,991	0.01	0.018	−0.055	0.060	0.024	0.120
KW	3,991	−0.01	0.019	−0.055	0.061	0.027	−0.053
MW	3,991	0.04	0.017	−0.052	0.058	0.067	0.370
O-	3,991	0.04	0.020	−0.061	0.067	0.095	0.291
RR	3,991	−0.01	0.014	−0.040	0.048	0.084	−0.108
S-	3,991	0.04	0.015	−0.052	0.049	0.015	0.443
SM	3,991	0.07	0.017	−0.057	0.054	0.028	0.657
W-	3,991	−0.02	0.020	−0.064	0.067	0.010	−0.116
Panel C: Livestock							
FC	3,981	0.00	0.010	−0.030	0.030	0.074	0.048
LC	3,981	0.00	0.010	−0.028	0.029	0.027	0.043
LH	3,991	−0.01	0.014	−0.043	0.044	0.053	−0.119
Panel D: Metals							
GC	3,979	0.03	0.011	−0.038	0.036	−0.015	0.398
HG	3,979	0.02	0.018	−0.064	0.060	−0.061	0.189
PA	3,979	0.06	0.019	−0.070	0.061	0.046	0.513
PL	3,979	0.00	0.014	−0.050	0.041	0.029	0.049
SI	3,979	0.03	0.020	−0.076	0.059	−0.039	0.245
Panel E: Softs							
CC	3,971	0.04	0.018	−0.060	0.057	0.006	0.332
CT	3,953	0.02	0.017	−0.056	0.055	0.078	0.145
JO	3,971	0.04	0.020	−0.066	0.065	0.106	0.297
KC	3,971	−0.01	0.019	−0.059	0.061	−0.025	−0.119
LB	3,991	−0.05	0.018	−0.046	0.051	0.090	−0.444
SB	3,971	−0.01	0.020	−0.066	0.057	0.000	−0.106
Panel F: Commodity indices							
GSCI	3,992	−0.02	0.014	−0.083	0.075	−0.040	−0.245
BCOM	3,986	−0.02	0.011	−0.062	0.058	−0.031	−0.247
NIDX	3,992	0.02	0.009	−0.047	0.044	0.073	0.420

Notes. This table provides some descriptive statistics of each commodity/index' daily returns (after winsorization) in columns (2)–(7). In column (8), we calculate the annualized Sharpe ratio (scaled by $\sqrt{252}$) of each commodity. NIDX denotes the equal-weighted portfolio of nonindexed commodities. The sample is of daily frequency ranging from January 3, 2006, to November 6, 2018.

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have become more willing to invest in commodities to diversify mainstream stock and bond markets, especially since the start of financialization, given the ease of trading commodity indices.

The energy sector, especially crude oil and natural gas, did not perform well in our sample period. Because both the GSCI and BCOM place heavy weights on the energy sector, both indices suffered losses in the same period. Nonindexed commodities, as a group (i.e., NIDX), earned a small positive average daily return of 2.5 basis points (5% per annum).

2.2. Commodity Index Exposure

Every Friday, the CFTC releases a weekly Commitments of Traders report with data collected on the previous Tuesday, which includes the total open interest of each commodity and the long/short positions of all types of traders.[6] It also includes a supplemental CIT report that shows the positions of a set of index traders identified by the CFTC since January 3, 2006.

According to the CIT manual, total open interest in the supplementary CIT report can be recovered from the nine components detailed in the report:

$$\begin{aligned} &2(Open\ Interest^{All}) \\ &= \underbrace{(Long + Short + 2Spread)}_{Non-commercial} + \underbrace{(Long + Short)}_{Commercial} \\ &\quad + \underbrace{(Long + Short)}_{Index\ Trading} + \underbrace{(Long + Short)}_{Non-reportable}. \end{aligned} \tag{2}$$

Naturally, we can define index open interest as the average of the long and short positions of index traders: $OpenInterest^{Idx} = (Long^{Idx} + Short^{Idx})/2$. Based on these data, we can estimate the index trader market share of indexed commodity i on day t as the ratio of its index open interest to its total open interest during the prior week:

$$Index\ Market\ Share_{it} = \frac{Open\ Interest^{Idx}_{i,w(t)}}{Open\ Interest^{All}_{i,w(t)}}, \tag{3}$$

where $w(t)$ denotes the Tuesday immediately before or on day t.

The CIT report only contains 13 agricultural commodities (listed in Table 1) and covers no commodities in the energy and metals sectors. Masters (2008) introduces an interpolation method to estimate the position of unreported indexed commodities by taking advantage of the difference in commodity coverage between the GSCI and BCOM. Hamilton and Wu (2015) refine Masters' (2008) approach in a regression setting. We, thus, employ Hamilton and Wu's (2015) method to obtain each nonreported indexed commodity's estimated index market share. Online Appendix A.2 describes the methods of Masters (2008) and Hamilton and Wu (2015).

Based on the estimated index market share, we obtain each commodity's index trading volume as follows:[7]

$$\begin{aligned} &Index\ Trading\ Volume_{it} \\ &= Index\ Market\ Share_{it} \times Trading\ Volume_{it}, \end{aligned} \tag{4}$$

and define the index exposure of commodity i on day t as the standardized version of the detrended index trading volume with the past 250-day average in the spirit of Campbell et al. (1993):

$$\begin{aligned} &Index\ Exposure_{it} \\ &= \text{standardize}\{Detrended\ Index\ Trading\ Volume_{it}\}. \end{aligned} \tag{5}$$

Detrending is useful because commodity trading volumes trended up during our sample period owing to the implementation of electronic trading systems and lower broker charges. Standardization makes it possible to compare trading activities among commodities with different contract sizes. As trading volume is measured by the number of contracts, price information does not enter our measure of index exposure for an individual indexed commodity.

Finally, the total index exposure for the commodity markets is computed as the simple average of the index exposures across all I indexed commodities:

$$Total\ Index\ Exposure_t = \frac{1}{I}\sum_{i=1}^{I} Index\ Exposure_{it}. \tag{6}$$

Total index exposure can, therefore, be interpreted as the abnormal trading volume on day t that reflects index trading. Figure 3 plots the daily total index exposure. As a measure of abnormal index trading, it does not display any long-term trend. Our subsequent empirical analyses link daily fluctuations in index exposure to daily return autocorrelation measures. Commodity trading volume drops at the end of the year, contributing to the observed seasonality in Figure 3 in which the index exposure measure dips predictably. We winsorize the index exposure measures at a 1% level in our empirical analyses to alleviate excessive fluctuations.

3. Stylized Facts

We conduct two sets of empirical analyses in this section. We first examine trading strategies to evaluate the economic significance of the index-level autocorrelations presented in Figure 2. We then conduct panel regressions at the individual commodity level and confirm that the relation between indexed commodities' return autocorrelations and the index exposure measure is robust.

3.1. Trading Strategies

In Table 3, we evaluate the economic significance associated with index autocorrelation patterns reported in Figure 2, using several index trading strategies. For example, we study a contrarian strategy based on the

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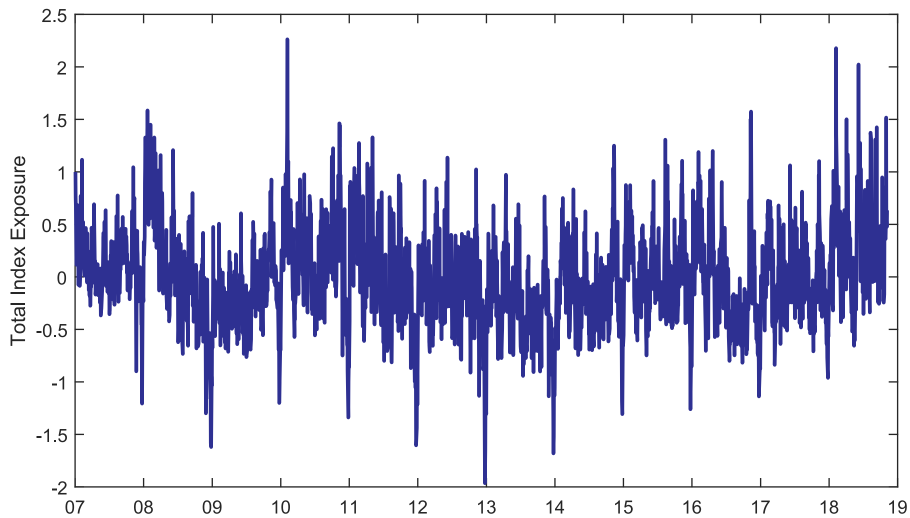
Figure 3. (Color online) Total Index Exposure



Notes. This figure plots the daily total index exposure from 2007 to 2018. The total index exposure is calculated by averaging the individual index exposure, which is the standardized detrended index trading volume.

Table 3. Contrarian (Momentum) Trading Strategy Based on Short-Term Return Reversal (Continuation) of GSCI/BCOM (NIDX)

Statistics	Full sample	High index exposure (real-time)
Panel A: Reverse portfolio (GSCI)		
Mean return (before cost)	0.093	0.105
Standard deviation (before cost)	2.977	2.318
Annualized Sharpe ratio (before cost)	0.494	0.719
Mean return (after cost)	0.085	0.100
Standard deviation (after cost)	2.976	2.317
Annualized Sharpe ratio (after cost)	0.452	0.687
Panel B: Reverse portfolio (BCOM)		
Mean return (before cost)	0.035	0.052
Standard deviation (before cost)	1.473	1.187
Annualized Sharpe ratio (before cost)	0.380	0.695
Mean return (after cost)	0.028	0.048
Standard deviation (after cost)	1.472	1.186
Annualized Sharpe ratio (after cost)	0.305	0.640
Panel C: Momentum portfolio (NIDX)		
Mean return (before cost)	0.070	0.045
Standard deviation (before cost)	1.021	0.783
Annualized Sharpe ratio (before cost)	1.088	0.920
Mean return (after cost)	0.033	0.024
Standard deviation (after cost)	1.021	0.782
Annualized Sharpe ratio (after cost)	0.516	0.479

Notes. This table presents the descriptive statistics of implementing a time-series contrarian (momentum) strategy based on short-term return reversals (continuation) of commodity indices (nonindexed portfolios). For contrarian (momentum) strategy, we sell (buy) the GSCI/BCOM (NIDX) when the past daily return is positive and buy (sell) the GSCI/BCOM (NIDX) when the past daily return is negative. The daily trading position of each index is $|r^p_{t-1}|$, $p \in \{\text{GSCI, BCOM, NIDX}\}$, respectively. The portfolio is rebalanced on a daily basis. To account for the trading cost, we use the weighted average of one tick bid–ask spreads for indexed commodities (1.04 bps for GSCI and 1.26 bps for BCOM) and the weighted average of two-tick bid–ask spreads for nonindexed commodities (7.74 bps for NIDX). The high index exposure refers to the period when total index exposure is above zero. The real-time index exposure is calculated using a window of the past 250 days instead of a full sample for standardization. The averaged daily returns and the standard deviations are reported in basis points. The data ranges from January 3, 2006, to November 6, 2018.

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short-term return reversal for the commodity indices (GSCI and BCOM). Specifically, for the contrarian strategy, we sell (buy) the GSCI or BCOM when its returns on the previous trading day are positive (negative). We take a position r_{t-1} so that the daily return of our strategy is simply $-r_t r_{t-1}$. As shown in column (1), this trading strategy has an annual Sharpe ratio of 0.49 for the GSCI (Panel A) and 0.38 for the BCOM (Panel B) for 2006–2018, consistent with Figure 2, which shows a significantly negative daily autocorrelation for both indices after 2006.

Commodity futures contracts are liquid and easy to trade. Nevertheless, to account for the trading cost, we use the weighted average of one-tick bid–ask spreads for indexed commodities (1.04 basis points for the GSCI and 1.26 basis points for the BCOM) and the weighted average of two-tick bid–ask spreads for nonindexed commodities (7.74 basis points for the NIDX).[8] Column (1) shows sizable annual Sharpe ratios even after transaction costs (0.45 for the GSCI and 0.31 for the BCOM).

Trading strategies implemented during high index exposure periods confirm the pattern that the return autocorrelation for indexed commodities is more negative when their index exposure is high. Because our index exposure measure is constructed using a full-sample standardization procedure, it is not observable in real time. To ensure that our conditional trading strategy can be implemented in real time, in column (2), we reconstruct a real-time index exposure measure in which the standardization procedure is carried out using a backward 250-day rolling window. Using this real-time measure, we find that the annual after-cost Sharpe ratio improves to 0.69 for the GSCI and 0.64 for the BCOM during high index exposure periods.

Panels A and B demonstrate that return reversals among indexed commodities are highly significant economically, especially during the high index exposure period. When we focus on nonindexed commodities, a different yet robust momentum pattern emerges (see Figure 2). To evaluate its economic significance, we consider a momentum trading strategy. Specifically, we buy (sell) the equally weighted NIDX portfolio when its return on the previous trading day is positive (negative). We still take a position r_{t-1} so that the daily return on our strategy is simply $r_t r_{t-1}$. Panel C reports the results.

The momentum pattern on the NIDX is also economically significant. Its annual after-cost Sharpe ratio is 0.51 during the full sample period (2006–2018). Interestingly, the after-cost Sharpe ratio changes little when focusing on high index exposure periods (0.48 in column (2)). Overall, the momentum pattern of the NIDX serves as a nice placebo. The momentum here could reflect the continuing underreaction to common shocks among nonindexed commodities as they receive little attention from index investors.

3.2. Panel Regressions

To formally test the correlation between the return serial dependence and index trading, we directly link the autocorrelation measure to (lagged) total index exposure using panel regressions in Table 4, taking advantage of the high-frequency nature of our measure and our large cross-section of commodities. In particular, we regress the commodity return autocorrelations measure, $AC(1)_{it} := r_{it} r_{i,t-1}/\sigma_i^2$, on the lagged total index exposure and other controls:[9]

$$AC(1)_{it} = \beta_0 + \beta_1 \textit{Total Index Exposure}_{t-1} + \theta' \mathbf{X}_{i,t-1} + \varepsilon_{it}, \tag{7}$$

where σ_i^2 is the sample variance of commodity i's returns[10] and vector $\mathbf{X}$ contains each commodity's lagged log basis[11] and lagged Amihud's illiquidity as control variables following Nagel (2012), Szymanowska et al. (2014), Bianchi et al. (2016), and Koijen et al. (2018).[12] In particular, we use the log basis to control for the state of inventories (Gorton et al. 2012) and choose Amihud's illiquidity to control for liquidity because of its better performance than other low-frequency liquidity measures (Marshall et al. 2012). The commodity fixed effects are included in all regressions. Because there could be confounding factors (e.g., production) that affect the commodities' weights on commodity indices, which are determined on a yearly basis, we also check the cases when the year fixed effects are included in the regression.[13] We compute the commodity and day double-clustered standard errors to account for potential cross-commodity and cross-time error correlations.

We confirm that the return autocorrelations of indexed commodities become more negative when total index exposure is higher. Specifically, in column (4) of Panel A, a coefficient of −0.051 means that a one standard deviation increase in total index exposure makes its daily return autocorrelations 2.32% more negative for indexed commodities. In contrast, nonindexed commodities do not show such a pattern. The different behavior between indexed and nonindexed commodities is significant as shown in columns (3) and (6), consistent with the notion that index trading drives the findings among indexed commodities.[14]

To make sure that the reversals go beyond the bid–ask bounce and other related market microstructure noise that primarily affects the next-day return, we rerun Regression (7) using a multiperiod return autocorrelations measure after skipping the next day, or $AC(2,5)_{it} := 1/4\sum_{k=2}^{5} AC(k)_{it} = \sum_{k=2}^{5} r_{it} r_{i,t-k}/4\sigma_i^2$, as the dependent variable. $AC(2,5)$ captures the average return autocorrelations over the week net of the first day.[15] A coefficient of −0.029 in column (10) of Panel A implies that a one standard deviation increase in total index exposure makes the average return autocorrelations (excluding the first lag) 1.29% more negative. The multiperiod

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Table 4. Return Serial Dependence and Commodities' Total/Sectoral Index Exposure

	$AC(1)$						$AC(2, 5)$					
Variables	Indexed	Nonidx	All	Indexed	Nonidx	All	Indexed	Nonidx	All	Indexed	Nonidx	All
Panel A: Total index exposure												
L.Total Index Exposure	−0.036***	0.007	0.007	−0.051***	0.004	−0.007	−0.027***	−0.006	−0.006	−0.029***	−0.010	−0.007
	(−2.99)	(0.43)	(0.43)	(−3.83)	(0.22)	(−0.39)	(−3.74)	(−0.62)	(−0.62)	(−3.54)	(−0.88)	(−0.71)
L.(Total Index Exposure × Indexed)			−0.044**			−0.038*			−0.021*			−0.023*
			(−2.09)			(−1.81)			(−1.70)			(−1.86)
L.Basis				0.578*	3.204***	1.166***				−0.167	−0.704	−0.281
				(1.78)	(3.97)	(3.77)				(−0.78)	(−1.20)	(−1.33)
L.Illiquidity				−0.008	0.030***	0.008				0.004	0.002	0.003
				(−0.85)	(3.10)	(1.19)				(0.78)	(0.44)	(0.82)
Intercept	−0.007	0.073***	0.021***	−0.005	0.080***	0.026***	0.004	0.004	0.004	0.004	0.003	0.003
	(−1.43)	(10.21)	(4.90)	(−0.83)	(10.07)	(5.27)	(1.33)	(0.85)	(1.57)	(1.05)	(0.55)	(1.10)
Commodity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Number of observations	44,715	23,874	68,589	44,579	23,516	68,095	44,643	23,866	68,509	44,507	23,508	68,015
Number of commodities	15	8	23	15	8	23	15	8	23	15	8	23
Overall R^2, %	0.17	0.07	0.26	0.24	0.59	0.36	0.06	0.02	0.04	0.09	0.10	0.07
Panel B: Sectoral index exposure												
L.Sectoral Index Exposure	−0.031***	0.008	0.008	−0.039***	0.014	0.002	−0.012**	0.001	0.001	−0.012**	0.000	0.002
	(−3.55)	(0.55)	(0.55)	(−4.17)	(0.98)	(0.17)	(−2.50)	(0.13)	(0.13)	(−2.20)	(0.02)	(0.33)
L.(Sectoral Index Exposure × Indexed)			−0.038**			−0.037**			−0.013			−0.015*
			(−2.37)			(−2.26)			(−1.50)			(−1.67)
L.Basis				0.620**	2.687***	1.107***				−0.162	−0.609	−0.252
				(2.04)	(3.60)	(3.81)				(−0.80)	(−1.13)	(−1.27)
L.Illiquidity				−0.009	0.032***	0.009				0.004	0.003	0.003
				(−0.92)	(3.29)	(1.33)				(0.74)	(0.49)	(0.85)
Intercept	−0.007	0.073***	0.021***	−0.005	0.079***	0.026***	0.004	0.004	0.004	0.004	0.003	0.003
	(−1.43)	(10.21)	(4.90)	(−0.81)	(9.99)	(5.24)	(1.33)	(0.85)	(1.57)	(1.05)	(0.61)	(1.16)
Sectoral fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Number of observations	44,715	23,874	68,589	44,579	23,516	68,095	44,643	23,866	68,509	44,507	23,508	68,015
Number of sectors	5	3	5	5	3	5	5	3	5	5	3	5
Number of commodities	15	8	23	15	8	23	15	8	23	15	8	23
Overall R^2, %	0.13	0.04	0.15	0.21	0.52	0.26	0.03	0.00	0.02	0.06	0.07	0.04

Notes. This table presents the results of regressing commodities serial dependence measures on commodities' total index exposure (panel A) and sectoral index exposure (panel B), respectively. We use two serial dependence measures, that is, $AC(1)$ and $AC(2, 5)$. $AC(1)$ is defined as $(r_{it}r_{i,t-1})/\sigma_i^2$, and $AC(2, 5)$ is defined as $\left(\sum_{k=2}^{5} r_{it}r_{it-k}\right)/4\sigma_i^2$. The total index exposure is the average of the indexed commodities' individual index exposure. The index trading share is defined as the ratio of indexed open interest to the total open interest for a certain commodity. The sectoral index exposure is the average of the indexed commodities' individual index exposure by sectors. The index trading volume for a certain commodity is the production of the market trading volume and its corresponding index trading share. The index exposure is, thus, obtained by detrending the index trading volume with its past 250-day average and then standardizing the time series. Indexed is a dummy variable, which equals one when the commodity is indexed and zero otherwise. The data ranges from January 3, 2006, to November 6, 2018. The t-statistics reported in the parenthesis are based on commodity and day double-clustered standard errors.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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negative impact of total index exposure on the return autocorrelations indicates that the short-term return reversals are not simply driven by market microstructure noises.

Because of data limitations and heavy weights in the energy sector, the total index exposure may suffer from serious measurement error issues. This measurement error could generate an attenuation bias that pushes the coefficient estimate from positive and significant (indicating a general commodity return predictability factor) to positive and insignificant. To address this concern, we construct sectoral index exposures by averaging the individual index exposure measures by sectors:

$$\textit{Sectoral Index Exposure}_{S,t} = \frac{1}{\#S} \sum_{i \in S} \textit{Index Exposure}_{it}, \quad (8)$$

where S is a set of the commodities within the same sector and $\#S$ is the cardinality of this set. Then, we reconduct the analysis in Panel A by replacing the total index exposure with the sectoral index exposure. Panel B shows that the sectoral index exposure measure continues to significantly predict the negative future return autocorrelations, whereas having no impact on the nonindexed commodities. Specifically, the coefficients of -0.039 and -0.012 indicate that a one standard deviation increase in the sectoral index exposure is associated with 2.43% and 0.73% more negative $AC(1)$ and $AC(2, 5)$ tomorrow, respectively.

4. Causal Evidence

So far, we have documented a large and economically significant daily association between commodity index trading and negative return autocorrelation, which indicates price overshoots and reversals even at the index level. This section conducts additional tests to provide a causal interpretation that index trading results in negative return autocorrelation. These tests also help to address various identification concerns affecting our previous empirical analyses. These concerns include (1) violation of the parallel pretrends assumption, (2) omitted factors, and (3) reverse causality. We explain these concerns and how we address them in detail.

4.1. Synthetic Matching

Both Tang and Xiong (2012) and Basak and Pavlova (2016) consider year 2004 as the start of financialization in the commodity markets. However, Figure 2 shows that the return autocorrelation of indexed commodities started to diverge from that of the nonindexed ones even before 2004. The divergence violates the parallel pretrends assumption and raises concerns that some unobserved factors, unrelated to index trading, could also drive the difference between indexed and nonindexed commodities.

To address the pretrend concerns and better construct a control group using nonindexed commodities, we employ the method of synthetic matching, which is first introduced in Abadie and Gardeazabal (2003) and Abadie et al. (2010) and then extended by Acemoglu et al. (2016). The basic idea behind this method is to construct portfolios of nonindexed commodities that resemble indexed commodities as closely as possible in returns (and, therefore, also autocorrelations) before 2004. Put differently, the synthetic matching imposes parallel pretrends on the treatment (indexed commodities) and control (nonindexed commodities) groups.

Following Acemoglu et al. (2016), we construct a synthetic match for each indexed commodity by solving the following optimization problem:

$$\min_{\{w_j^i\}_{j \in \mathcal{N}}} \sum_{t \in \text{Pre-financialization}} \left(r_{it} - \sum_{j \in \mathcal{N}} w_j^i r_{jt} \right)^2,$$
$$\text{s.t.} \sum_{j \in \mathcal{N}} w_j^i = 1, \ \forall i \in \mathcal{I}$$

where r_{it} is the daily excess return on date t of indexed commodity i, w_j^i is the weight of nonindexed commodity j employed in the optimal weighting for indexed commodity i, and $\mathcal{I}$ and $\mathcal{N}$ denote the collection of indexed and nonindexed commodities, respectively.[16] According to Acemoglu et al. (2016), it is important that the estimation window does not include the period of intervention (i.e., financialization), and it is typically selected as some period prior to the intervention. Therefore, we use 10 years ending one year prior to 2004, namely, from January 1993 to December 2002, as our estimation window. After finding the optimal weights (see Online Table A4) through iteration for each indexed commodity, the return for the synthetic commodity is constructed as

$$r_{it}^s = \sum_{j \in \mathcal{N}} \hat{w}_j^i r_{jt}, \quad (9)$$

and the return autocorrelation is computed as $AC(1)_t^s = r_{it}^s r_{it-1}^s / \sigma_i^{s2}$, where σ_i^{s2} is the sample variance of commodity i's synthetic commodity's returns.

Figure 4 displays the yearly median gaps in average $AC(1)$ between the indexed commodities and their synthetic counterparts during the period 1993–2018.[17] We extract the trend in daily $AC(1)$ gap by moving average the series with a 10-year backward rolling window. Figure 4 clearly suggests that financialization had a significantly negative effect on return autocorrelations and this effect increased in time.[18]

To formally verify the parallel pretrends assumption and alleviate the concern of overfitting, we adopt a cross-validation procedure by iteratively leaving one year out from 1993 to 2002 as our validation sample and then estimate the portfolio weights with the

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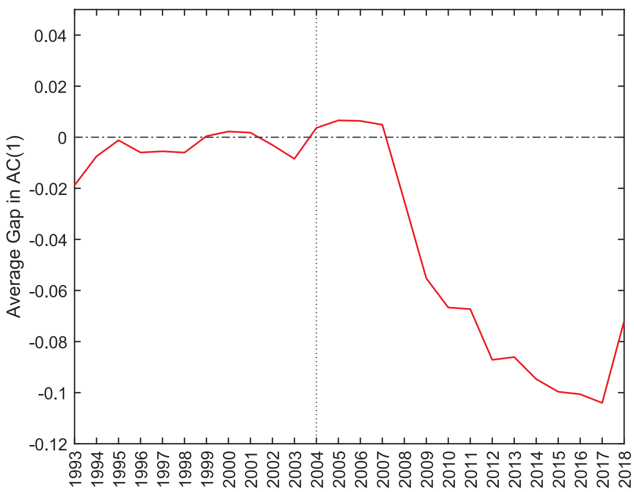
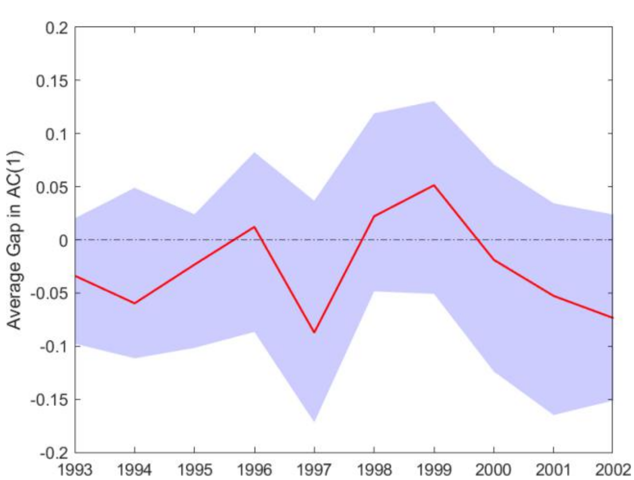
Figure 4. (Color online) Return Autocorrelation Gap



Notes. This figure plots the yearly median of the smoothed average $AC(1)$ gap between the indexed commodities and the synthetic portfolios based on a 10-year backward rolling window. Each indexed commodity's $AC(1)$ gap is computed with the $AC(1)$s of indexed commodity subtracting the $AC(1)$s of the corresponding matched portfolio.

remaining nine-year sample. Figure 5 displays yearly median of the average $AC(1)$ gaps between the indexed commodities and the synthetic indexed commodities of the validation sample and its corresponding 95% confidence interval.[19] For example, the median gap for year 2000 is estimated using the nine-year sample of 1993–1999 and 2001–2002. The cross-validation result clearly shows that the median gap is not significantly different from zero, or our synthetic matches track the trends of indexed

Figure 5. (Color online) Cross-Validated Prefinancialization Return Autocorrelation Gap



Notes. This figure plots the yearly median of the average $AC(1)$ gap between the indexed commodities and the matched portfolios using the cross-validated sample in the prefinancialization period. We compute each indexed commodity's $AC(1)$ gap with the $AC(1)$s of indexed commodity subtracting the $AC(1)$s of the corresponding matched portfolio. The shaded area is the corresponding 95% confidence interval.

commodities in return autocorrelations sufficiently well over the prefinancialization period, and our results in Table 5 are not subject to overfitting.

To evaluate the marginal effect of index trading, we replace the nonindexed commodities with the synthetic commodities for the placebo test, we rerun the panel regression analysis in Table 4. Following Abadie et al. (2010), we exclude all the control variables and year fixed effects in the regressions and summarize the results in Table 5.

Evidently, both market-level and sectoral-specific index exposure exhibit significantly negative impacts on the return autocorrelations of index commodities and show no effects on the synthetic commodities. The differences between the coefficients are significantly large and comparable (above 70%) to those in Table 4.

4.2. Weight Differences Across Two Indices

Could omitted factors drive this link between index trading and negative daily return autocorrelations? In the past 15 years, institutional investors might have simply become more willing to invest in a basket of certain commodities as an asset class. Such investment demand would result in correlated order flows across these commodities and, thus, negative commodity portfolio return autocorrelations regardless of whether commodity-indexed products have been introduced. It may simply be a coincidence that part of that correlated order flow is also satisfied through indexed products (rather than through trading the underlying commodity futures directly). One could even argue that the commodity-indexed products were introduced precisely to cater to correlated demand from institutional investors in trading these commodities (that are chosen to be included in the GSCI and BCOM).

Although such a correlated demand story could explain the low-frequency trends, it is harder to justify the high-frequency relation (between the index exposure measure and negative daily return autocorrelations) in Table 4. An increasing trend toward investing in broad commodity baskets is unlikely to be highly correlated with abnormal trading activities in two specific commodity indices on a day-to-day basis. Nevertheless, we conduct an additional test to pin down the causality from index trading to index return autocorrelations.

This test is similar in spirit to those in Greenwood (2008) that take advantage of the different weighting schemes across two Japanese equity indices. Similar to the case of equity indices, the same commodity can receive different weights across GSCI and BCOM. This relative weighting is determined at the beginning of the year and then held constant throughout the year. Therefore, a testable implication of index trading goes as follows: for commodities overweighted in BCOM (relative to GSCI), daily return autocorrelations should be more

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Table 5. Causality Test: Synthetic Matching

	Dependent variable: $AC(1)$					
Variables	Indexed	Synthetic	All	Indexed	Synthetic	All
L.Total Index Exposure	−0.036***	−0.007	−0.007			
	(−2.99)	(−0.49)	(−0.49)			
L.(Total Index Exposure × Indexed)			−0.030*			
			(−1.66)			
L.Sectoral Index Exposure				−0.031***	−0.001	−0.001
				(−3.55)	(−0.09)	(−0.09)
L.(Sectoral Index Exposure × Indexed)						−0.030**
						(−2.37)
Intercept	−0.007	0.067***	0.030***	−0.007	0.067***	0.030***
	(−1.43)	(12.71)	(8.09)	(−1.43)	(12.71)	(8.08)
Commodity fixed effects	Yes	Yes	Yes	—	—	—
Sector fixed effects	—	—	—	Yes	Yes	Yes
Number of observations	44,715	44,775	89,490	44,715	44,775	89,490
Number of commodities	15	15	30	15	15	30
Number of sectors	5	5	5	5	5	5
Overall R^2, %	0.17	0.02	0.21	0.13	0.01	0.04

Notes. This table presents the causality result of regressing the indexed/synthetic commodities serial dependence measure on the lagged total/sectoral index exposure. The serial dependence measure $AC(1)$ is defined as $(r_{it}r_{i,t-1})/\sigma_i^2$, and the total index exposure is the average of the indexed commodities' individual index exposure. For each indexed commodity, its synthetic match is the weighted average of nonindexed commodities that minimizes the mean squared errors between the excess returns over the prefinancialization period. The t-statistics reported in the parenthesis are based on commodity and day double-clustered standard errors. The prefinancialization sample ranges from January 4, 1993, to December 31, 2002. The regression uses the sample ranging from January 3, 2007, to November 6, 2018.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

negatively correlated with the trading measure on BCOM (relative to that on GSCI).

We implement the test by constructing a portfolio (BCOM OW portfolio) based on the commodity's overweight in BCOM. We first compare commodity i's weight in BCOM, $w_{jy(t)}^{BCOM}$, to its weight in GSCI, $w_{jy(t)}^{BCOM}$:

$$OW_{jy(t)} = w_{jy(t)}^{BCOM} - w_{jy(t)}^{GSCI}, \tag{10}$$

where $y(t)$ is the year of date t. Then, we pick the top five overweighted commodities (B5) and take a position of $\varpi_{jt} = -OW_{jy(t-1)}r_{j,t-1}$ on each commodity j on day t and obtain the portfolio return

$$R_t^{OW} = \sum_{j\in B5} \varpi_{jt} r_{jt} = -\sum_{j\in B5} OW_{jy(t-1)} \times r_{j,t-1} r_{jt},$$

where r_{jt} is the return on commodity j. We report yearly B5 components and their corresponding OWs in Online Table A3. Evidently, these overweighted commodities come from very different sectors, and their composition changes every year. It is, therefore, unlikely that a specific sector or commodity drives the properties of the BCOM OW portfolio. By construction, the BCOM OW portfolio's return is higher when the B5 return autocorrelations are more negative.

Next, we compute the selected commodities' GSCI and BCOM exposure separately. Similar to the individual index exposure measure introduced in Equation (5), commodities' exposure on a specific commodity index is defined as each commodity's GSCI/BCOM market share times the total trading volume and then detrended with a 250-day backward rolling window. To compute the market share of a specific commodity index, we first employ Hamilton and Wu's (2015) method to estimate indexed commodities' open interest on that index (see Online Appendix A.2 for more details). Then, we obtain commodity i's GSCI/BCOM market share as well as its index exposure on GSCI/BCOM as follows:

$$Index\ Market\ Share_{it}^{p} = \frac{Open\ Interest_{it}^{p}}{Open\ Interest_{it}^{All}}, \tag{11}$$

$$Index\ Trading\ Volume_{it}^{p} = Index\ Market\ Share_{it}^{p} \times Trading\ Volume_{it}, \tag{12}$$

$$Index\ Exposure_{it}^{p} = \text{standardize}\{Detrended\ Index\ Trading\ Volume_{it}^{p}\}, \tag{13}$$

where $p \in \{GSCI, BCOM\}$. Then, we obtain the portfolio's exposure on GSCI and BCOM by aggregating the selected commodities' GSCI and BCOM exposure measure, respectively, that is,

$$Index\ Exposure_{t}^{p} = \sum_{j\in B5} OW_{jy(t-1)} \times Index\ Exposure_{jt}^{p}, \quad p \in \{GSCI, BCOM\}. \tag{14}$$

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Finally, we regress the BCOM OW portfolio return on the lagged GSCI and BCOM exposure measures with controls:

$$R_t^{OW} = \beta_0 + \beta_1 \cdot Index\ Exposure_{t-1}^{GSCI} + \beta_2 \cdot Index\ Exposure_{t-1}^{BCOM} + \theta' \mathbf{X}_{t-1} + \varepsilon_t, \quad (15)$$

where $\mathbf{X}$ is a vector of portfolio-level control variables that are aggregated from the commodity-level variables using OW as the weight. Because index weights are based on liquidity and production for BCOM and GSCI, respectively, $\mathbf{X}$ includes measures of liquidity and productions to control for forces directly related to BCOM overweights. As it is a time series regression, we adjust the standard errors using Newey–West covariance estimators that are robust to heteroskedasticity and autocorrelation.

The results in Table 6 strongly support a causal interpretation that index trading drives negative index return autocorrelations. The BCOM OW portfolio returns are significantly positively correlated with the BCOM exposure. This suggests that, for commodities that are relatively overweighted in BCOM, their daily return autocorrelations are indeed more negatively correlated with index exposure to BCOM rather than GSCI (χ^2-statistic of 4.05 and p-value of 0.04). The results still hold after excluding the roll weeks.

In unreported analyses, we find that the results continue to hold using different liquidity measures as the control variables and during December only. The latter result suggests that it is index trading rather than omitted fundamental factors that is driving negative return autocorrelation. Recall that the relative weight differences are determined at the beginning of the year and held constant throughout that year, and the overweighted commodities change every year. This means that the fundamental factors causing the weight differences at the beginning of the year are less relevant toward the end of the year.

4.3. ETF Arbitrage

Despite that the second test exploits differential index trading across two commodity indices, our third test zooms into a specific form of index trading: commodity index ETF arbitrage. When the ETF is temporarily overpriced (underpriced) relative to its underlying commodity index, arbitrageurs sell/create (buy/redeem) ETF shares and buy (sell) the underlying indexed commodities, thus propagating the price pressure from the ETF to the underlying. As the positive price pressure reverts subsequently, we should observe return reversals among the underlying indexed commodities. Following Brown et al. (2021), we employ the net creation and redemption activities on the commodity index ETFs or commodity index ETF flows to proxy for such ETF arbitrage activity.

Table 6. Causality Test: Overweighted Portfolio and Index Exposure

	Full sample		Exclude roll weeks	
Variables	(1)	(2)	(3)	(4)
L.GSCI Exposure	−0.039	−0.040	−0.016	−0.017
	(−0.80)	(−0.82)	(−0.29)	(−0.32)
L.BCOM Exposure	0.124**	0.126**	0.150**	0.152**
	(2.04)	(2.06)	(2.34)	(2.36)
L.Portfolio Basis	21.121*	21.301*	23.582*	23.803*
	(1.94)	(1.95)	(1.77)	(1.78)
L.Portfolio Illiquidity	0.173	0.180	0.204	0.213
	(1.17)	(1.20)	(0.98)	(1.02)
Ly.Portfolio WPQ	0.246		0.338	
	(0.86)		(1.04)	
Ly.Portfolio WPA		0.352		0.422
		(1.09)		(1.21)
Intercept	0.008	−0.015	−0.013	−0.028
	(0.11)	(−0.18)	(−0.15)	(−0.32)
Number of observations	2,985	2,985	2,519	2,519
Adjusted R^2, %	0.41	0.42	0.50	0.51
χ^2-Stat. (GSCI = BCOM)	4.05**	4.17**	3.77*	3.90**

Notes. This table presents the causality result of regressing the BCOM overweighted portfolio return on the portfolio's GSCI and BCOM exposure. The BCOM overweighted portfolio is constructed by the top five indexed commodities (B5) with the largest relative BCOM weights ($OW_{jy(t)} = w_{jy(t)}^{BCOM} - w_{jy(t)}^{GSCI}$) at the beginning of each year. We hold a position of $-OW_{jy(t-1)} r_{jt-1}$ of each B5 commodity, and the portfolio return is, thus, given by $-\sum_{j \in B5} OW_{jy(t-1)} r_{jt-1} r_{jt}$. The portfolio's index exposure on GSCI/BCOM is the sum of B5 commodity's GSCI (BCOM) index exposure weighted by OW. Each commodity's GSCI (BCOM) index exposure is the standardized version of detrended GSCI (BCOM) index trading volume with the past 250-day average. GSCI (BCOM) index trading volume is estimated by multiplying its total trading volume by the ratio of GSCI (BCOM) index open interest (see Online Appendix A.2) to its total open interest. The control variables include the lagged log basis, lagged illiquidity, lagged-year world production quantity (Ly.WPQ), and the lagged-year world production average (Ly.WPA). Each commodity's WPQ is normalized by its year 2000 WPQ and WPA of year $y(t)$ is the average of $WPQ_{y(t)-8:y(t)-4}$ according to the GSCI manual. All the control variables are aggregated to portfolio level based on the OW of each commodity. The t-statistics reported in the parenthesis in are based on Newey–West standard errors with optimal lags. The sample ranges from January 2007 to November 2018.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

We collect data of four major index-tracking commodity ETFs, that is, DJP, GSG, USCI, and DBC, from January 1, 2007, to November 6, 2018, from the Bloomberg terminal.[20] We use commodity ETF flows to create a commodity nonfundamental demand index (CNFDI). Specifically, for each ETF i, we calculate its weekly ETF flows as the change in shares outstanding $\Delta_{it} = SO_{it}/SO_{it-1} - 1$. We conduct our analyses at weekly rather than daily frequency because daily creation and redemption activities are potentially measured with errors.[21] Nevertheless, the weekly setting aligns with the multiperiod return autocorrelation results in Table 4 and shows return reversal to last up to a week. Finally, we compute

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the assets under management (AUM)-weighted average of the ETF flows as

$$CNFDI_t = \sum_i \omega_{it}\Delta_{it}, i \in \{DJP, GSG, USCI, DBC\}, \quad (16)$$

where $\omega_{it} = AUM_{i,t-1}/\sum_i AUM_{i,t-1}$. By construction, CNFDI measures the aggregate index trading on the underlying commodities coming from ETF arbitrage activities.

Using the CNFDI measure, we conduct the following weekly panel predictive regressions by regressing the week t's excess return on the week t CNFDI and week $t-1$ CNFDI with controls, respectively:[22]

$$r_{it} = \beta_0 + \beta_1 \cdot CNFDI_t + \theta' \mathbf{X}_{i,t-1} + \varepsilon_{it}, \quad (17)$$

$$r_{it} = \beta_0 + \beta_1 \cdot CNFDI_{t-1} + \theta' \mathbf{X}_{i,t-1} + \varepsilon_{it}, \quad (18)$$

where $\mathbf{X}$ is a vector of control variables that contains the log basis and Amihud illiquidity.

Table 7 confirms that the nonfundamental demand for commodity ETFs predicts a strong return reversal of indexed commodities. Specifically, a one standard deviation increase in CNFDI is associated with an average of 0.48% increase in the current week indexed commodity returns and an average of −0.10% decrease in the following week indexed commodity returns. Importantly, no such return reversal is observed among nonindexed commodities. The result suggests that ETF arbitrage, as a specific form of index trading, propagates nonfundamental shocks only to indexed commodities. It is consistent with the findings in Ben-David et al. (2018) that ETF arbitrage channels serial dependence in ETF products into the underlying securities as liquidity providers hedge their exposure to the index products by taking an offsetting position in the underlying.

Our ETF-based test also rules out a reverse causality concern that the predictable return reversal in the future causes index trading today. Crucially, if index trading occurs in order to explore return reversal, we expect index traders to buy (sell) before a positive (negative) return reversal. This intuition is contradictive to what we find: ETF arbitrageurs' buying (selling) of the underlying indexed commodities predicts negative (positive) returns on these commodities.

5. Digesting Results and Sentiment Spillover

So far, we have presented novel empirical evidence that index trading exposure results in negative daily return autocorrelations among indexed commodities. To help us digest these empirical facts, we present a stylized model of commodity index trading in Online Appendix A.3. In the model, index traders propagate nonfundamental shocks to indexed commodities, giving rise to price overshoots and subsequent reversals and so negative return autocorrelations. The model makes a testable prediction. To the extent we can measure the nonfundamental shocks, such shocks should negatively predict the next period return of indexed commodity. As a placebo test, nonfundamental shocks should not be correlated with future returns on nonindexed commodities.

Table 7. Causality Test: ETF Arbitrage

	All		Indexed		Nonindexed	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
CNFDI	0.493***		0.480***		0.518***	
	(11.55)		(8.91)		(7.44)	
L.CNFDI		−0.069*		−0.103**		−0.007
		(−1.66)		(−2.01)		(−0.10)
L.Basis	−0.531	−0.757	−1.741	−2.041	3.373	3.317
	(−0.22)	(−0.31)	(−0.66)	(−0.78)	(0.55)	(0.54)
L.Illiquidity	−0.047	−0.043	−0.055	−0.048	−0.040	−0.041
	(−1.11)	(−1.00)	(−0.91)	(−0.79)	(−0.69)	(−0.69)
Intercept	0.021	0.025	−0.033	−0.028	0.115*	0.117*
	(0.56)	(0.66)	(−0.68)	(−0.58)	(1.82)	(1.83)
Commodity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	14,181	14,158	9,273	9,258	4,908	4,900
Number of commodities	23	23	15	15	8	8
Overall R^2, %	2.08	0.95	2.12	1.01	2.09	0.92

Notes. This table presents the causality result of regressing the weekly commodities returns (in percentage) on the contemporaneous or lagged nonfundamental demand index for commodity ETFs (CNFDI). The CNFDI is defined as the AUM-weighted average of the changes in shares outstanding of four index-tracking ETFs, that is, DJP, GSG, USCI, and DBC. In each regression, CNFDI is standardized to have zero mean and unit variance. The t-statistics reported in the parenthesis are based on commodity and month double-clustered standard errors. The sample ranges from January 2007 to November 2018.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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In the third causal test, we focus on a specific form of nonfundamental shock propagated by ETF arbitrage. In this section, we test this prediction more broadly using cross-sectoral news-based (connected) sentiment as the nonfundamental shock.

The news data we use come from the Thomson Reuters News Analytics–Commodities data (TRNA-C). TRNA-C data provide three news tones (positive, negative, and neutral) for each piece of commodity news, and the sample coverage starts in January 2006.[23] Averaging all the news tones on each piece of news in a trading day for each commodity, we obtain a daily panel of three news tones for each commodity.

For each commodity, we first regress the minus negative news tone on its first lag and the day-of-week dummies by running the following regression:

$$-Tone_t^{Neg} = \beta_0 + \beta_1 \cdot (-Tone_{t-1}^{Neg}) + \beta_2 \cdot Day\text{-}of\text{-}week_t + \varepsilon_t. \tag{19}$$

We focus on negative news tones as Tetlock (2007) points out that negative tones are better measured in most of the textual data. We take the minus negative tone to align with the noise signal α in the theoretical model. Wang et al. (2018) show that news has a momentum effect (i.e., current news sentiment depends significantly on its lagged level). Hafez (2009, 2011) and Healy and Lo (2011) report strong seasonality in news flows at various sampling frequencies (e.g., intrahour, intraday, and intraweek). Therefore, we include the lagged news tones and day-of-week dummies to ease the potential momentum effect and seasonality in news tones.

We then treat the residual of the regression ($\hat{\varepsilon}_t$) as the sentiment measure for each commodity. Online Table A5 shows the descriptive statistics of our sentiment measure for each commodity. Evidently, crude oil receives more news coverage than other commodities. The sentiment measures have zero means by construction. Their average standard deviation is 0.062 ranging from 0.031 for oat (O-) and rough rice (RR) to 0.112 for orange juice (JO).

The sentiment measure for commodity i likely contains fundamental shocks to that commodity. To study the sentiment propagation across the indexed commodities, we construct a connected sentiment measure that mostly captures nonfundamental shocks for each commodity. Take corn (C-) for example. To construct its connected sentiment on day t, we take a weighted average of the sentiment measures on all indexed commodities from other sectors on that day:

$$Cnn.\ Sentiment_{it} = \sum_{j \notin S(i)} W_{jy(t)} Sentiment_{jt}, \tag{20}$$

where $S(i)$ is the set that collects commodities within the same sector of commodity i and the weight $W_{jy(t)}$ is defined as

$$W_{jy(t)} = \frac{E_{y(t)}(\$Open\ Interest_{jt}^{Idx})}{\sum_j E_{y(t)}(\$Open\ Interest_{jt}^{Idx})}, \tag{21}$$

with $E_{y(t)}(\$OpenInterest_{jw(t)}^{Idx})$ being the average of the weekly dollar-valued open interest on index trading in year $y(t)$. In other words, the weight on connected indexed commodity j is determined by its average dollar-valued open interest relative to the total dollar-valued open interests across both indices.

In this definition, the set of indexed commodities connected to corn only includes indexed commodities from other sectors, such as energy and metals, but not other indexed commodities from the same grains sector, such as soybean (S-) and wheat (W-). To the extent that a sentiment measure that includes commodities from the same sector may still contain fundamental factors common to that sector, our connected sentiment measure is more likely to be dominated by sentiment or idiosyncratic fundamental shocks from other commodities (α and $\theta_{i'}$ in the stylized model presented in Online Appendix A.3).[24] It is possible that the connected sentiment measure may still contain fundamental shocks common to all commodities (including those off the index), for example, the business cycle factors can influence demand and supply of all commodities. But if such shocks dominate, the connected sentiment measure should not negatively predict future indexed commodity returns as fundamental shocks do not revert.

As a placebo test, we also construct the connected sentiment measure for nonindexed commodities in the same fashion except that we use an equal weighting scheme (to replace Equation (21)) as in the construction of the NIDX. According to our stylized model, the connected sentiment should positively correlate with contemporaneous indexed commodity returns but negatively predict future indexed commodity returns. In addition, it should not predict the returns on nonindexed commodities.

We now test these predictions by running the following day/commodity panel regressions for indexed and nonindexed commodities separately:

$$r_{it} = \beta_0 + \beta_1 \cdot Cnn.\ Sentiment_{it} + \theta' \mathbf{X}_{i,t-1} + \varepsilon_{it}, \tag{22}$$

$$r_{it} = \beta_0 + \beta_1 \cdot Cnn.\ Sentiment_{i,t-1} + \theta' \mathbf{X}_{i,t-1} + \varepsilon_{it}, \tag{23}$$

where $\mathbf{X}$ is a vector of the control variables including the lagged log basis and lagged Amihud illiquidity. Both the commodity and year fixed effects are also controlled for in the regression. Szymanowska et al. (2014) find that the log basis, volatility, and liquidity might serve as determinants of the risk premium in commodity markets. We, thus, use these variables as controls. To assess the difference between the coefficients for indexed and nonindexed commodities, we also run the regressions

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Table 8. Spillover Effect of Sentiment on Returns Across Indexed/Nonindexed Commodities

	Panel A: Contemporaneous			Panel B: Predictive		
Variables	Indexed	Nonindexed	All	Indexed	Nonindexed	All
Cnn. Sentiment	16.089***	9.576***	9.580***			
	(44.98)	(19.15)	(19.25)			
Cnn. Sentiment × Indexed			6.098***			
			(10.03)			
L.Cnn. Sentiment				−1.026***	0.587	0.585
				(−2.92)	(1.20)	(1.20)
L.(Cnn. Sentiment × Indexed)						−1.584***
						(−2.65)
L.Basis	0.278	1.491	0.566	0.330	1.339	0.566
	(0.56)	(1.55)	(1.29)	(0.67)	(1.38)	(1.28)
L.Illiquidity	0.004	0.019	0.007	−0.003	0.016	0.004
	(0.42)	(1.59)	(0.90)	(−0.30)	(1.32)	(0.58)
Intercept	0.006	0.035***	0.016**	0.002	0.032***	0.013*
	(0.69)	(3.20)	(2.41)	(0.22)	(2.86)	(1.87)
Commodity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	51,784	27,526	79,310	51,770	27,521	79,291
Number of commodities	15	8	23	15	8	23
Overall R^2, %	4.19	1.68	3.30	0.18	0.22	0.19

Notes. This table presents the results of regressing commodities returns (in percentage) on the connected sentiment. We first get each commodity's news sentiment as the residuals from regressing the minus negative news tones on its first lag and the day-of-week dummies. We then obtain the connected sentiment for an indexed commodity by taking a value-weighted average of indexed commodities from other sectors. For connected sentiment of nonindexed commodities, we take a simple average on the sentiment of nonindexed commodities from other sectors. Indexed is a dummy variable, which equals one when the commodity is indexed and zero otherwise. The data ranges from January 3, 2006, to November 6, 2018. The *t*-statistics reported in the parenthesis are based on commodity and day double-clustered standard errors.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

with an interaction term between the connected sentiment measure and a dummy variable (one for indexed commodities and zero for nonindexed commodities). Table 8 reports the results.

Focusing on Panel A, we confirm the positive and significant contemporaneous relation between the indexed commodity return and its connected sentiment measure in column (1). Our connected sentiment measure may still contain fundamental information that affects all commodities, explaining why its contemporaneous return correlation is also positive and significant for nonindexed commodities in column (2), in which index trading is not possible. Nevertheless, the positive coefficient (16.089) is significantly larger than that for nonindexed commodities (9.576), consistent with the notion that index trading propagates noise, in addition to fundamental information, across commodities within the same index.

Panel B shows the negative and significant return predictability of the connected sentiment measure, but for indexed commodities only. The coefficient of connected sentiments is likely to capture the impact of noise propagation. For instance, a predictive coefficient of −1.026 (*t*-statistic of −2.92) on the connected sentiment measure implies that a one standard deviation increase in the sentiment of connected indexed commodities propagates a noise that reverts by 2.3 basis points the next day. Column (2) in Panel B does not show any significant return predictability among nonindexed commodities. The difference between indexed and nonindexed commodities is also large (−1.588) and statistically significant as shown in the third column of Panel B.

Turning to the control variables, consistent with Szymanowska et al. (2014) and Gorton et al. (2012), the lagged log basis makes a positive prediction (although insignificant) on the commodity returns listed in Table 8, whereas liquidity showing no significant predictive power for commodity returns on a daily frequency. Consistent with table 9 in Kang et al. (2020), the R^2 of the predictive panel regression is generally small for futures markets, that is in the neighborhood of several 10ths of a percent.

If index trading propagates sentiment and creates price pressure at the index level, we should observe a stronger effect when index trading exposure is abnormally high. To test this conjecture, we divide the sample into two subsamples based on the total index exposure measure defined in the previous section. Specifically, we classify a trading day whose total index exposure is above or below zero as "high" (*H*) and "low" (*L*) index exposure periods, respectively. We then rerun the previous regression analyses in the *H* and *L* subperiods

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Table 9. Spillover Effect of Sentiment on Returns Across Indexed/Nonindexed Commodities Under High/Low Total Index Exposure Episode

	Panel A: Contemporaneous				Panel B: Predictive			
	Indexed		Nonindexed		Indexed		Nonindexed	
Variables	High	Low	High	Low	High	Low	High	Low
Cnn. Sentiment	15.843***	16.234***	8.790***	10.193***				
	(31.89)	(31.37)	(12.66)	(14.10)				
L.Cnn. Sentiment					−1.712***	−0.169	−0.561	1.735**
					(−3.59)	(−0.32)	(−0.84)	(2.42)
L.Basis	0.178	0.519	0.734	1.807	0.098	0.707	0.443	1.763
	(0.26)	(0.72)	(0.53)	(1.34)	(0.14)	(0.98)	(0.32)	(1.31)
L.Illiquidity	−0.008	0.024	0.006	0.034**	−0.021	0.024	−0.001	0.035**
	(−0.62)	(1.54)	(0.37)	(2.00)	(−1.59)	(1.50)	(−0.07)	(2.07)
Intercept	−0.007	0.024*	0.063***	−0.000	0.020*	−0.015	0.067***	−0.013
	(−0.55)	(1.87)	(4.06)	(−0.03)	(1.66)	(−1.17)	(4.28)	(−0.82)
Commodity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	28,136	23,648	14,998	12,528	28,122	23,648	14,993	12,528
Number of commodities	15	15	8	8	15	15	8	8
Overall R^2, %	3.87	4.86	1.34	2.30	0.27	0.49	0.17	0.61

Notes. This table presents the results of regressing commodities returns (in percentage) on connected sentiment measures under different levels of total index exposure. The total index exposure is the average of the indexed commodities' individual index exposure. The index trading share is defined as the ratio of indexed open interest to the total open interest for a certain commodity. The index trading volume for a certain commodity is the production of the market trading volume and its corresponding index trading share. The index exposure is, thus, obtained by detrending the index trading volume with its past 250-day average and then standardizing the time series. We characterize the period when total index exposure is above (below) zero as high (low) exposure period. The data ranges from January 3, 2006, to November 6, 2018. The *t*-statistics reported in the parenthesis are based on commodity and day double-clustered standard errors.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

separately:

$$r_{it} = \beta_0 + \beta_1 \cdot Cnn.\ Sentiment_{it} + \theta'\mathbf{X}_{i,t-1} + \varepsilon_{it}, \quad t \in \{H, L\}, \quad (24)$$

$$r_{it} = \beta_0 + \beta_1 \cdot Cnn.\ Sentiment_{i,t-1} + \theta'\mathbf{X}_{i,t-1} + \varepsilon_{it}, \quad t \in \{H, L\}. \quad (25)$$

Both the commodity and year fixed effects are controlled for in the regression. Table 9 reports the results.

Focusing on the sentiment return predictability results in Panel B, we find that the return reversal is only significant during the high period for indexed commodities. The coefficient of the sentiment measure is −1.712 (*t*-statistic of −3.59) on trading days with high index trading. The economic magnitude is large. A coefficient of −1.712 implies that a one standard deviation increase in the sentiment of connected indexed commodities propagates a noise of 4.0 basis points. Consistent with the notion that index trading results in price overshoots and reversals, when we focus our attention on nonindexed commodities, we observe no return reversals in either high or low index exposure periods. In fact, nonindexed commodities have a significantly negative coefficient in the low index exposure period, indicating a delayed reaction to the negative sentiment that results in momentum instead of reversal.

Our results using news-based sentiment, thus, support the predictions from a stylized model and provide a concrete economic mechanism that generates negative daily return autocorrelations even at the index level. Specifically, index trading propagates nonfundamental noise across commodities in the same index; it creates correlated price overshoots and reversals at a daily frequency.

6. Robustness Checks

In this section, we perform extensive robustness checks of our main results using different regression specifications, different subsamples (excluding the energy sector, financial crisis, or index rolling periods), and different measures.

6.1. Decomposition of Indexed Trading

Considering our index exposure measure is a detrended product of the total trading volume and index market share, a natural concern is that our results could be driven by the total trading volume component rather than the index market share. To address this concern, we rerun Regression (7) by separately including the two components of the index exposure measure (as in Equation (4)). In particular, we use the sector-specific index market shares as the explanatory variable for nonindexed commodities and estimate the model with and without the day fixed effects and control variables.

The results in Online Table A7 show that both components are important for driving the autocorrelation of

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indexed commodity returns. The economic magnitude of both components is significant: the coefficients of −0.366 and −0.255 in column (6) indicate that a one standard deviation increase in each component results in a decrease in daily return autocorrelations by 4.00% and 2.86%, respectively. Hence, our results are not solely driven by the index traders' market share or the total trading volume. Consistent with the previous analysis, both components show no significant impact on the return autocorrelations in nonindexed commodities. This placebo result confirms that our analysis is robust to different specifications of the index exposure measure.

6.2. Individual Index Exposure

Because individual index exposure is not necessarily high when total index exposure is high, we conduct the following daily panel regression of each commodity's serial dependence measure on the lagged individual index exposure measure and controls for robustness:

$$AC(1)_{it} = \beta_0 + \beta_1 \cdot Index\ Exposure_{i,t-1} + \theta' \mathbf{X}_{i,t-1} + \varepsilon_{it}, \tag{26}$$

where Index Exposure$_{i,t-1}$ is the index exposure for commodity i at date $t-1$, and $\mathbf{X}$ is a vector of control variables. We run the panel regression for indexed and nonindexed commodities separately and use total index exposure as nonindexed commodities' index exposure.

Online Table A8 shows two sets of interesting results. First, we observe negative and significant coefficients of the index exposure measure only for indexed commodities. In other words, abnormally high index trading today implies a more negative correlation between the indexed commodity return today and that tomorrow, consistent with the notion that index trading results in price pressure at the index level today and that such price pressure is reverted tomorrow. The economic magnitude of such an effect is large. In terms of the economic magnitude, a coefficient of −0.023 in column (2) means that a one standard deviation increase in index exposure makes its daily return autocorrelations 2.05% more negative.

Second, to the extent that negative return autocorrelations reflect price overshoots and reversals, we expect it to be stronger when liquidity is poor (see, e.g., Campbell et al. 1993, Nagel 2012). Columns (5) and (6) confirm this conjecture. The coefficients of the interaction term between lagged index exposure and the indicator for high illiquidity are negative and highly significant. In other words, when index investors trade illiquid commodities, their trading more likely generates negative return autocorrelations for those commodities in the index. Columns (7) and (8) again show no such interaction among nonindexed commodities.

6.3. Index Rolling Activity

Unlike equity index funds that invest directly in underlying assets, commodity index funds trade futures contracts instead, and this requires them to unwind maturing contracts before they expire and roll their positions to the contracts with later maturity dates. According to the rolling schedule of the GSCI and BCOM, both indices shift the basket of contracts from the nearest to the second nearest contracts at a rate of 20% per day on the fifth to ninth business days in each month. This routine rolling activity results in abnormally high index trading volumes during the roll period that likely affect our index exposure measure. Therefore, it is important to ensure that our results are not driven by these roll dates.

For each commodity, we identify the week containing the roll date of its continuous contract, which is the seventh calendar day of the maturity month. Using this setting, we can cover most of the index roll dates without affecting the return structure of the continuous contract. We then rerun the panel regressions in Table 4 on a sample excluding roll weeks and report the results in Online Table A9. The results, when excluding roll weeks, are similar to those using the whole sample, suggesting that index rolling is not the driver of our findings.

In addition, we reconduct the analyses in Online Table A7 and report the results in A10. This table shows that our results are jointly robust to different index exposure definitions and commodity index-rolling activities.

6.4. Energy Sector

Because there are zero energy commodities in the nonindex sample, one may question whether the results are because of a time-varying energy-specific factor. This is especially concerning because energy carries an enormous weight in the commodity indexes, and energy commodities behaved wildly during the sample period. To address this concern, we reconduct the analysis in Table 4 and Online Table A7 by excluding the commodities from the energy sector. The results in Online Tables A11 and A12 exhibit a similar pattern to those using the whole sample, suggesting that our findings are not solely driven by the energy commodities.

6.5. Financial Crisis

The financial crisis may drive some of our results. Hence, following Tang and Xiong (2012), we choose the period from September 15, 2008, when Lehman Brothers filed for bankruptcy, to June 30, 2009, the trough of the business cycle identified by the National Bureau of Economic Research, as the period of the financial crisis. We then rerun the regressions in Tables 4 and 8 excluding the financial crisis period with the results reported in Online Tables A13 and A14. Our robustness check results are consistent with those in Tables 4 and 8. That is, through index investment, connected news sentiment leads to a price overshoot and a subsequent reversal and

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index exposure decreases in futures return autocorrelations. On the contrary, nonindexed commodities do not have such effects.

6.6. Net News Tone

In Section 5, we use the minus negative news tone in the regression, and as a robustness check, we rerun the regression in Tables 8 and 9 using net news tone (positive tone minus negative tone). Online Tables A15 and A16 present the results. Again, using net news tone, we obtain results similar to those with minus negative tones (as shown in Tables 8 and 9).

7. Conclusion

We provide causal evidence of the recent financialization in commodity markets on the return serial dependence of indexed commodities. We first document a striking divergence between the daily return autocorrelation of indexed commodities and nonindexed commodities. Even though the autocorrelation of nonindexed commodities has become slightly more positive, the autocorrelation of commodity indices had switched to become negative when financialization began. We present novel causal evidence that exposure to index trading results in negative daily return autocorrelations among commodities in that index. The reason is that index trading can propagate nonfundamental noises to indexed commodities, giving rise to price overshoots and subsequent reversals, consistent with the prediction of a stylized model. We present direct evidence for such noise propagation using news sentiment data.

Given the attractive risk–return trade-off and diversification benefits associated with commodity index investments, the commodity financialization process can be expected to continue. We do not dispute such benefits. Instead, we highlight an unexpected side effect to these benefits as negative serial dependence in commodity index returns signals excessive price comovements even at the index level. Price overshooting and the subsequent reversal could impose costs on institutional investors who trade often and individual investors who invest in commodities through those institutions. Our results agree with the theoretical studies Sockin and Xiong (2015) and Goldstein and Yang (2022), which propose that index traders can inject unrelated noise into futures prices and diminish market efficiency. They also suggest that proactive investors can generate economically significant profits by providing liquidity to index traders on a systematic basis.

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Endnotes

[1] See https://www.barclayhedge.com/solutions/assets-under-management/cta-assets-under-management/cta-industry/.

[2] We first calculate an equally weighted index for each sector of indexed and nonindexed commodities and then calculate the average correlation among five sector indices for an annual rolling window. Because there are no nonindexed commodities in the energy and livestock sectors, we take heating oil, reformulated blendstock for oxygenated blending, and lean hogs as nonindexed commodities because of their small weights in the index. Note that the "indexed" and "nonindexed" classification in Figure 1 strictly follows Tang and Xiong (2012) for the replication purpose. In subsequent analyses, we use a more strict commodity classification as defined in the last two columns of Table 1.

[3] The GSCI was initially developed in 1991 by Goldman Sachs. In 2007, ownership was transferred to Standard & Poor's. The BCOM was originally launched in 1998 as the Dow Jones–AIG Commodity Index and renamed the Dow Jones-UBS Commodity Index in 2009 when UBS acquired the index from AIG. On July 1, 2014, the index was rebranded under its current name.

[4] We do not focus on the commodities overweighted in GSCI because GSCI constantly overweights commodities in the energy sector, that is, crude oil and its products (heating oil and gasoline). Therefore, the causality may be driven by energy shocks.

[5] If the seventh is not a business day, we use the next business day as our roll date.

[6] Traders are classified into three types: commercial (C), noncommercial (NC), and nonreportables (NR). In the CIT report, the CFTC separates the index trading positions (Idx) from the positions of the commercial traders.

[7] Because the nearest and second nearest contracts are the most liquid and considering commodity indices' rolling activity (see, e.g., Stoll and Whaley 2010, Mou 2011), we calculate the total trading volume of each commodity as the sum of trading volume on the nearest and second nearest contracts.

[8] Arzandeh and Frank (2019) show that the bid–ask spreads of large agricultural commodities are about one tick. In contrast, those of small agricultural commodities are slightly less than two ticks. We take a half tick as the trading cost of indexed commodities and one tick as the trading cost of nonindexed commodities.

[9] As we explain in Section 3.1, one can view our $AC(1)$ measure as the (minus of) day t return to a dynamic short-term reversal trading strategy, in which one buys recent losers and sells recent winners, and the weight is based on the magnitude of return on day $t-1$ ($r_{i,t-1}$). In other words, day $t-1$ information determines the strategy weight at the end of day $t-1$ but should not mechanically predict the strategy return in day t.

[10] The scaling factor in AC, σ_i^2, is a constant. Statistical inference is not affected if we drop this constant. Thus, our results are not

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subject to a forward-looking bias. In Online Table A6, we show results with no scaling and with σ_i^2 computed based on prefinancialization period samples. It shows that our conclusions are robust to choices of the scaling factor.

[11] The log basis is defined as

$$Basis_{it} = [\ln(F_i(t, T_1)) - \ln(F_i(t, T_2))]/(T_2 - T_1),$$

where $F_i(t, T_1)$ and $F_i(t, T_2)$ are the futures prices of the nearest and second nearest contracts with T_1 and T_2 as their maturities, respectively.

[12] For each commodity, we compute its illiquidity measure according to Amihud (2002):

$$Illiquidity_{it} = |r_{it}|/(\$billion)TradingVolume_{it}.$$

To mitigate the effect of outliers and heavily positive skewness, we first winsorize the illiquidity measure at the top 5% and then perform the standardization.

[13] We include year fixed effects instead of day fixed effects, which would fully absorb the daily total index exposure. The fact that ETF flows are neither highly persistent nor correlated with contemporaneous returns alleviates the concern of Stambaugh (1999) bias, which may arise from the inclusion of time fixed effects.

[14] We acknowledge that the indexed commodities and nonindexed commodities may have distinctive features in the covariates (see summary statistics in Online Table A2), which may result in the violation of the parallel pretrends assumption. In Section 4.1, we provide a more sophisticated approach to address the issue.

[15] Similar to $AC(1)$, one can also interpret the $AC(2, 5)$ measure as the (minus of) day-t return to a dynamic short-term reversal trading strategy, in which one buys recent losers and sells recent winners, and the weight is based on the magnitude of returns from day $t-2$ ($r_{i,t-2}$) to $t-5$ ($r_{i,t-5}$).

[16] Following Abadie (2021), we do not impose the "convex hull" assumption by allowing the portfolio weights to be negative. This relaxation is economically meaningful as investors can short the commodity futures easily.

[17] We use the median as it is more robust against outliers than the mean. In addition, we study the cross-sectional average of $AC(1)$s because it aligns with the panel regression setting in (7) in which the coefficient is constant across commodities. The constant coefficient just corresponds to the "mean group" in heterogeneous panels (Pesaran and Smith 1995).

[18] Because the commodity financialization is a continuing process instead of an event with a specific origination year, its impact is not necessarily to emerge immediately after 2004. Figure 2 also shows that the return autocorrelation coefficients of commodity indices become significantly negative after 2006.

[19] The confidence interval for the median is constructed by following Conover (1999).

[20] The iPath Bloomberg Commodity Index Total Return ETN (DJP) is designed to track the Bloomberg Commodity Index Total Return. The iShares S&P GSCI Commodity-Indexed Trust (GSG) is designed to track the S&P GSCI Total Return. The Invesco DB Commodity Index Tracking Fund (DBC) is designed to track the DBIQ Optimum Yield Diversified Commodity Index Excess Return. The U.S. Commodity Index Fund (USCI) is designed to track the SummerHaven Dynamic Commodity Index Total Return. Despite that we refer to all four index products as ETFs, strictly speaking, DJP is an ETN, which is a structured product issued as a senior debt note. The difference between ETF and ETN, however, is less relevant for our flow analyses in this section.

[21] See Brown et al. (2021) for a detailed discussion of the measurement issues.

[22] To mitigate the outliers, we winsorize 1% of the CNFDI measure at the top and bottom 0.5 percentiles each.

[23] According to the TRNA-C manual, news tones are calculated based on a neural network algorithm, and reported accuracy is around 75%.

[24] As shown by Casassus et al. (2012), different commodities from the same sector are likely to have fundamental relationships of production (e.g., heating oil and crude oil) and substitution (e.g., Chicago wheat and Kansas wheat).

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