BEYOND OIL: THE ORIGINS OF COMMODITY PRICE FLUCTUATIONS

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ABSTRACT. We construct measures of supply and demand disturbances in commodity markets using textual analysis in news articles spanning the 2001 to 2023 period. Our empirical analysis utilizing text-derived indicators establishes an important role for supply-side disturbances coming from the non-petroleum markets: negative supply shocks lead to declines in measures of economic activity and increases in inflation. The implied passthrough of these supply-side disturbances to both quantities and prices is significantly larger than those arising in oil markers during our sample period.

JEL classification codes: C19, F30, G15, Q02.

Keywords: commodities, textual analysis, news, demand, supply, business cycles, geopolitical risk, natural disasters, climate change.

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1. Introduction

Ever since the fundamental work of Kydland and Prescott (1982), which attributes business-cycle fluctuations to supply shocks, macroeconomists have been in search of empirical measures of supply-side disturbances. Despite their central importance in the theory of real business cycles, success in measuring these disturbances has been limited. The most notable progress in identifying supply-side shocks comes from the oil markets (Hamilton, 1983, 2003).[1] Yet, oil represents a relatively small share of modern economies and plays a less dominant role than during the oil crises of the 1970s. Modern economies depend on diverse commodity inputs that extend far beyond petroleum, whose supply is subject to random disturbances that could plausibly drive fluctuations in quantities and prices. Despite the richness of methodologies that developed to study the oil market, much less attention has been devoted to other key commodities, whose importance has only grown in light of the COVID-19 pandemic, Russia's invasion of Ukraine, and ongoing geopolitical tensions.

In this paper, we fill this gap by constructing broad measures of supply-side disturbances originating in commodity markets, derived from news coverage of commodity developments. Because commodities are essential inputs across most production sectors, shocks to their supply represent a plausible source of business-cycle fluctuations. Using these measures, we show that commodity-driven supply disturbances have sizable effects on both output and prices. Our text-based approach spans the full commodity spectrum and delivers high-frequency real-time indicators that decompose price movements into supply and demand components, with additional granularity on their underlying drivers.

The key identification challenge is to separate supply-driven from demand-driven fluctuations in commodity prices. We address this by extracting information from news articles that explicitly link price changes to their underlying drivers. Starting with a market-wide commodity index, we then extend the approach to distinct commodity categories, including energy, industrial and precious metals, agricultural commodities, and livestock. The breadth of news content allows us to decompose both supply and demand indices into key determinants that have shaped commodity markets since the early 21st century, such as business-cycle conditions, geopolitical risks, natural disasters, and climate change. This, in turn, enables us to trace how the influence of long-standing drivers has evolved over time and to document the emergence of new trends affecting commodity prices.

We find that supply disruptions in commodity markets matter for macroeconomic outcomes and firms' decisions alike. Importantly, we show that disturbances arising from non-oil commodities, despite having been long overlooked, are quantitatively and statistically significant. In fact, supply-driven fluctuations in non-oil markets are cumulatively more stagflationary than those originating in oil markets and are often more persistent. Our methodology also extracts demand signals across

[1] More recent work in this area includes Kilian (2009); Antolín-Díaz and Rubio-Ramírez (2018); Baumeister and Hamilton (2019); Caldara, Cavallo, and Iacoviello (2019), and Känzig (2021).

commodity markets, providing a natural bridge to the New Keynesian paradigm. Although New Keynesian models emphasize the central role of aggregate demand in driving business cycles, the empirical literature has long struggled to distinguish demand shocks from supply shocks. Our text-based approach delivers narratively identified demand signals, enabling direct tests of New Keynesian predictions about how demand disturbances propagate through the economy.

Using structurally estimated oil supply shocks as a benchmark, we validate our approach through a series of tests demonstrating that our indicators capture meaningful information in previously understudied commodities. Diagnostic regressions further reveal robust correlations between tradable commodity returns and our text-based indicators.

Our indices capture major market events. The market-wide demand measure contracts sharply during the 2008 Great Recession and the COVID-19 crisis, while the supply measure successfully identify significant supply disruptions, including natural disasters and logistical bottlenecks. At the individual commodity level, our measures track market-specific developments with precision. Demand indicators for commodities with relatively elastic demand, such as oil, copper, and sugar, exhibit pro-cyclical behavior. Supply indicators display patterns that reflect each commodity's unique production characteristics: oil supply responds primarily to OPEC decisions that partially accommodate demand and inventory conditions, whereas wheat supply is largely driven by weather fluctuations. At the macroeconomic level, our findings confirm the theoretical distinction between supply and demand shocks: supply contractions raise prices while reducing output and employment, while demand expansions increase both prices and economic activity. This asymmetry, long predicted in theory, emerges clearly in our estimations. We also examine how developments in commodity markets affect firm-level decisions. Supply contractions are associated with higher input costs, reduced investment rates (consistent with real options theory), and higher sales, as scarcity effects can outweigh recessionary pressures. In contrast, demand expansions correspond with rising input costs, increased investment, and higher sales volumes, reflecting standard economic intuition about firm responses to strengthening market conditions.

Our methodology provides a coherent and comprehensive framework for tracking global commodity market developments in real time. By extracting supply and demand signals from news narratives, we construct daily indicators that can stand alone or enhance the predictions of structural models. We develop a two-stage textual analysis protocol to systematically capture commodity market developments. First, we conduct a rigorous content analysis to identify lexical patterns (words and word combinations) associated with the underlying determinants of commodity prices. This process involves constructing an audited taxonomic dictionary from our comprehensive corpus. We then compute standardized frequency measures–occurrences of dictionary terms paired with directional modifiers, normalized by the total number of articles–yielding robust metrics of supply and demand dynamics. Second, to decompose the multidimensional sources of commodity price movements, we draw on

training libraries of authoritative texts covering business cycles, geopolitical risks factors, natural disasters, and climate change developments. By computing the conditional frequencies of these topical patterns within supply and demand contexts, we can map the origins of commodity market fluctuations. This framework produces nuanced indicators that capture both the prevalence and directional impact of commodity-related developments, offering valuable signals for economic analysis and forecasting (Malliaropoulos, Petroulakis, and Passari, 2025). We also conduct an extensive audit study of randomly selected articles from the full sample and use the results to evaluate the performance of our computer-based indices. The correspondence between the human-coded and machine-generated indices is strong, with correlations reaching up to 85% in quarterly data.

A key contribution of our work is is the decomposition of commodity supply and demand into their underlying fundamental drivers. Building on the taxonomies used in the IMF's *Commodity Special Feature* and the World Bank's *Commodity Markets Outlook*, we classify the components that shape commodity market fluctuations. This decomposition uncovers distinct patterns in the economic mechanism governing commodity markets. We find that natural disasters are the dominant drivers of supply fluctuations across commodities, while business cycle dynamics primarily determine net demand variations-with the notable exception of the COVID-19 pandemic, which appears as a severe negative natural disaster shock in 2020. Net supply disruptions are concentrated in grains, softs, and energy markets and occur asynchronously, whereas net demand fluctuations broadly display cyclical patterns across commodity categories (apart from grains, which exhibit lower demand elasticity outside episodes of trade conflict). Our decomposition of drivers across commodity categories reveals systematic patterns. Business cycle fluctuations primarily affect energy, industrial metals, precious metals, and biofuel-related soft commodities. Geopolitical risks disproportionately impact energy, precious metals, and softs. Natural disasters mainly disrupt grains and softs with secondary spillovers into energy markets. Climate-change-related concerns are most pronounced in energy markets and increasingly relevant for industrial metals.

Although supply shocks have long been thought to play a central role in macroeconomic fluctuations, empirical evidence has remained surprisingly limited. Theoretical models, from the multi-sector real business cycle model of Long and Plosser (1983) to the production network models by Acemoglu et al. (2012), and the multi-Sector DSGE models of Horvath (2000), Atalay (2017) and Baqaee and Farhi (2022), all highlight supply-side propagation. Our contribution is to provide direct empirical evidence for these mechanisms by showing how commodity supply shocks transmit through the economy and generate stagflationary pressures.[2] The recent experience of COVID-19 has also renewed interest in supply-side explanations. Bernanke and Blanchard (2025) emphasize that supply chain disruptions were a key driver of inflation during the pandemic. But was COVID an exception or part of

[2]Other notable contributions to the production network literature include the works of Baqaee and Farhi (2019, 2020) and Carvalho and Tahbaz-Salehi (2019).

a broader pattern? Our analysis shows that a wide range of commodity supply disruptions, including those stemming from geopolitical conflicts, natural disasters, and climate change, systematically shape macroeconomic outcomes.

Our work builds on several growing strands of the literature. First, it relates to the expanding body of research that uses textual analysis to measure economic outcomes, including Tetlock (2007), Gentzkow and Shapiro (2010), Hoberg and Phillips (2010), Boudoukh, Feldman, Kogan, and Richardson (2013), Alexopoulos and Cohen (2015), Baker, Bloom, and Davis (2016), Allcott and Gentzkow (2017), and Hassan et al. (2019). We contribute by bringing these textual methods to the commodity space, where the breadth and heterogeneity of price drivers make narrative approaches particularly powerful and adaptable. Second, our work complements the extensive literature that identifies supply and demand shocks in energy markets (Kilian, 2008, 2009; Kilian, Rebucci, and Spatafora, 2009; Kilian and Vigfusson, 2017; Känzig, 2021). We extend this line of work beyond energy to the full spectrum of commodity markets, providing a unified framework for capturing sources and drivers of commodity price fluctuations. Third, our analysis relates to the recent literature that constructs narrative measures for shock identification in the spirit of Romer and Romer (2010), including Wu and Cavallo (2012), Caldara, Cavallo, and Iacoviello (2019), Datta and Dias (2019), and Loughran, McDonald, and Pragidis (2019). In our setting, the indices identify whether commodity price fluctuations originate from supply or demand pressure and trace their underlying sources (business-cycle dynamics, geopolitical risk, natural disasters, or climate change). To our knowledge, this is the first attempt to build a real-time global commodity index and obtain measures of major commodity categories, including agricultural commodities, industrial and precious metals, and livestock, using an automated narrative approach. Although commodity markets are heavily dominated by energy, the broad coverage of news outlets, combined with our standardized methodology and natural language processing (NLP) algorithms, ensures that the resulting indices are comparable across categories. More importantly, the additional refinement step in our algorithm enables us to distinguish among different types of supply and demand developments, each of which has distinct implications for the real price of the commodity in question.

The remainder of the paper is organized as follows. Section 2 presents our methodology and introduces our commodity indices. In Section 3 we evaluate the indices by relating them to tradable commodity returns, as well as through a comprehensive human audit exercise. Section 4 compares our crude oil indices with standard oil shocks identified using structural methods. Section 5 compares the macroeconomic responses to oil and non-oil disturbances and reveals that the latter are quantitatively larger. Section 6 decomposes the indices into factors driving commodity price fluctuations and documents the time-varying importance of these factors. In Section 7, we examine the differential effects of our commodity indices on firm-level outcomes. Section 8 concludes.

2. Building Supply and Demand Commodity Measures

The fundamental identification challenge in commodity market analysis is distinguishing supply-driven from demand-driven fluctuations. Although sophisticated structural methods have been developed for the oil market, extending these approaches to the much broader set of commodity markets poses substantial methodological difficulties. These challenges arise from data limitations as well as the problem of choosing suitable identifying restrictions across markets that differ dramatically–from energy to agriculture to metals–each with its own production structure, adjustment dynamics, and capacity constraints.

Consequently, few papers derive structurally-estimated supply measures outside the energy sector, with few exceptions that model food and agricultural production shocks by focusing on harvest disturbances and extreme weather events (Winne and Peersman, 2016; Castelnuovo, Mori, and Peersman, 2024), or leverage the use of USDA announcements in the spirit of Känzig (2021) (Adjemian and Jo, 2025). Rather than attempting to construct fully identified structural shocks across numerous heterogeneous markets, our narrative methodology builds robust proxies for supply and demand disturbances that span the commodity universe in a consistent and comparable way across markets.

Our methodological innovation exploits the information content of financial news reporting, operating under the premise that 1. economically significant shocks manifest in news coverage with minimal delay, and 2. that shock magnitude correlates positively with reporting breadth and intensity. We construct indices through textual analysis that simulates systematic news-reading protocols. These indices capture supply and demand developments using a narrative econometric approach that quantifies both the frequency and directional content of commodity news reporting.

Beginning with a framework that captures market-wide commodity sentiment, we extend our methodology to encompass the complete spectrum of commodity categories: energy, industrial and precious metals, agricultural commodities, and livestock, providing comprehensive coverage of global commodity markets through a unified methodological framework.

Our methodology employs a two-stage process for extracting commodity market information from textual data. In the first stage, we conduct systematic content analysis, identifying lexical patterns–specific words and phrasal combinations–that signal supply and demand factors within sentence-level contexts.

The second stage implements refinement algorithms that enhance measurement precision through contextual filtering. These algorithms account for semantic negations and incorporate commodity-specific exceptions that adjust for the idiosyncratic reporting patterns across different commodity categories. This refinement process substantially improves signal extraction by reducing classification errors that would otherwise arise from linguistic complexities and market-specific reporting conventions.

Prior to implementing text-reading algorithms, we standardize the structure of news articles through a series of preprocessing procedures. First, we segment article content into sentence-level units, which serve as the fundamental semantic domains for our subsequent analysis. This sentence-level approach provides the appropriate contextual boundaries for identifying economically relevant word patterns.

We then apply lemmatization to reduce inflectional forms to their canonical representations, ensuring that morphological variants of the same lexical item are treated as equivalent. Following standard econometric practice in textual analysis, we eliminate stop words and punctuation from the corpus. This normalization procedure serves multiple functions: it neutralizes journalist-specific stylistic variations, reduces computational storage requirements, and enhances algorithmic efficiency.

Although stop word inventories vary across Natural Language Processing applications, they consistently encompass high-frequency functional terms (e.g., "the," "is," "at," "which," "and," "on") that carry minimal informational content relevant to economic analysis. The removal of these elements allows our algorithms to focus exclusively on content-bearing terms that signal substantive economic information.

We proceed to identify words and word combinations that can be attributed to supply and demand factors. Initially, we perform frequency analysis to identify high-occurrence terms within our corpus. [3] Subsequently, we evaluate each high-frequency term individually, classifying relevant items into supply-related and demand-related categories based on their economic significance.

This computational classification process is supplemented with extensive human validation checks conducted on a representative sample of news articles to ensure semantic consistency and contextual accuracy. These verification procedures establish the foundation for our supply and demand dictionaries.

To capture directional information, we incorporate standardized dictionaries of terms that signal increase and decrease and have been validated in the economic textual analysis literature. The operational implementation combines supply and demand terminology with directional indicators, creating compound semantic units that capture both the market dimension (supply/demand) and directionality (expansion/contraction) of commodity market developments.

Our methodology quantifies lexical co-occurrences of market dimension terms (supply/demand) and directional modifiers within defined sentence-level proximity parameters. Specifically, we count the instances where supply or demand words and word combinations appear in conjunction with directional indicators within a specified word-distance threshold on either side of the focal market term.

[3] Refer to Appendix A. Article Handling, for details pertaining to article selection.

From these numbered co-occurrences, we derive directionally sensitive market indicators by constructing net measures. The net supply indicator represents the differential between supply contractions and supply expansions, while the net demand indicator captures the excess of demand expansions over demand contractions. These net indicators provide continuous measures of directional market pressure that can be analyzed at various time frequencies.

To enhance measurement precision, we augment our baseline methodology with contextual refinement algorithms that address semantic negations and commodity-specific idiosyncrasies. This refinement is particularly critical for ensuring that the paired market dimension and directional terms accurately reflect the underlying economic information content of news articles.

Certain commodity categories exhibit systematic semantic inversions that would otherwise generate measurement error. For agricultural commodities, phrases combining positive directional terms with supply-related words may counterintuitively signal supply contractions rather than expansions–for instance, "high temperature" indicates adverse growing conditions and supply contraction rather than supply expansion. Similarly, in energy markets, "long maintenance" represents supply disruption rather than increase. Our algorithm implements commodity-specific exception handling to correct these semantic inversions, ensuring consistent economic interpretation across diverse commodity classes.

Additionally, the refinement process enables the classification of supply and demand developments into distinct subcategories by exploiting supplementary identifier terms. This approach permits the disaggregation of supply and demand fluctuations into components associated with global economic activity, consumption patterns, geopolitical events, natural disasters and other economically relevant categories, providing a multidimensional characterization of commodity market dynamics.

Our approach strives to provide simple, global and transparent measures that are both informative and accurate. Our starting point is a concise, generalizable dictionary that measures market-wide commodity sentiment and distills the important news announcements into supply and demand components. [4] Building upon this core framework, we extend the baseline commodity-wide dictionary to develop commodity-specific lexicons that cover different markets. Additionally, we build algorithms that provide substantial refinements, correct errors, and are able to further characterize the type of supply and demand development.

2.1. **News Outlets and Article Selection.** Our empirical analysis utilizes Reuters news articles as the primary data source for constructing commodity market indicators. The dataset encompasses more than 1,100,000 articles spanning May 2000 through May 2023, providing extensive temporal coverage of market developments across multiple commodity cycles. All textual data are accessed through

[4] We incorporate selective exception handling for cases where there is classification ambiguity–such as the word "plant," which carries supply connotations in agricultural contexts (planted crops) but demand implications in manufacturing contexts (pasta plants).

the Factiva database, ensuring consistent article formatting and comprehensive coverage of market-relevant information.

Our data preparation protocol implements a multi-stage filtering process to ensure the corpus contains only relevant and non-redundant articles. Initially, we eliminate both identical and near-duplicate articles from the raw Factiva sample to prevent double-counting of information. We then apply a commodity-specific relevance filter to exclude articles primarily focusing on substitute commodities, which could otherwise introduce measurement error.

For commodity-specific indices, we employ a relative frequency criterion to ensure topical relevance: articles are excluded when mentions of competing commodities exceed commodity-specific references by a factor of two or greater. For example, in constructing wheat market indicators, we filter out articles where terms such as "corn," "soybean," "barley," "rice," "maize," "coffee," "cocoa," "sugar," "cotton," "palm," "oilseed," and other competing agricultural commodity terminology dominate the content. Conversely, for the aggregate commodity index, we employ an inclusive approach, incorporating all articles containing commodity-related terminology, with procedural details documented in Appendix A.

To ensure textual fidelity, we validate that scraped article content precisely matches the original published documents. Additional data integrity procedures include verification of sentence segmentation accuracy, disambiguation of proper nouns that might otherwise be conflated with dictionary terms through capitalization checks, and systematic handling of negations that could otherwise distort frequency-based measurements.

2.2. **Do News Report Commodity Shocks?** To establish the empirical validity of our methodological assumption-that shocks that have a big impact on commodity markets generate immediate news coverage-we conduct a validation exercise using exogenous, unforeseeable events. This approach allows us to assess the temporal relationship between actual market disruptions and their corresponding media footprint.

We present systematic evidence on this relationship, documenting the news coverage patterns following an exogenous supply disruption: mining output disruptions resulting from seismic events in South America. The empirical patterns in these data serve as the foundation for our subsequent textual analysis framework by confirming that market-relevant information is indeed captured with minimal lag in financial news reporting.

Table 1 documents the correspondence between seismic events in major copper-producing regions and our textual supply indicators. Merging seismic data from EM-DAT with our high-frequency copper supply indicators, we compute the first-difference response in both the natural disaster component of copper supply disturbance and the aggregate supply measure on earthquake dates relative to the preceding day's values. The empirical pattern demonstrates systematic covariation between

TABLE 1. Major Earthquake in Peru and Chile and Change in Copper Net Supply Indices

Country	Date	Magnitude	Total Affected	Δ Net Supply (Copper, Nat. Dis.)	Δ Net Supply (Copper, All)
PER	2005-09-26	7.5	2,505	0.98	0.25
CHL	2007-11-14	7.7	25,155	4.9	0.83
CHL	2010-02-27	8.8	2,671,556	4.2	0.45
PER	2021-11-28	7.2	17,912	2.4	0.63

significant seismic events (magnitude greater than 7.0) in Chile and Peru and our textual indicators, with particularly pronounced responses to earthquakes close to mining operations that materially disrupt production capacity.[5] This high-frequency response pattern provides validation that our textual methodology captures exogenous supply disruptions with temporal precision.

2.3. **A Market-wide Measure of Commodity Supply and Demand.** For the aggregate commodity market indicator, we implement an inclusive sampling approach that encompasses all articles that contain references to commodities included in the Standard & Poor's Goldman Sachs Commodity Index (GSCI) spot price series. This selection criterion ensures comprehensive coverage of economically significant commodity markets, as the GSCI tracks major physical commodities characterized by active and liquid futures markets, thereby providing a representative measure of broad commodity market developments.

Table 2 presents the taxonomic classification of individual commodity constituents by category, defining the universe of commodities considered in our analysis. This commodity set encompasses the full range of major tradable commodities across energy, metals, and agricultural markets.

TABLE 2. The S&P GSCI Composite Index Constituents Used as Keywords for the Construction of the Global Commodity Supply & Demand Index Series

Energy	**Industrial Metals**	**Precious Metals**	**Agricultural**		**Livestock**
			Grains	**Softs**	
Crude Oil	Aluminum	Gold	Corn	Cocoa	Cattle
Heating Oil	Copper	Silver	Soybeans	Sugar	Lean Hogs
Natural Gas	Nickel		Wheat	Coffee	
	Zinc			Cotton	

For each individual commodity, we derive directional market pressure measures. First, we construct four primary indicators capturing supply increases, supply decreases, demand increases, and

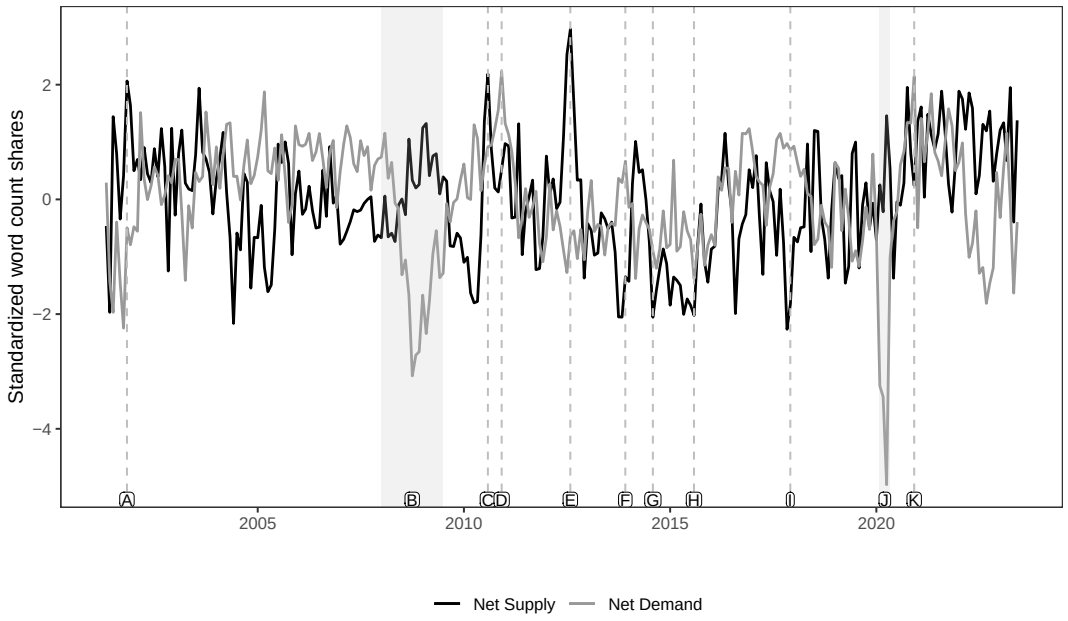
[5]We implement an exclusion criterion for the November 16, 2015 Chilean earthquake (magnitude 8.3) despite its substantial seismic intensity, as its epicentral location exhibited significant spatial distance from active mining operations.

demand decreases. Second, we calculate net measures by differencing the opposing directional indicators: net supply represents the excess of supply contractions over supply expansions, while net demand captures the surplus of demand expansions over demand contractions. Figure 1 presents the standardized monthly net supply and demand indicators derived from our comprehensive Reuters article corpus. These indicators are normalized by the daily count of retained articles to control for potential measurement distortions arising from variations in publication volume over time. The resulting time series exhibit pronounced correspondence with established commodity market developments. Significant inflection points align with systemic economic events, including substantial fluctuations during the global financial crisis (2007-2009), the COVID-19 pandemic (2020-2021), and the U.S. debt ceiling crisis. Supply-side indicators register substantial volatility during periods of significant production adjustments, notably during OPEC interventions following the 2001 recession and the September 2001 terrorist attacks, as well as during subsequent quota revisions. Agricultural supply indicators display pronounced contractions coinciding with severe drought episodes that significantly impaired global grain production.

Figures 2 and 3. present the decomposition of supply and demand indicators and their constituent drivers across major commodity categories. The cross-sectional analysis reveals distinct patterns in the incidence and synchronicity of market developments. Supply disturbances manifest predominantly in grains, softs, and energy markets, with notably asynchronous temporal distributions, suggesting commodity-specific rather than systemic supply-side pressures.

Demand fluctuations, conversely, display substantial cross-sectional correlation, with cyclical patterns evident across most commodity categories. This synchronization is consistent with common macroeconomic determinants of demand conditions. A notable exception is observed in grain markets, which exhibit lower demand elasticity outside periods of trade conflict, reflecting the relatively inelastic consumption patterns characteristic of staple agricultural commodities.

FIGURE 1. Standardized Net supply and Standardized Net Demand across All Commodity-Related News Articles (Reuters sample)



Note: This figure plots the standardized net supply and demand indicators for the period between 2001 and 2023. The bars map a number of well-known commodity-wide developments. These events are: [A] US recession and 9/11 weighs on commodity markets, [B] OPEC to raise output quotas, [C] Global Financial Crisis, [D] Worst drought in more than 50 years in the US cuts corn and soybeans productions [E] Oil market oversupply due to record-high US crude oil production and stronger-than-expected production recovery in Libya; better-than-expected growth in all major economies bolsters demand. [F] Covid-19 dents demand and disrupts supply chains. [G] Russo-Ukrainian War concerns about supply shortages in grains, oil, and metals, [H] Demand concerns from rising global interest rates, China's COVID-19 lockdown extensions, [I] US debt-ceiling crisis.

FIGURE 2. Decomposition of Composite Index across Categories: CSI

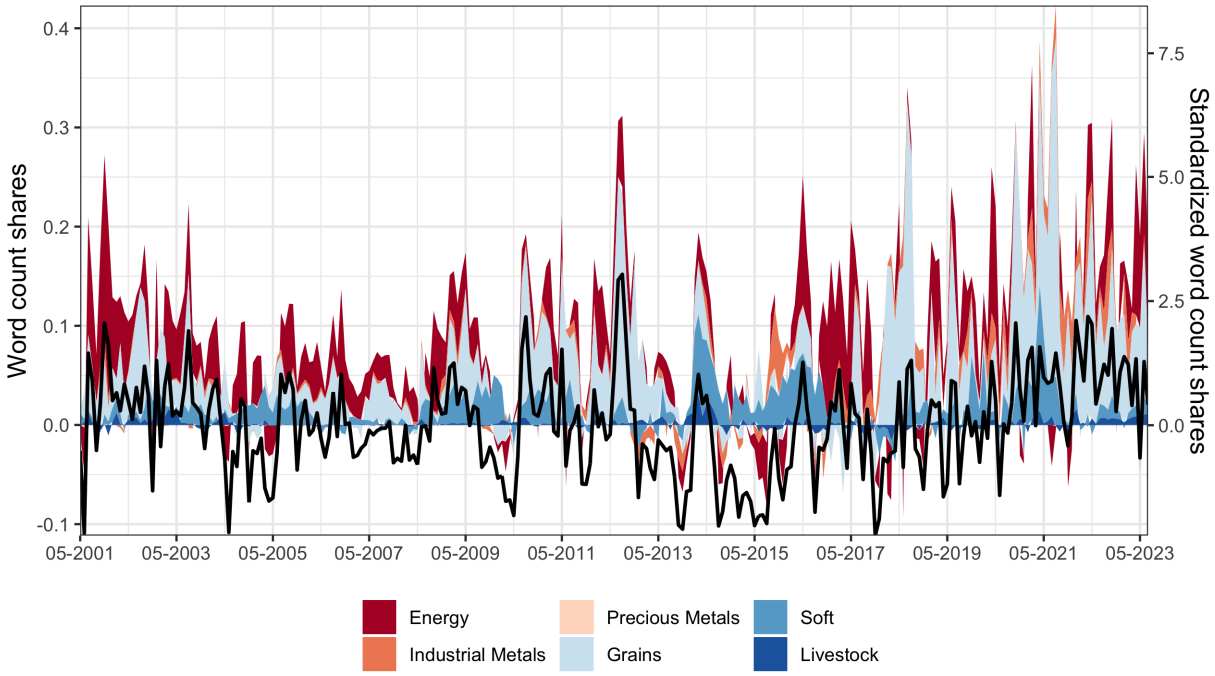
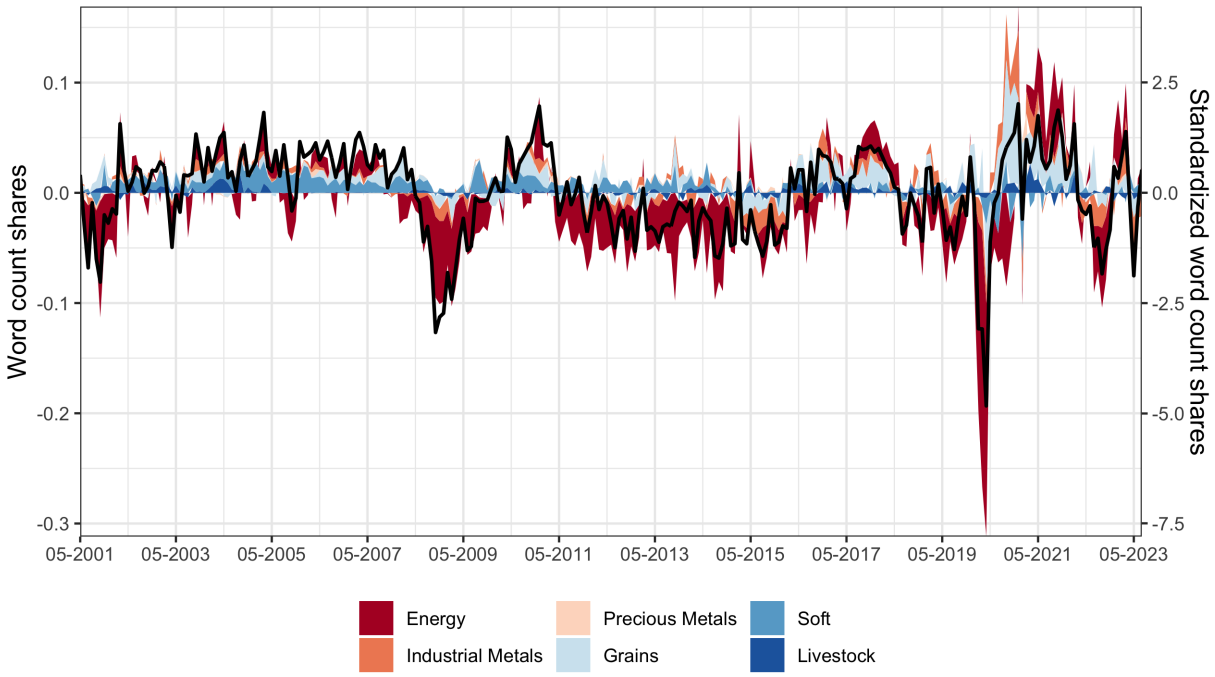


FIGURE 3. Decomposition of Composite Index across Categories: CDI



2.4. **Measure of Supply and Demand Developments for Individual Commodities.** We extend our methodological framework to encompass the complete spectrum of commodity categories, including energy, industrial metals, precious metals, agricultural commodities, and livestock products.

To implement this extension, we augment the core lexicons employed in the aggregate index construction with commodity-specific terminology that captures idiosyncratic supply and demand factors. Tables B2, B3, and B4, in the Appendix, present the dictionaries for crude oil, natural gas and wheat. present the specialized dictionaries developed for crude oil, natural gas, and wheat markets, respectively. These commodity-specific lexicons maintain parsimony and structural simplicity to minimize classification errors and attribution inaccuracies.

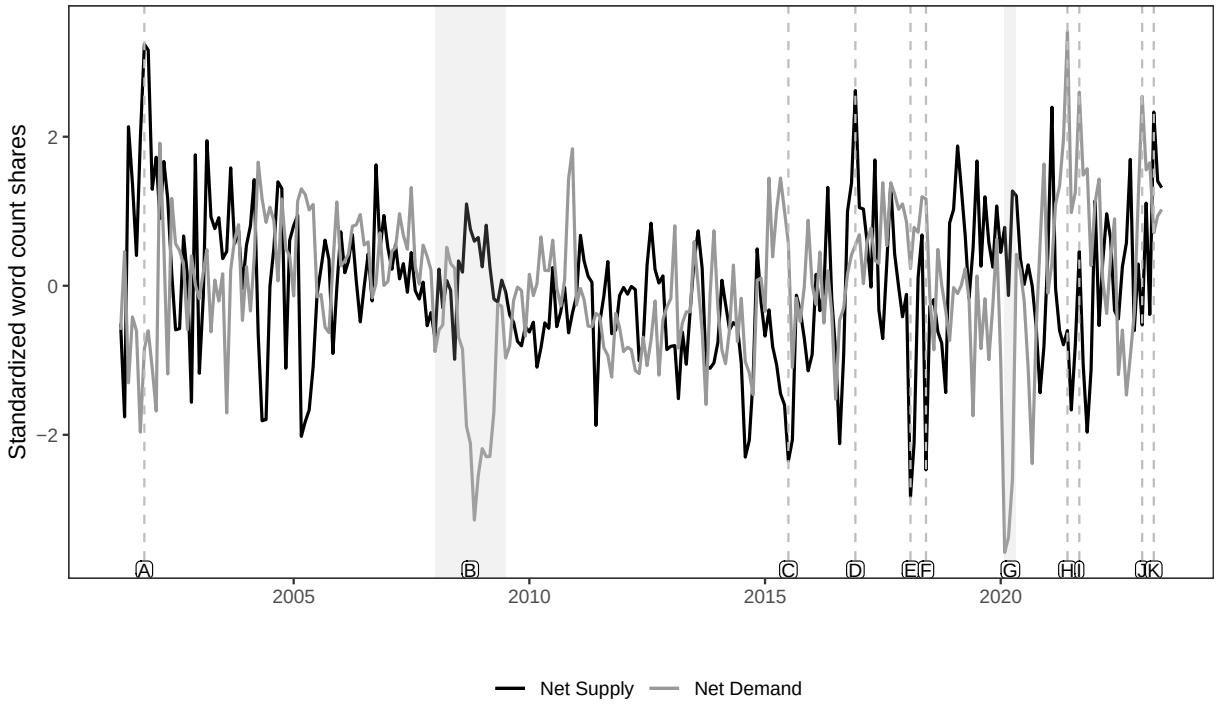
The algorithmic implementation incorporates contextual filtering to ensure appropriate attribution of market developments. Specifically, the algorithm identifies sentences containing explicit references to the target commodity while excluding informational content from sentences referencing competing commodities, thereby preserving measurement specificity.

The resulting commodity-specific indicators–presented for crude oil, wheat, corn, sugar, and copper–reveal substantial heterogeneity in the underlying drivers of market developments across commodity categories. The energy and metals markets exhibit pronounced sensitivity to the business cycle, with demand fluctuations closely following macroeconomic conditions. In contrast, agricultural commodities, both grains and softs, show greater sensitivity to natural disaster events and characteristically inelastic demand structures, reflecting their distinct production processes and consumption patterns.

2.4.1. *Energy Commodities: Crude Oil.* Our crude oil indicators capture well-documented market developments, particularly production adjustments following OPEC ministerial meetings. OPEC supply management decisions constitute the predominant source of supply-side variation in global oil markets. Additional supply disruptions stem from production impairment due to natural disasters (storms), the structural expansion of U.S. production capacity during 2014-2016, and the acute oversupply conditions of April 2020, which–combined with pandemic-induced demand contraction–precipitated both price collapse and physical storage constraints.

Demand for petroleum products exhibits pronounced cyclicality, with significant demand contractions coinciding with major macroeconomic downturns: the 2001 U.S. recession, the 2007-2009 global financial crisis, and the initial phase of the COVID-19 pandemic. Figure 4 further illustrates the rapid demand recovery patterns observed in 2021, following global vaccination deployment, and early 2023, subsequent to China's economic reopening, demonstrating the sensitivity of petroleum consumption to mobility restrictions and economic activity.

FIGURE 4. Crude Oil Index: Standardized Net supply and Standardized Net Demand Share of Total Number of Words per Month



Note: This figure plots the standardized net supply and demand indicators for the period between 2021 and 2023. The bars map a number of well-known oil sector developments. These events are: [A] OPEC cuts output to lift oil prices following US 2001 recession. [B] 118th OPEC Meeting, production cut following US economic slowdown & 9/11. [C] OPEC to raise output quotas (131st E.M.). [D] OPEC pumps at 25-year highs to cater for high demand expected from China. [E] 150th & 151st OPEC E.M.: production cut (GFC). [F] Faster than expected recovery of Libyan oil production & unaffected Iraq production: perceived glut. [G] Worries about oversupplied oil market (China's slowdown); Middle East producers pump crude at record levels. [H] OPEC 171st Meeting: OPEC & non-OPEC to cut output for first time in 8 years. [I] OPEC+ extended cuts in oil output to battle global glut. [J] US record oil production: oversupply worries. [K] OPEC to raise oil production amid calls from top consumers to cool prices & support world economy. [L] OPEC production cuts & US sanctions on Iranian and Venezuelan crude. [M] COVID-19. [N] Winter storm in Texas causes US crude production drop. [O] Global economy and oil demand recover faster than expected following vaccination. [P] The US announces release of millions of barrels from strategic reserves in coordination with China, India, South Korea, Japan & Britain, to cool prices. [Q] Subsiding recession risks in major economies & reopening of China's economy boost demand. [R] Surprise decision by OPEC+ to cut output (48th JMMC).

2.4.2. *Agricultural Commodities: Wheat, Corn and Sugar.* Figure 5 presents the standardized net supply and demand indicators for wheat markets from 2001 through 2023. The supply indicator identifies major production disruptions coincident with extreme meteorological events affecting global wheat

cultivation. Adverse growing conditions–including drought episodes, extreme temperature events, and other detrimental weather patterns–register as significant negative supply developments in our index.

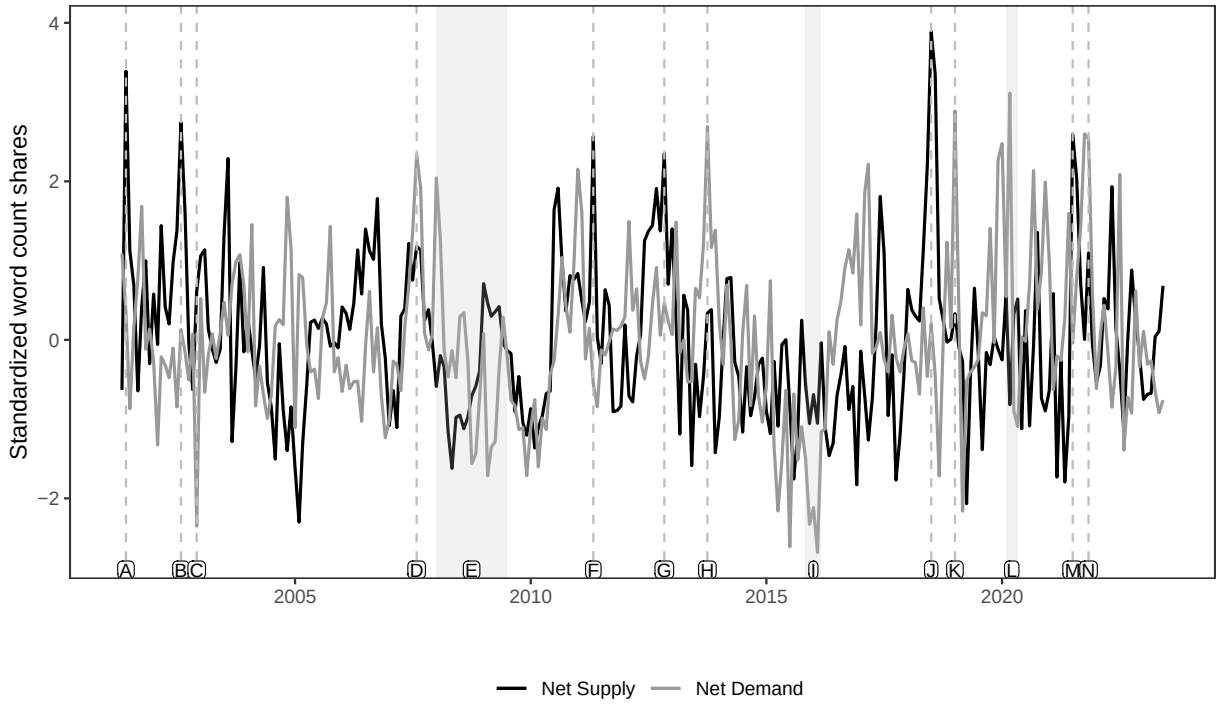
Demand indicators for wheat exhibit distinct patterns relative to energy commodities, with pronounced positive demand shocks corresponding to bilateral trade agreements between major market participants (notably U.S.-China agricultural procurement commitments) and precautionary consumption behaviors, particularly evident in the stockpiling observed during the initial pandemic phase. This pattern highlights an important cross-commodity distinction: while energy demand indicators primarily reflect cyclical variations in economic activity, agricultural commodity demand indicators are more responsive to precautionary consumption motives and trade policy developments.

Figure 6 presents the standardized net supply and demand indicators for corn markets throughout the sample period. Corn demand exhibits distinctively different patterns compared to wheat, displaying greater elasticity and industrial utilization sensitivity. Pronounced demand increases frequently coincide with biofuel sector expansion, reflecting corn's significant role as an ethanol feedstock. This industrial demand component introduces cyclical sensitivity absent in more consumption-oriented agricultural commodities. The COVID-19 pandemic demonstrates this relationship, as corn demand contracted significantly following the collapse in both ethanol production and livestock markets–key downstream sectors dependent on corn inputs. Additional demand fluctuations stem from trade policy adjustments and tariff implementations that affect international market access.

Supply-side developments in corn markets, similar to wheat, are predominantly influenced by meteorological conditions affecting cultivation outcomes. Differences in supply disruption timing typically reflect the geographical distribution of production regions rather than fundamentally different causal mechanisms.

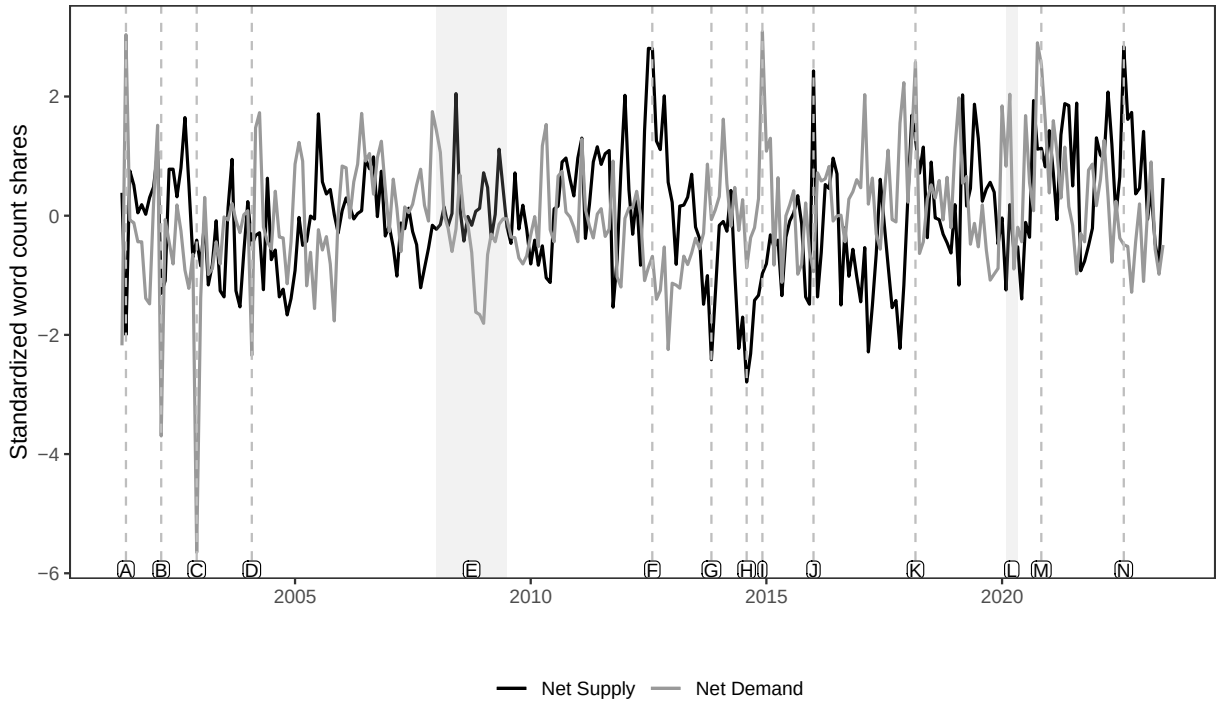
Figure 7 displays the standardized net supply and demand indicators for sugar markets from 2001 through 2023. Sugar demand exhibits distinctive temporal patterns, with pronounced seasonality driven by international holidays and festivals that generate systematic consumption peaks. Additionally, discrete demand surges coincide with geopolitical tensions as market participants engage in precautionary inventory accumulation during periods of elevated uncertainty. Supply-side fluctuations primarily reflect weather-induced production variability and policy-driven adjustments to production quotas, particularly changes in regulatory constraints on sugar beet cultivation over the sample period.

FIGURE 5. Wheat Index: Standardized Net supply and Standardized Net Demand Share of Total Number of Words per Month



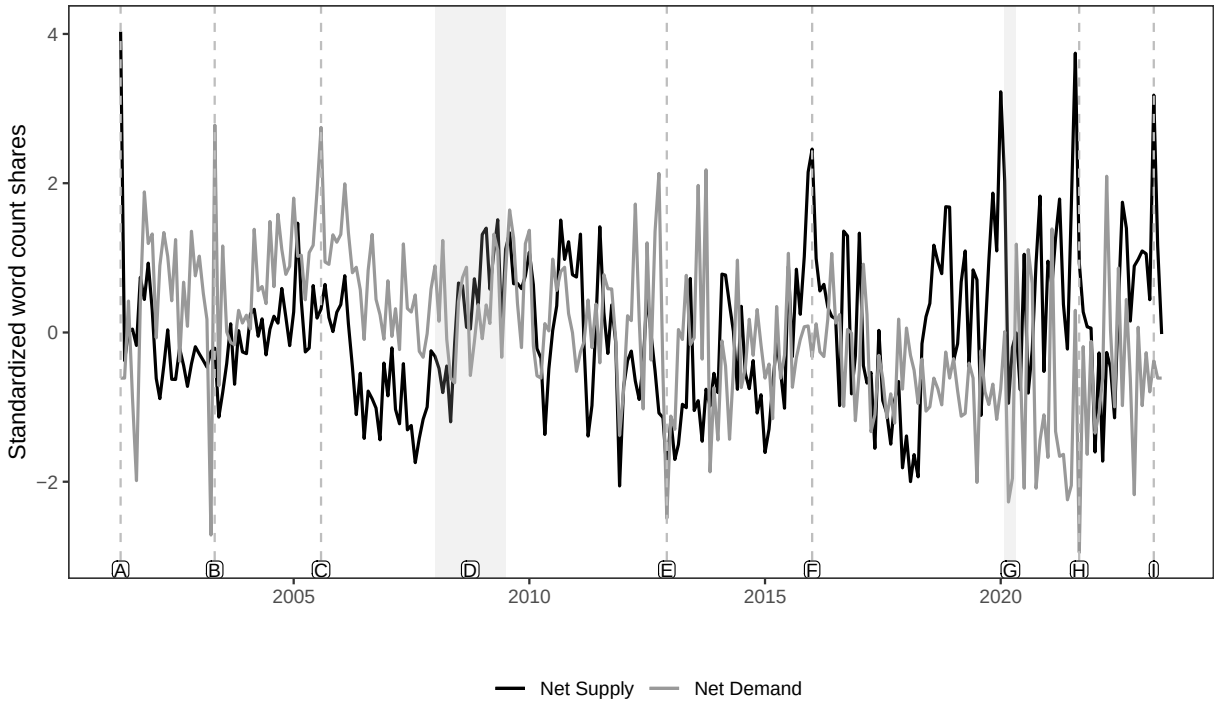
Note: This figure plots the standardized net supply and demand indicators for the period between 2001 and 2020. The bars map a number of important developments in the wheat sector. These events respectively are: [A] Severe drought in Canada cuts wheat production by more than 25%. Dry weather in Australia & US Northern Plains. [B] Hot & dry weather trims European output & Canada's crop. [C] Ample world wheat supplies amid bumper crops. [D] Heatwave: Russia bans exports of wheat; Ukraine imposes export quotas. [E] Dry weather stresses crops in Plains. [F] Weather sparks worries about world supply. [G] Prospects of strong demand from China. [H] Sluggish demand for US supplies due to China's policy shift. [I] Dry weather in US northern Plains threatens crops. [J] Severe drought in Europe cuts harvests. [K] Resuming trade talks between China & the US boosts wheat demand. [L] Abundant world supplies due to crop-friendly weather in key areas. [M] China & the US reach phase one trade deal. [N] Covid-19 cause panic shoppers around the world to stock up on wheat-based items. [O] Strong demand from China following trade deal with the US. [P] Improved US wheat condition ratings. [Q] Above-average global yield expectations pressures wheat markets. [R] Adverse weather conditions & reduced expectations for Russia's harvest. [S] Easing fears of recession; renewed import demand. [T] US winter crop ratings fall amid droughts.

FIGURE 6. Corn Index: Standardized Net supply and Standardized Net Demand Share of Total Number of Words per Month



Note: This figure plots the standardized net supply and demand indicators for the period between 2001 and 2023. The bars map a number of important developments in the corn sector. These events respectively are: [A] (04-2004): Strong domestic and export demand for U.S. corn. [B] (11-2004): Bumper U.S. corn crop. [C] (06-2006): Strong demand for U.S. corn amid booming ethanol sector. [D] (11-2006): Strong demand for U.S. corn by exporters, ethanol manufacturers and livestock producers. [E] (01-2008): Strong demand for corn from the U.S. ethanol sector and importing nations. [F] (06-2008): Crop damage caused by the worst flooding in the U.S. Corn Belt since 1993. [G] (01-2012): Low Argentina's corn crop, which was diminished by hot and dry weather, impacting global supply replenishment efforts following a disappointing U.S. harvest. [H] (07-2012): Low corn supply amid the worst drought since 1956 in the U.S. grain belt. [I] (12-2012): Poor export demand and negative margins at ethanol plants are limiting demand for corn. [J] (11-2013): Record-large U.S. corn production. [K] (08-2014): Bumper crop in the US, Brazil and South Africa. [L] (12-2014): Strong global demand for U.S. corn from traditional buyers, including Mexico, Japan and South Korea. [M] (11-2017): Ample old-crop supplies and favorable weather for the U.S. harvest, large Argentinian corn crop amid good climate conditions, while the French maize crop's yield estimate indicated significant upside potential due to favorable summer weather. [N] (12-2017): Rising demand for corn shipments: China removes VAT on corn-based distillers' dried grains imports, boosting U.S. purchases, and record U.S. corn export sales to Mexico. [O] (03-2018): Strong export demand for U.S. corn. [P] (08-2021): Supply worries after the USDA cut its estimate of U.S. corn production, and drop in Brazil corn crop due to drought and frosts. [Q] (04-2020): Coronavirus outbreak triggered a collapse in ethanol demand (40% of US corn use) and reduced feed demand amid meat plant closures, weighting on corn demand. [R] (08-2022): Lower U.S. and EU corn crops amid dry weather.

FIGURE 7. Sugar Index: Standardized Net supply and Standardized Net Demand Share of Total Number of Words per Month

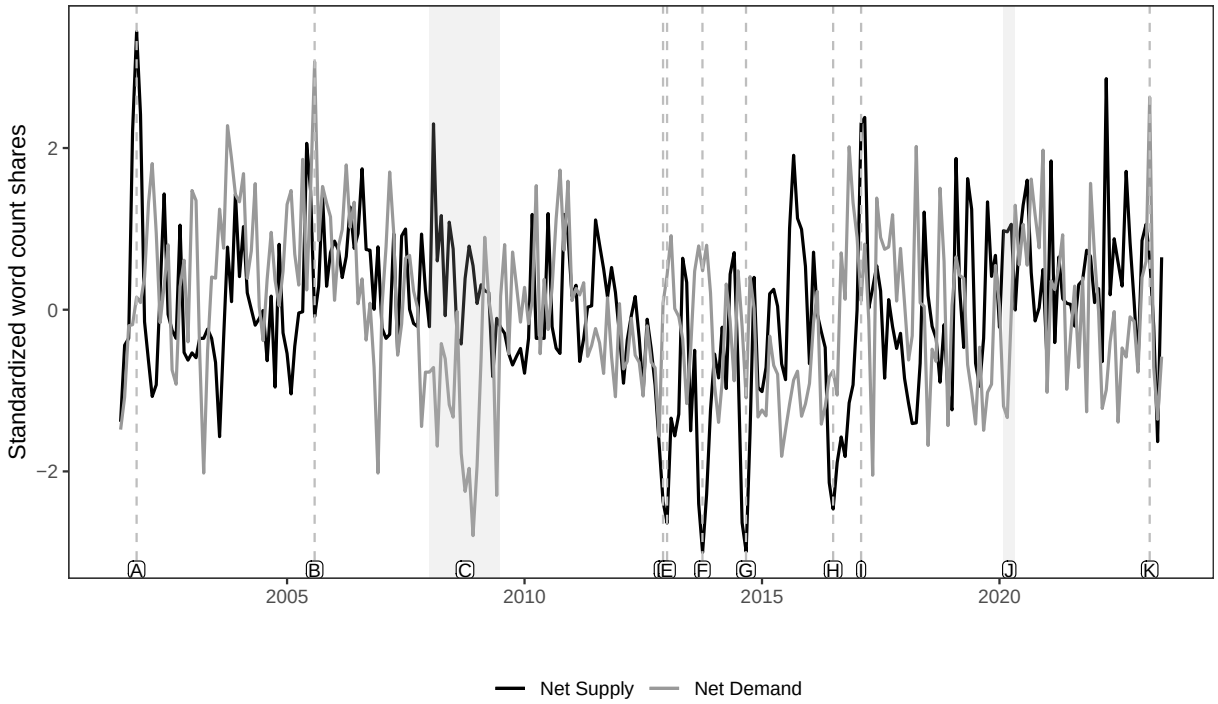


Note: This figure plots the standardized net supply and demand indicators for sugar, for the period between 2001 and 2023. The bars map a number of important developments in the sugar sector. These events respectively are: [A] A (04-2003): shrinking demand partly triggered by the U.S.-led war in Iraq, as Middle East countries had already stockpiled sugar in recent months over war fears. [B] (05-2003): Notable uptick in sugar futures driven by trade (Libya, Taiwan, Russia) and speculative buying, buoyed the market from a recent low. [C] (08-2005): Robust consumer buying from Russia, Pakistan and the Middle East. [D] (08-2007): Global oversupply of sugar driven by higher production in Brazil and India. [E] (08-2009): Excess rain in Brazil disrupted the harvest, while concerns over low output in India following erratic monsoon rains triggered panic buying ahead of the festival season, driving raw sugar prices to 28-year highs. [F] (09-2010): Adverse weather in key producers such as Brazil, Central America, India, Russia and Australia. [G] (07-2011): Brazil expects a smaller cane crop due to aging plants and adverse weather, with recent rains slowing harvesting. [H] (04-2012): Improved seasonal buying by soft-drink and ice-cream makers in the spot market. [I] (10-2012): Rise in physical demand with approaching indian festival season. [J] (12-2012): Sluggish demand due to winter season and rising supplies amid ongoing cane crushing in India. [K] (10-2013): Rising demand from Southeast Asia, the Middle East and Africa, and expectations of higher demand in India ahead of Diwali festival. [L] (01-2016): Lower-than-expected sugar output worldwide, with drought affecting India, slow start in Central America due to rainfall, disappointing yields in Thailand, and lowest EU beet crop in 40 years amid smaller planted area and adverse weather. [M] (04-2018): Surging production in India, Thailand, and EU (amid abolishment of limits on sugar beet production) led to an oversupply of sugar. [N] (11-2019): Freezing conditions have curbed sugar production in the United States and Canada while drought has dented Mexico's output. [O] (04-2020): Collapse in demand for food services (ice cream, beverages) and biofuels (ethanol) as Covid-19 lockdowns curb consumption. [P] (04-2021): Frosts in Europe damaged recently planted beet, while drier-than-normal weather in Brazil is expected to reduce the sugar cane crop. [Q] (08-2021): Lower production in Brazil due to the earlier drought and recent waves of frost.

2.4.3. *Industrial Metals: Copper.* Figure 8 presents the standardized net supply and demand indicators for copper markets spanning 2001 through 2023. Supply-side developments predominantly reflect production conditions in the major copper-producing nations–Chile, Peru, China, Russia, and Indonesia. Negative supply shocks correspond to several distinct categories of production disruptions: natural disasters (predominantly earthquakes) affecting mining operations, technical disruptions to extraction and refining processes, labor disputes manifesting as production stoppages, and international sanctions restricting market access.

Demand for copper exhibits pronounced cyclicality, with significant sensitivity to macroeconomic conditions in major consuming regions, particularly the United States and China. The indicator captures substantial demand contractions during systematic economic downturns, most notably the 2007-2009 global financial crisis and the COVID-19 pandemic. This cyclical sensitivity reflects copper's extensive utilization in construction, electrical infrastructure, and durable goods production-sectors characterized by high income elasticity and pronounced business cycle exposure.

FIGURE 8. Copper Index: Standardized Net supply and Standardized Net Demand Share of Total Number of Words per Month



Note: This figure plots the standardized net supply and demand indicators for the period between 2001 and 2023. The bars map a number of important developments in the copper sector. These events respectively are: [A] Producers in North and South America and Asia announced production cuts to battle steep mining and processing costs and historically low metal prices. [B] Worries that the SARS outbreak would dampen economic growth in some Asian countries and depress copper demand. [C] A boom in Chinese copper demand and stronger economic growth in Western industrialized nations. [D] Strong demand from China and good U.S. manufacturing-related news indicated demand for copper would remain sustained. [E] Soft U.S. economic data (housing) triggered fears of slowing demand for copper. [F] Worries about Zambia's copper output amid a power crisis. [G] GFC. [H] Economic worries and market speculation that China would curtail near-term purchases of copper. [I] Well-supplied market amid higher output from mining groups such as BHP Billiton, and China's domestic production. [J] Higher copper output (In China, copper output jumped by 21 percent from a year ago, while Chilean copper mine's output surged back after tough 2012). [K] Concerns about rising supply were highlighted when Newmont Mining Corp raised its full-year copper production forecast. [L] The global copper market is expected to move into surplus this year, as boom time-driven new mine supply ramps up mostly from Peru. [M] Concerns about supplies after disruptions in top producer Chile (strikes), Indonesia (dispute with the government over mining rights) and Peru (strikes). [N] Moody's downgraded China's credit ratings for the first time in 30 years, raising concerns about copper demand. [O] Protests hitting top mines in Peru, halting 20% of national copper output, coupled with a drop in output from top producer Chile and the potential for more sanctions on Russia raised supply shortages. [P] Signs of improving copper demand from China amid the easing of COVID-19 restrictions.

3. Evaluating the Commodity-Price Measures

3.1. **Human Benchmark Assessment for Supply-Demand Textual Classification.** We validate our algorithmic classification through a structured human audit protocol designed to minimize biases. Fixed monthly article samples with randomized evaluation order neutralize coverage trends and learning effects, while two independent audits per article enhance reliability. The assessment framework evaluates commodity relevance, identifies market developments, and verifies dictionary completeness.

Quarterly correlation between human and algorithm-generated indicators ranges from 0.75-0.85 across different market dimensions, demonstrating robust concordance. The temporal comparison of human and algorithmic classifications confirms strong time-series correspondence, providing an empirical validation of our computational approach. We provide further details regarding the auditing process in section C of the Appendix. Figures C1 through C4 present the temporal evolution of human and algorithm-derived indicators across supply and demand components and composite measures, visually confirming the strong time-series correspondence between the alternative measurement approaches.

3.2. **Relating Market-Wide Commodity-Price Measures to Tradable Index Returns.** To illustrate how our commodity supply and demand indicators correlate with commodity prices, we regress changes in commodity prices on our global commodity supply and demand indicators, the VIX index and the fed funds rate. We employ concurrent, daily commodity price changes and approximate the commodity market returns with the returns of the S&P GSCI Composite Index. Table 3, presents the results of this exercise. The first specification features the net supply indicator which is positive and significant. Similarly, the second specification reveals that the net demand indicator is positively signed and highly significant. The results remain largely unchanged once we include both regressors in the final specification [6]. The preliminary analysis is highly encouraging. Sampling articles from broad news outlets using a streamlined dictionary of four lemmas our global commodity supply and demand indicators correlates in a meaningful way with the returns of a market-wide, tradable commodity index controlling for the VIX and a daily interest rate measure.

3.2.1. *Relating Individual Commodity-Price Measures to Tradable Index Returns.* Given that the use of NLP methods can raise accuracy issues we address the latter by running some diagnostic regressions in the spirit of Table 3.

Table 4, presents the results of this exercise for crude oil, gasoline, natural gas, copper, aluminum, zinc, gold, corn, wheat, soybean, sugar, cocoa, cotton, hogs and live cattle. The net supply and net

[6] Net Supply is defined as Supply Decrease minus Supply Increase so a Net Supply increase is expected to correlate with positive returns for the GSCI Composite Index.

TABLE 3. Regression of S&P GSCI composite daily returns on supply & demand indicators

	Net Supply	**Net Demand**	**Net Supply & Net Demand**
Net supply	0.07942***		0.09401***
	(5.29)		(6.31)
Net demand		0.16190***	0.17077***
		(8.75)	(9.37)
Fed funds rate	-0.01505	-0.01921	-0.02286*
	(-1.15)	(-1.48)	(-1.76)
VIX	-0.12417***	-0.05604**	-0.06942**
	(-4.32)	(-2.02)	(-2.49)
R2	0.018	0.035	0.043
N	4730	4730	4730

demand indicators are positively signed and highly significant across all commodities (the only exception is the net supply indicators for natural gas and gold which do not appear to be statistically significant). The results of Table 4 suggest that our individual-commodity supply and demand indicators again correlate in a meaningful way with the returns of the highly-tradable, individual-commodity indices of the S&P GSCI group controlling for the level of the VIX index and a daily interest rate measure.

Table 4: Regression of S&P GSCI Commodity-Specific Daily Returns on Net Supply and Demand Indicators

Panel A: Energy			
	Crude Oil	Gasoline	Natural Gas
Net demand (std.)	0.08135***	0.02928*	0.08955***
	(4.51)	(1.92)	(6.71)
Net supply (std.)	0.08974***	0.03366**	0.00029
	(6.26)	(2.51)	(0.02)
Fed funds rate	-0.02433**	-0.02361*	-0.01506
	(-2.25)	(-1.83)	(-0.97)
VIX	-0.08927***	-0.11481***	-0.02295
	(-2.78)	(-3.38)	(-1.42)
N	4889	4847	4833
R2	0.024	0.015	0.009

Panel B: Industrial & Precious Metals				
	Copper	Aluminum	Zinc	Gold
Net demand (std.)	0.17000***	0.03342**	0.02754**	0.07939***
	(10.93)	(2.50)	(2.20)	(6.38)
Net supply (std.)	0.06198***	0.04127***	0.04287***	0.01759

	(4.69)	(2.90)	(2.84)	(1.36)
Fed funds rate	-0.02363	-0.01117	-0.01194	0.01853
	(-1.43)	(-0.70)	(-0.62)	(1.19)
VIX	-0.07385***	-0.09143***	-0.07856***	-0.00126
	(-2.73)	(-4.68)	(-3.11)	(-0.05)
N	4882	4748	3863	4888
R2	0.040	0.011	0.008	0.007

Panel C: Grains

	Corn	Wheat	Soybean
Net demand (std.)	0.11497***	0.13778***	0.12268***
	(8.76)	(10.69)	(9.47)
Net supply (std.)	0.03210**	0.10808***	0.07598***
	(2.34)	(3.81)	(5.07)
Fed funds rate	0.00324	0.01680	0.00071
	(0.21)	(1.18)	(0.05)
VIX	-0.02487	-0.01061	-0.03682*
	(-1.18)	(-0.57)	(-1.77)
N	4849	4878	4863
R2	0.016	0.033	0.022

Panel D: Soft

	Sugar	Cocoa	Cotton
Net demand (std.)	0.11271***	0.09715***	0.11770***
	(8.02)	(5.86)	(7.83)
Net supply (std.)	0.07710***	0.04562***	0.07486***
	(5.78)	(3.29)	(5.03)
Fed funds rate	-0.01000	0.00260	-0.00480
	(-0.71)	(0.20)	(-0.37)
VIX	-0.02134	-0.02140	-0.04181**
	(-1.24)	(-1.16)	(-2.04)
N	4858	4842	4851
R2	0.020	0.013	0.022

Panel E: Livestock

	Hogs	Live Cattle
Net demand (std.)	0.15884***	0.14736***
	(10.04)	(9.57)
Net supply (std.)	0.05816***	0.03526***
	(3.82)	(2.70)
Fed funds rate	-0.00376	-0.01932
	(-0.29)	(-1.39)
VIX	-0.02173	-0.05260**
	(-1.17)	(-2.00)
N	4704	3842
R2	0.031	0.028

3.2.2. *Placebo Test - Relating Individual Commodity-Price Measures to Tradable Index Returns.* In Table 5, we report placebo tests, whereby we regress GSCI daily returns on a given commodity i on our net supply and demand indices for any commodity other than i. This serves as a placebo test to check if the results reported in Table 4 are spurious. None of our indices regressors appear to be statistically significant, strengthening the notion that the results obtained in Table 4 are to be taken at face value.

TABLE 5. Placebo Regression of S&P GSCI Commodity-Specific Daily Returns on Net Supply and Demand Indicators

Panel A. Across Categories				
	Corn on Aluminum	Wheat on Copper	Cattle on Soybean	Gold on Oil
Net demand (std.)	0.00076	0.01666	0.01063	0.02187
	(0.07)	(1.36)	(0.69)	(1.42)
Net supply (std.)	0.00273	0.01250	-0.00845	0.01211
	(0.25)	(1.04)	(-0.55)	(1.06)
Fed funds rate	0.01800	0.02516	-0.01442	0.01910
	(1.16)	(1.72)	(-1.15)	(1.22)
VIX	-0.03367	-0.01607	-0.05842**	0.00793
	(-1.59)	(-0.84)	(-2.45)	(0.32)
N	4893	4893	4893	4893
R2	0.002	0.001	0.004	0.001
Panel B. Soft Indicators				
	Sugar on Cocoa	Cotton on Cocoa	Sugar on Cotton	Cocoa on Cotton
Net demand (std.)	0.01155	0.00261	0.00761	-0.00348
	(0.82)	(0.19)	(0.51)	(-0.25)
Net supply (std.)	0.00151	-0.00032	0.01843	0.00604
	(0.12)	(-0.02)	(1.41)	(0.46)
Fed funds rate	-0.00792	-0.01121	-0.00661	0.00870
	(-0.56)	(-0.86)	(-0.46)	(0.67)
VIX	-0.01853	-0.04682**	-0.01939	-0.02840
	(-1.06)	(-2.27)	(-1.11)	(-1.54)
N	4893	4893	4893	4893
R2	0.001	0.002	0.001	0.001

4. VALIDATING TEXT-BASED OIL SUPPLY INDICATORS AGAINST STRUCTURAL BENCHMARKS

4.1. **Local Projections.** Recent macroeconomic disruptions–specifically the COVID-19 pandemic and Russia's invasion of Ukraine–have reinvigorated scholarly interest in the classical question regarding transmission mechanisms through which commodity price fluctuations, particularly in natural gas, wheat, and crude oil markets, propagate through the broader economy. The fundamental identification challenge in this literature stems from the endogenous determination of commodity prices, which respond systematically to prevailing macroeconomic conditions, thus complicating causal inference. The methodological approach predominant in the literature that studies the oil market addresses this

endogeneity concern through the implementation of structural vector autoregression (SVAR) frameworks. These models impose identifying restrictions that facilitate the decomposition of commodity price movements into structurally interpretable components, thereby isolating exogenous price variations suitable for analyzing causal macroeconomic impacts. These have been identified using (i) no restrictions (Kilian, 2009), (ii) sign restrictions (Kilian and Murphy, 2012; Lippi and Nobili, 2012; Baumeister and Peersman, 2013; Baumeister and Hamilton, 2019), (iii) narrative information (Antolín-Díaz and Rubio-Ramírez, 2018; Caldara, Cavallo, and Iacoviello, 2019; Zhou, 2019), and more recently (iv) high-frequency variation in oil prices around OPEC announcements (Känzig, 2021). Despite the substantial methodological sophistication that has emerged in modeling oil price dynamics, there exists a significant analytical asymmetry in the literature, with comparatively limited analysis of other economically significant tradable commodities. This methodological gap is particularly consequential for commodities that have exhibited heightened macroeconomic relevance during recent periods of market turbulence, notably natural gas and agricultural commodities such as wheat.

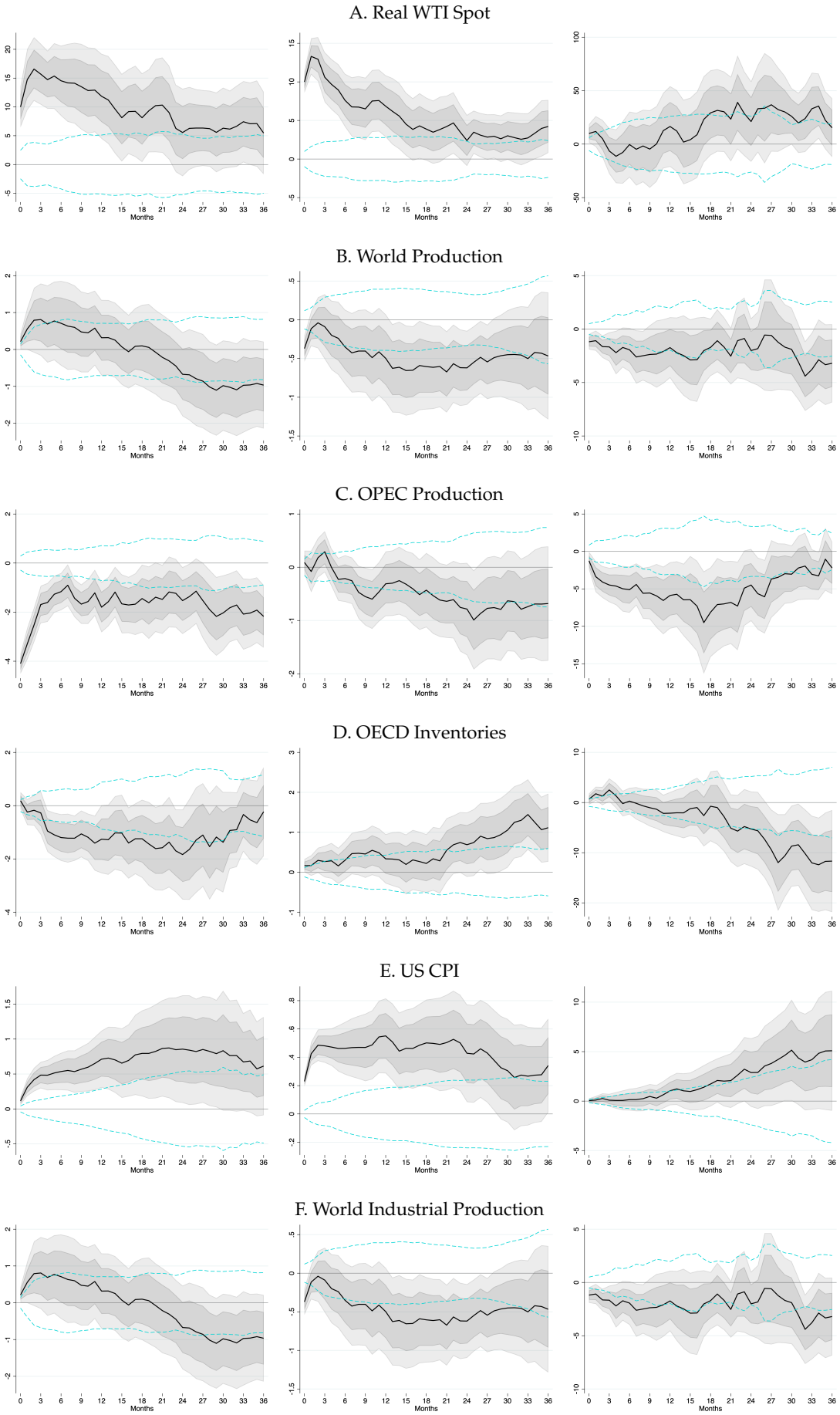
Our contribution does not center on developing novel methodologies for identifying oil price shocks, but rather on demonstrating that our textually derived Net Supply and Net Demand Oil indicators contain economically significant information relevant to the analysis and forecasting of macroeconomic fundamentals. The impulse response functions generated using our Net Supply Oil Index exhibit substantial correspondence with established structural measures from the literature that represent methodological benchmarks for oil market analysis.

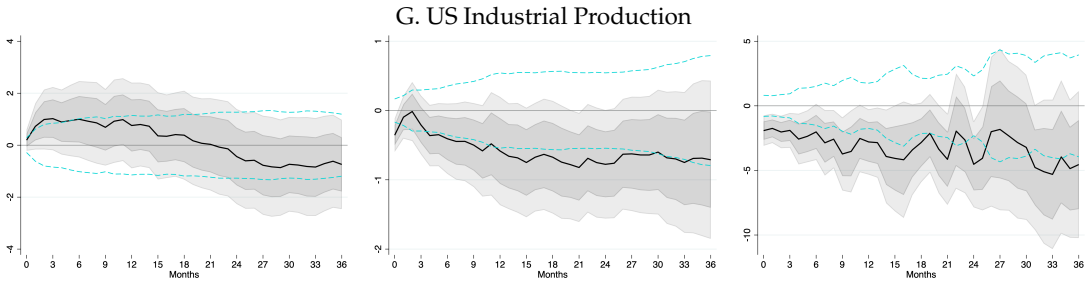
Establishing this concordance between our textual indicators and conventional structural measures for oil markets serves a critical methodological purpose: it provides validation for our approach against established benchmarks in a market where such comparisons are feasible. This validation is particularly valuable given the absence of analogous structural proxies for other commodity markets– a significant gap in the existing literature that our methodology addresses. By extending our textual approach to commodities beyond oil, we provide novel measures of supply and demand factors across previously underanalyzed commodity markets where conventional structural identification strategies face substantial implementation constraints.

In the subsequent analysis, we present empirical evidence establishing the correspondence between our textually derived indices and conventional structural methodologies. Our validation exercise demonstrates comparable predictions between these alternative measurement approaches, suggesting that our text-based indicators capture economically equivalent information to that identified through structural econometric techniques. In particular, in Figure 9, we benchmark the impulse responses of a "surprise" series of our Net Supply Oil Index (MPRP 2023), against the oil supply measure of Baumeister and Hamilton (2019) and the news shock about future oil supply of (Känzig (2021)), which are important indicators for the future real price of oil, global oil production, global inventories US CPI and global growth.

The study of the impulse responses of the local projections (Figure 9) reveals that a negative surprise of our Net Supply Index correctly predicts a future increase in the real WTI price, a significant short- and medium-run decrease in global and OPEC oil production, a decrease in future OECD inventories, an increase in US CPI, as well as a medium-run decrease in world industrial production.Notably, despite the exclusion of price data from our methodological framework, our approach demonstrates the capacity to identify market dynamics comparable to those captured by methodologies that explicitly incorporate oil price series in their estimation procedures. Our methodology suggests that textual sources contain sufficient informational content to recover the underlying structural factors driving commodity markets without relying on endogenous price signals.

FIGURE 9. Local Projections Impulse Responses





(I) Baumeister & Hamilton, 2019 (II) Kanzig, 2021 (III) MPRP, 2025 .

Note: This figure shows the impulse responses to a one standard deviation oil supply shock for the Real Spot Price of Oil, World Production, OPEC Production, OECD Inventories, US CPI and World Industrial Production, employing the oil supply shock series of Baumeister and Hamilton (2019), Känzig (2021) and a "surprise" series, calculated from our Net Supply Crude Oil Index as the residual of an AR(1), reported in Columns, I, II, and III, respectively.

5. Macroeconomic Transmission of Oil and Non-Oil Commodity Disturbances

We next exploit the comprehensive coverage of our methodology to assess the macroeconomic propagation of broad-based commodity market disturbances. This represents a significant contribution, as systematic measures of supply developments across non-petroleum commodity categories have been previously unavailable, limiting empirical assessment of their aggregate economic implications.

Our analysis therefore focuses specifically on isolating the macroeconomic impact of non-petroleum commodity markets, addressing a notable gap in the literature that has potentially understated their economic significance. For this purpose, we construct a composite indicator that excludes petroleum commodities. Unlike our earlier composite index construction, which employed news-coverage weights to aggregate across commodities, we now implement production-based weights to enhance the economic interpretability of estimated transmission effects.

To ensure appropriate weighting that reflects the relative economic importance of each commodity, we utilize the time-varying production weights embedded in the GSCI composite index calculation. These weights, constructed as five-year moving averages, provide a market-based representation of each commodity's relative significance in global production, thereby facilitating a more accurate assessment of the aggregate pass-through from commodity supply disturbances to macroeconomic outcomes.[7]

Our empirical results indicate substantial homogeneity in the macroeconomic implications of supply contractions across both petroleum and non-petroleum commodity markets. Figure 10 illustrates that negative supply shocks, regardless of the specific commodity category, generate consistent stagflationary effects across key macroeconomic indicators. Supply contractions produce inflationary pressures evident in both consumer and producer price indices, concurrent with contractionary

[7] We implement a methodological adjustment to account for the absence of lead from our composite indices. This omission necessitates a reweighting procedure to ensure proper representation of relative commodity importance in both the aggregate and non-petroleum composite measures, thereby maintaining the economic interpretability of transmission estimates despite incomplete commodity coverage relative to the standard GSCI production-weighted benchmark.

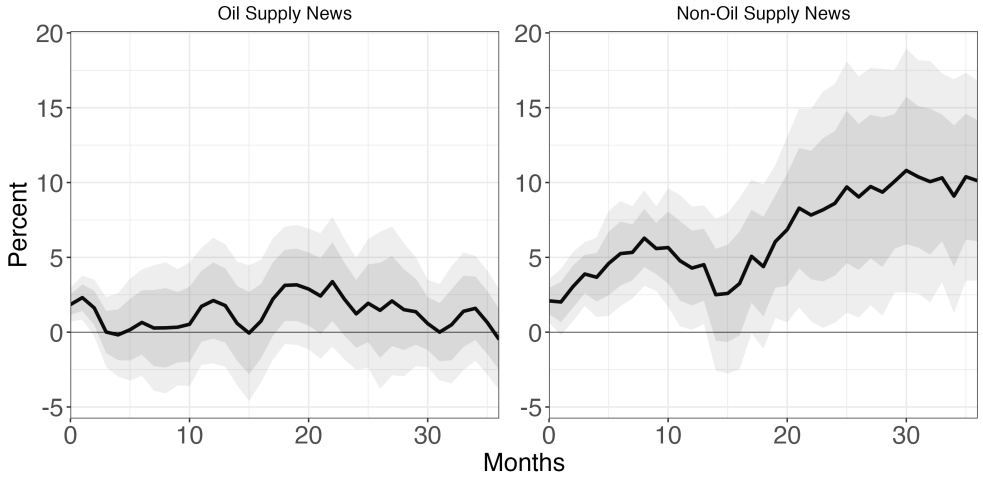
real economic effects manifested through reduced industrial production and manufacturing output. These supply-driven contractions simultaneously generate labor market deterioration, with elevated unemployment rates, likely operating through the channel of increased production costs that constrain productive capacity and labor demand.

Notably, the local projections reveal that the estimated passthrough of supply shocks originating from non-oil commodities to both quantities and prices is substantially greater than that observed in oil markets over the sample period. This has important implications for economic modeling and calibration under the presence of market-wide supply bottlenecks.

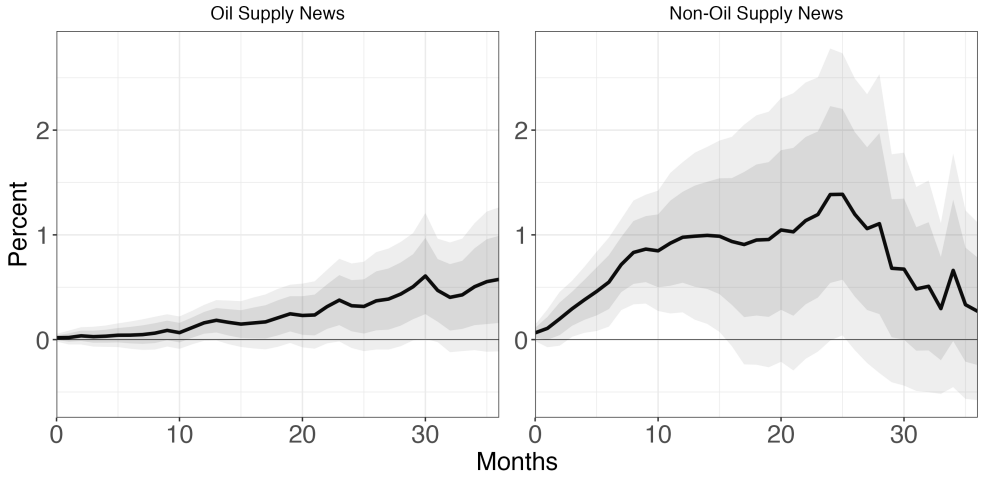
Underestimating the magnitude, frequency, or persistence of commodity supply disruptions generates several significant distortions, including misattribution of inflationary pressures, biased estimates of structural parameters, distorted output gap measurement and inefficient resource allocation. These distortions are particularly consequential during periods of significant supply chain reconfiguration, technological transitions, or following large exogenous disruptions where conventional assumptions of supply processes tend to be most severely violated.

FIGURE 10. Local Projections Oil & Non-Oil Impulse Responses

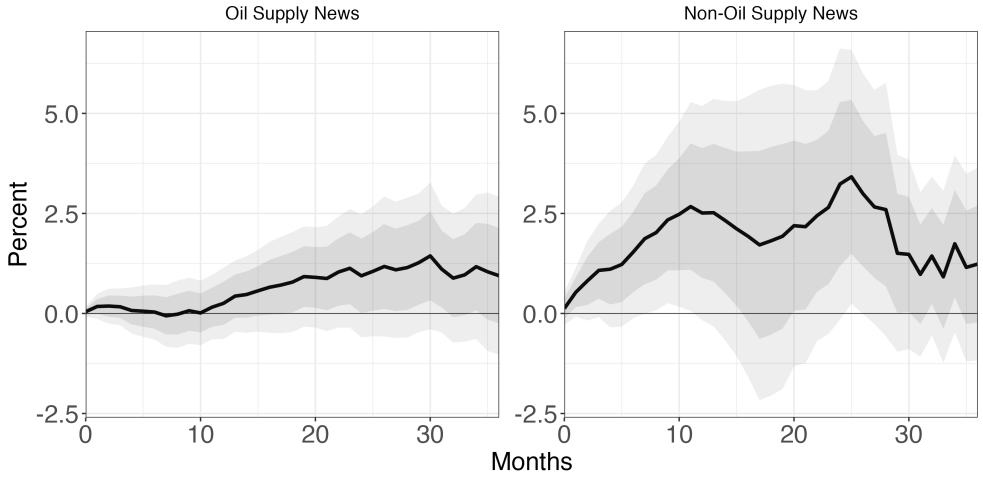
A. Real WTI Spot



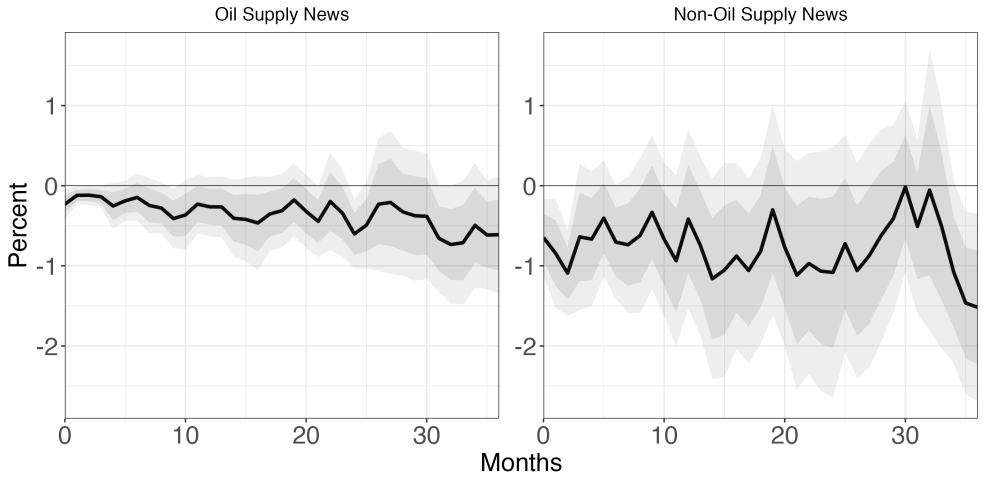
B. US CPI



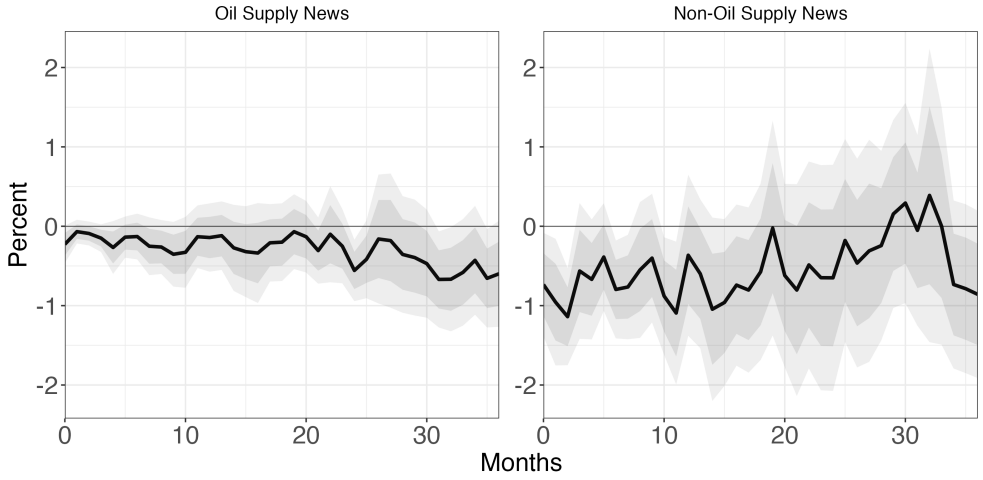
C. US PPI



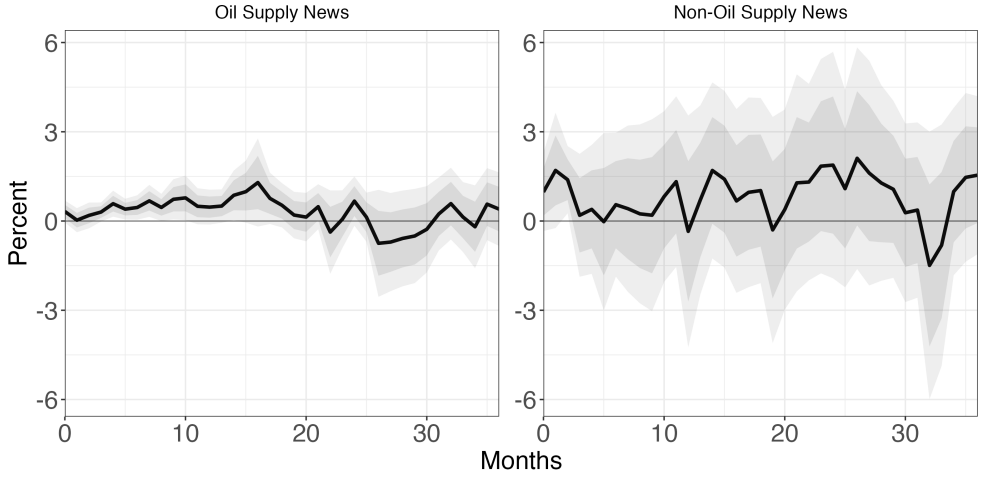
D. US IP



E. US Manufacturing



F. US Unemployment



(I) Oil Responses (II) Non-Oil Responses

Note: This figure shows the impulse responses to a standard deviation oil supply shock for the Real Spot Price of Oil, US CPI, US PPI, US Industrial Production, US Manufacturing, US Investment and US Unemployment employing the "surprise" series, calculated from our Net Supply Crude Oil Index and the Non-Oil production-weighted Composite Index as the residual of an AR(1) process, reported in Columns, I and II, respectively.

6. Decomposing the drivers of supply and demand developments

The origins of supply and demand developments can have different implications for financial and price stability. For instance, natural disasters tend to have an impact mostly on short- to medium-term inflation while environmental regulation could have a lasting effect on inflation by permanently affecting relative prices through expectations. Hence, the decomposition of commodity price fluctuations into a number of key drivers will allow us to distinguish between short- and long-term impacts of commodity price developments, and discern the severity and propagation mechanisms of a given shock. In what follows, we attempt to identify the main drivers of commodity supply and demand developments. We rely on the "Commodity Special Feature" of the IMF's World Economic Outlook and on the "Commodity Markets Outlook" from the World Bank to categorize potential components of commodity supply and demand developments. We define four main drivers of commodities, namely, the business cycle, geopolitical risk, natural disasters, and recent trends (e.g. shale revolution, climate change). A large share of commodity price variations is explained by these four drivers and our analysis helps uncover their time-varying significance. We derive the commodity drivers' dictionaries from a rich list of authoritative texts for each category, following the approach of Engle, Giglio, Kelly, Lee, and Stroebel (2020), as no well-defined dictionaries exist. In particular, the authoritative text for the business cycle is composed of the full history of the Business Cycle Dating Committee Announcements of the NBER (1979-2020). Similarly, we use the full history of the statements made to the press by the President of the United Nations Security Council to capture geopolitical risk. Moreover, for natural disasters we exploit the full database of EM-DAT (the International Disaster Database) of the Centre for Research on the Epidemiology of Disasters.[8] Finally, in the case of climate change, we use the same authoritative texts as Engle, Giglio, Kelly, Lee, and Stroebel (2020).

Figure 11 plots the business cycle driver for the period between 2001 and 2023. The bars map a number of important economic developments reflecting the state of the business cycle. The largest spikes correspond to key macroeconomic fluctuations resulting from the 2001 recession, the Global Financial Crisis, the August 2011 stock markets fall over fears of contagion of the European sovereign debt crisis, the Covid-19 crisis and the U.S. debt ceiling crisis.

Similarly, Figure 12 plots the geopolitical risk driver for the period between 2001 and 2023. A number of important geopolitical events are captured, including 9/11 attacks, the 2003 Iraq invasion, the Arab Spring, the trade war escalation between the United States and China and the Russian invasion of Ukraine.

The natural disasters theme is depicted in Figure 13 and highlights a number of important events such as the 2001 Gujarat earthquake, the Atlantic hurricane season (Katrina, Emily), the US Summer 2012 Drought, and the Covid-19 crisis.

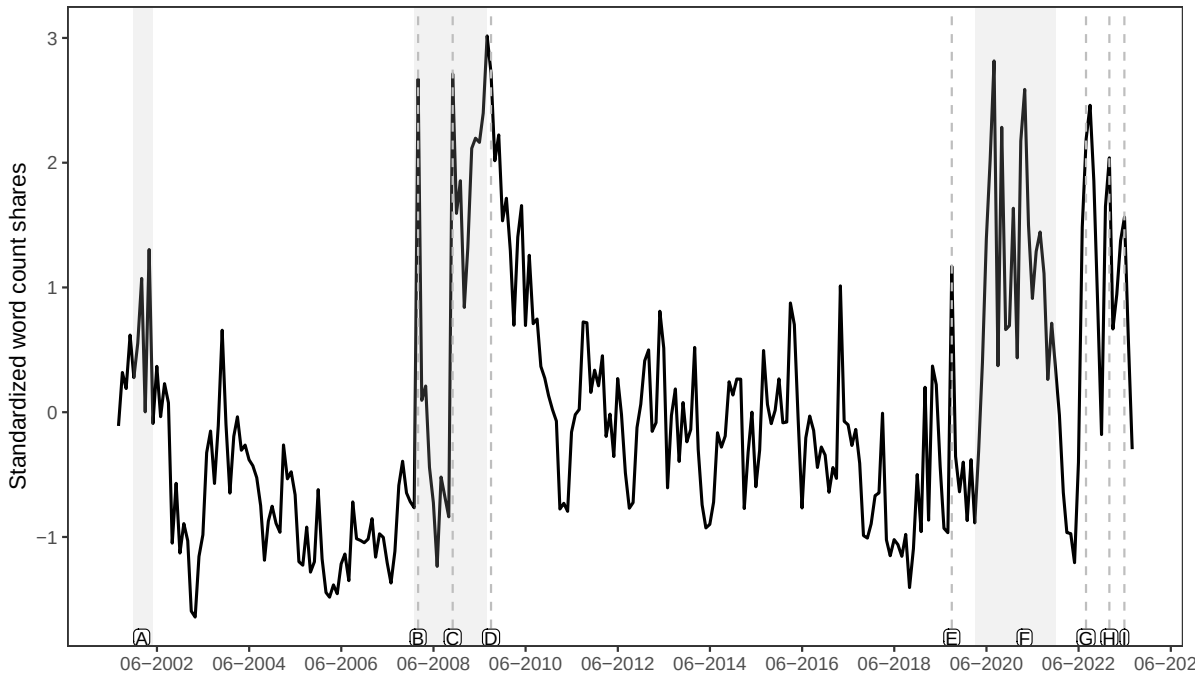
[8] To access the database, refer to the following website: https://www.emdat.be.

The climate change driver also spans the period between 2005 and 2023. The bars of Figure 14 map a number of climate change developments, warnings and protocols (e.g., European Commission proposals, U.S. Environmental Protection Agency regulations).

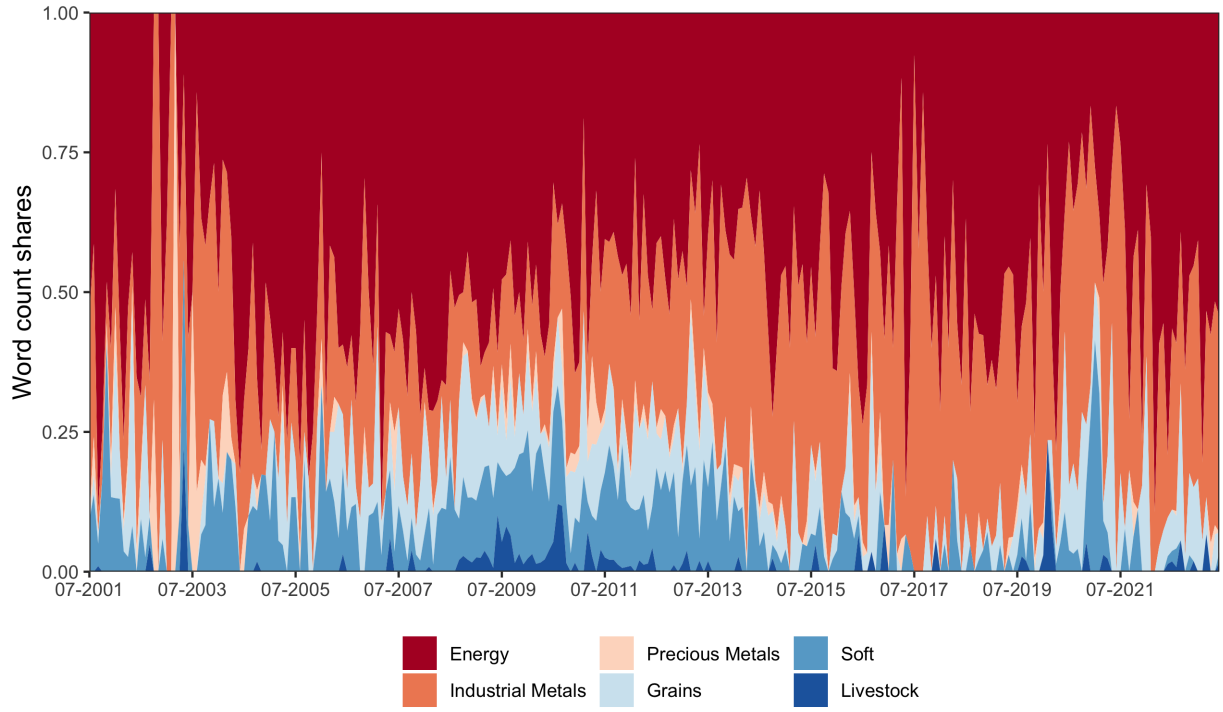
A decomposition of the drivers across commodity categories reveals that i) the business cycle is more relevant for energy, industrial metals, and soft commodities that are also used as biofuels, ii) geopolitical risk events tend to be more correlated with energy, and soft commodities, while grains only become important during the trade war period. iii) natural disasters mainly affect the categories of grains and softs and to a lesser extent energy, and iv) climate change concentrates around energy commodities and more recently industrial metals.

FIGURE 11. Business Cycle

A. Occurrence in News Articles



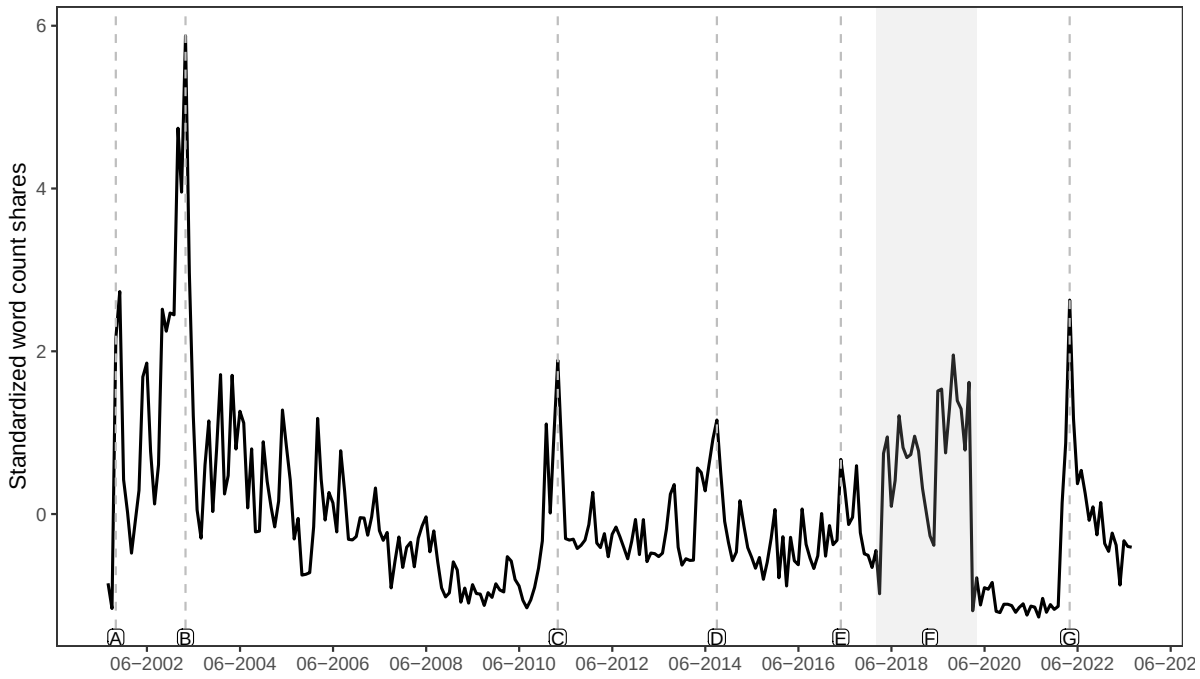
B. Decomposition across Commodity Categories



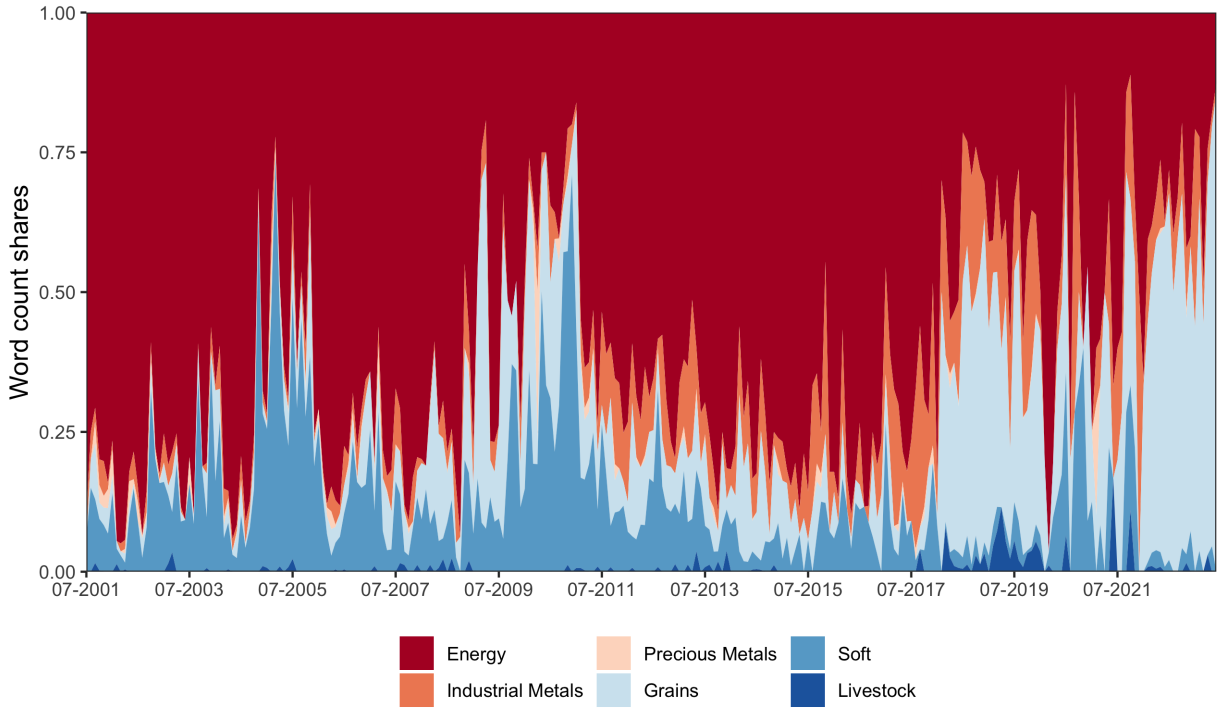
Note: This figure plots the Business Cycle Theme for the period between 2001 and 2023. The bars map a number of important economic developments reflecting the state of the business cycle. These events respectively are: [A] 2001 recession. [B] Global Financial Crisis (U.S. stocks had the worst January since 2000). [C] Global Financial Crisis (Many of the world's stock exchanges experienced the worst declines in their history). [D] Signs of optimism after Europe's biggest economies, Germany and France, end their recessions. [E] Fears of recession amid U.S.-China trade war. [F] Covid-19 crisis. [G] U.S. economy shrinks for second straight quarter. [H] Worries about looming U.S. economic slump amid rising interest rates. [I] 2023 U.S. debt-ceiling crisis.

FIGURE 12. Geopolitical Risk

A. Occurrence in News Articles



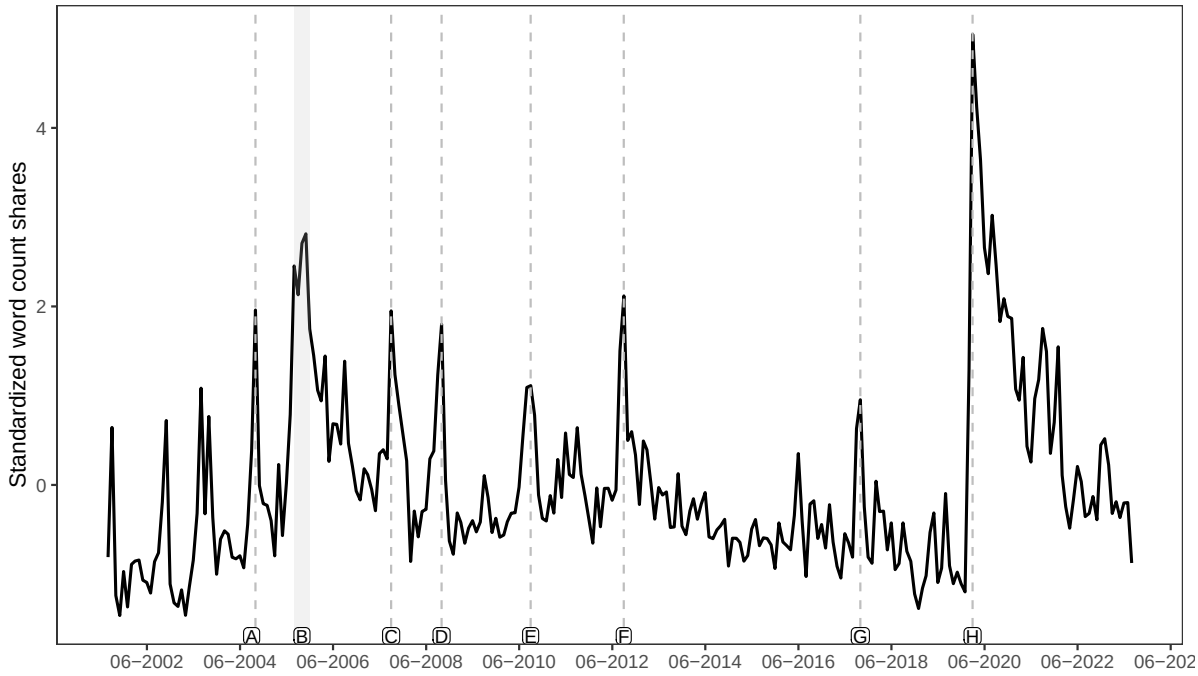
B. Decomposition across Commodity Categories



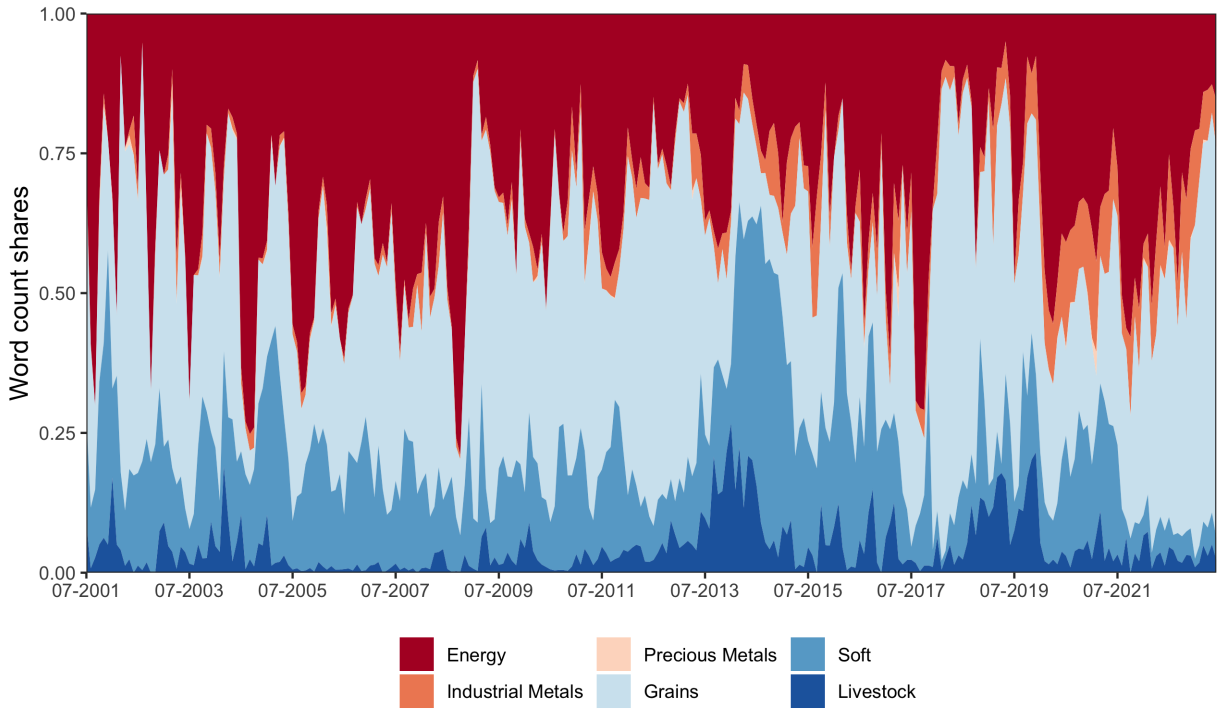
Note: This figure plots the Geopolitical Risk Theme for the period between 2001 and 2023. The bars map a number of important geopolitical events. These events respectively are: [A] 9/11 attacks. [B] 2003 Iraq invasion. [C] Arab Spring: Syrian and Libyan War. [D] 2014 Gaza War and Donbas war. [E] United States launched cruise missiles against an airbase in Syria, raising the risk of confrontation with Russia and Iran. [F] China-United States trade war. [G] Russian invasion of Ukraine.

FIGURE 13. Natural Disaster

A. Occurrence in News Articles



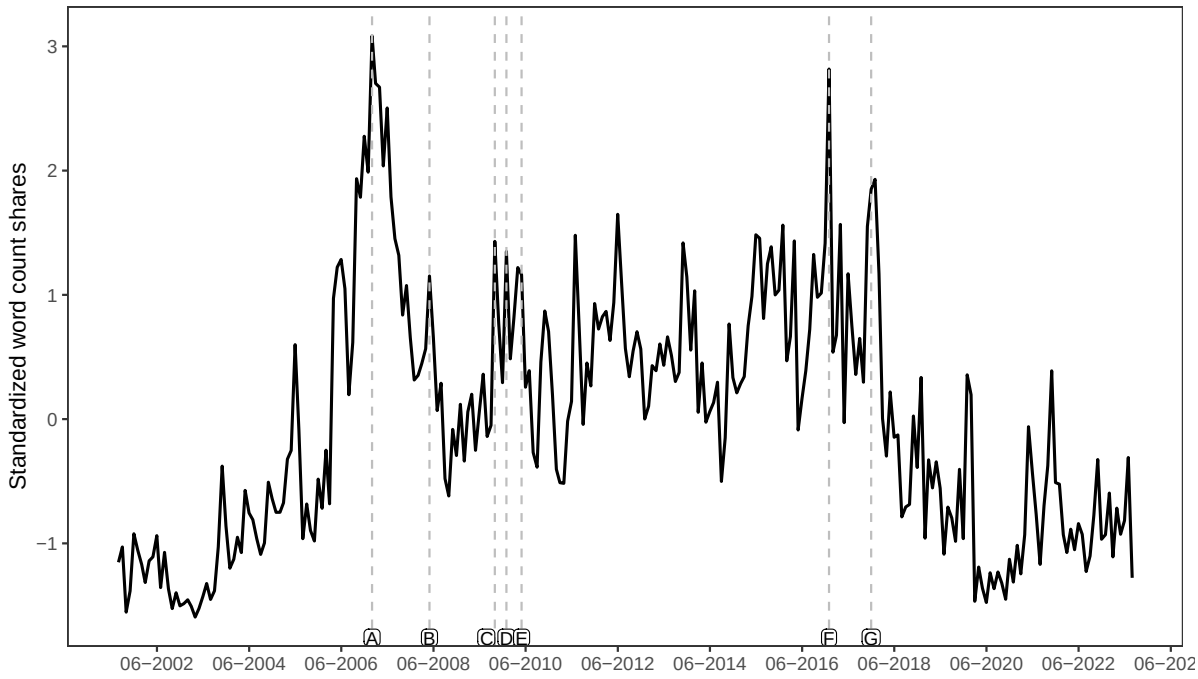
B. Decomposition across Commodity Categories



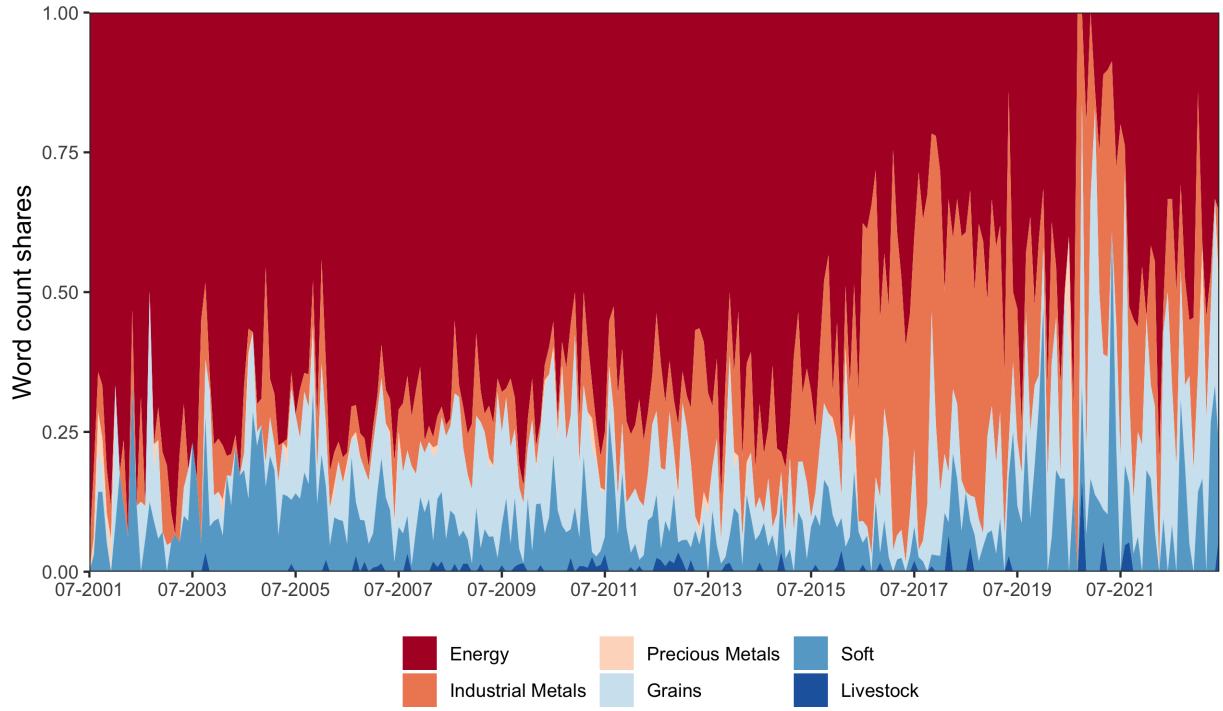
Note: This figure plots the Natural Disasters Theme for the period between 2001 and 2023. The bars map a number of important natural disasters. These events respectively are: [A] 2004 Atlantic hurricane season (Ivan). [B] 2005 Atlantic hurricane season (Katrina, Emily). [C] 2007 Atlantic hurricane seasons and severe droughts across Europe and US. [D] 2008 Atlantic hurricane seasons. [E] Severe droughts in the Black Sea Region. [F] US Summer 2012 Drought. [G] 2017 Atlantic hurricane season (Irma, Harvey). [H] Covid-19.

FIGURE 14. Climate Change

A. Occurrence in News Articles



B. Decomposition across Commodity Categories

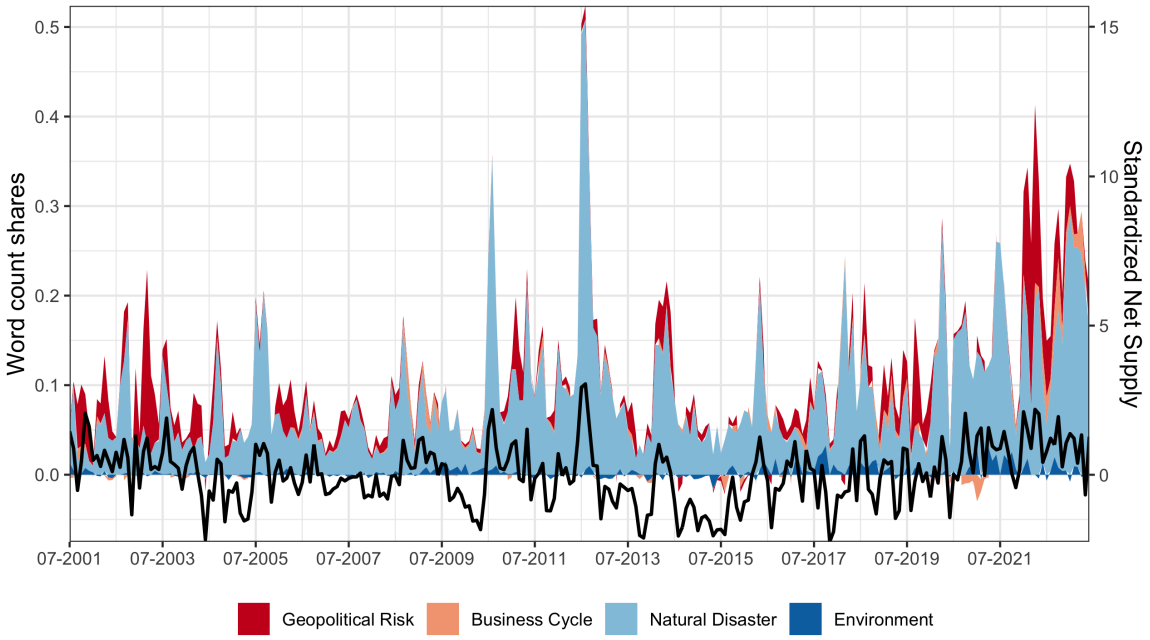


Note: This figure plots the Climate Change Theme between 2001 and 2023. [A] The European Commission presents proposals setting targets of greenhouse gases reduction [B] U.N. IMO discusses reduction of ship pollutants & climate changing gases [C] EU proposes U.N. war chest for climate funds; the U.S. Interior Department unveils initiative to establish Climate Change Response Council [D] 2009 U.N. Climate Change Conference [E] Russian court rules in favor of suspending zinc production at Elektrotsink pending environmental clean-up. [F] Trump nominates climate change sceptics to run Interior Department & Environmental Protection Agency; Philippines cancels permits of nickel mines in environmental clampdown. [G] The U.S. Environmental Protection Agency requires fuel companies to blend more renewables into nation's fuel supply.

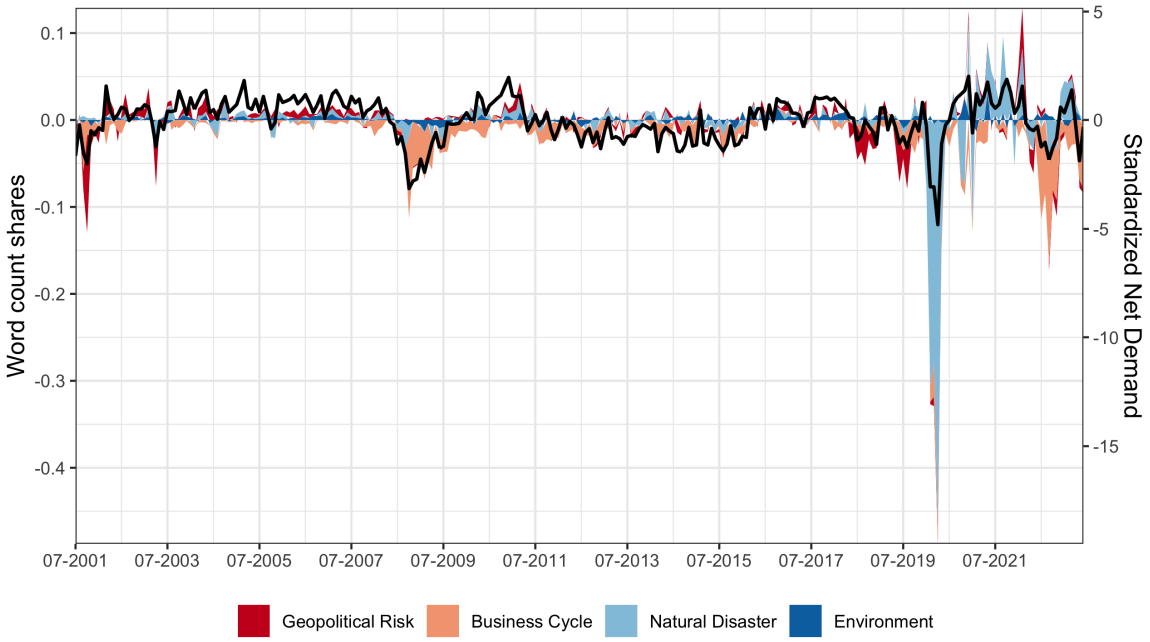
A significant methodological contribution of our analysis is the decomposition of commodity supply and demand components into their constituent fundamental drivers. The historical variance decomposition of net supply fluctuations across commodity categories reveals the predominance of exogenous natural disaster events as the primary source of supply-side variation. This contrasts markedly with the net demand decomposition, where endogenous business cycle dynamics constitute the principal explanatory factor–with the notable exception of the COVID-19 pandemic episode, which manifests empirically as an exogenous negative natural disaster shock of exceptional magnitude in 2020. This pattern of differential driver importance across supply and demand dimensions aligns with theoretical expectations regarding the relative exogeneity of supply disruptions versus the endogenous nature of demand fluctuations in commodity markets (Figure 15).

FIGURE 15. Factor Decomposition: Net Supply & Net Demand

A. Net Supply



B. Net Demand



Note: This figure plots the factor decomposition in commodity articles narrating supply and demand events between 2001 and 2023. The factors are: [A] Geopolitical Risk, [B] Business Cycle, [C] Natural Disaster, [D] Environment.

7. Impact on Firm-level Outcomes

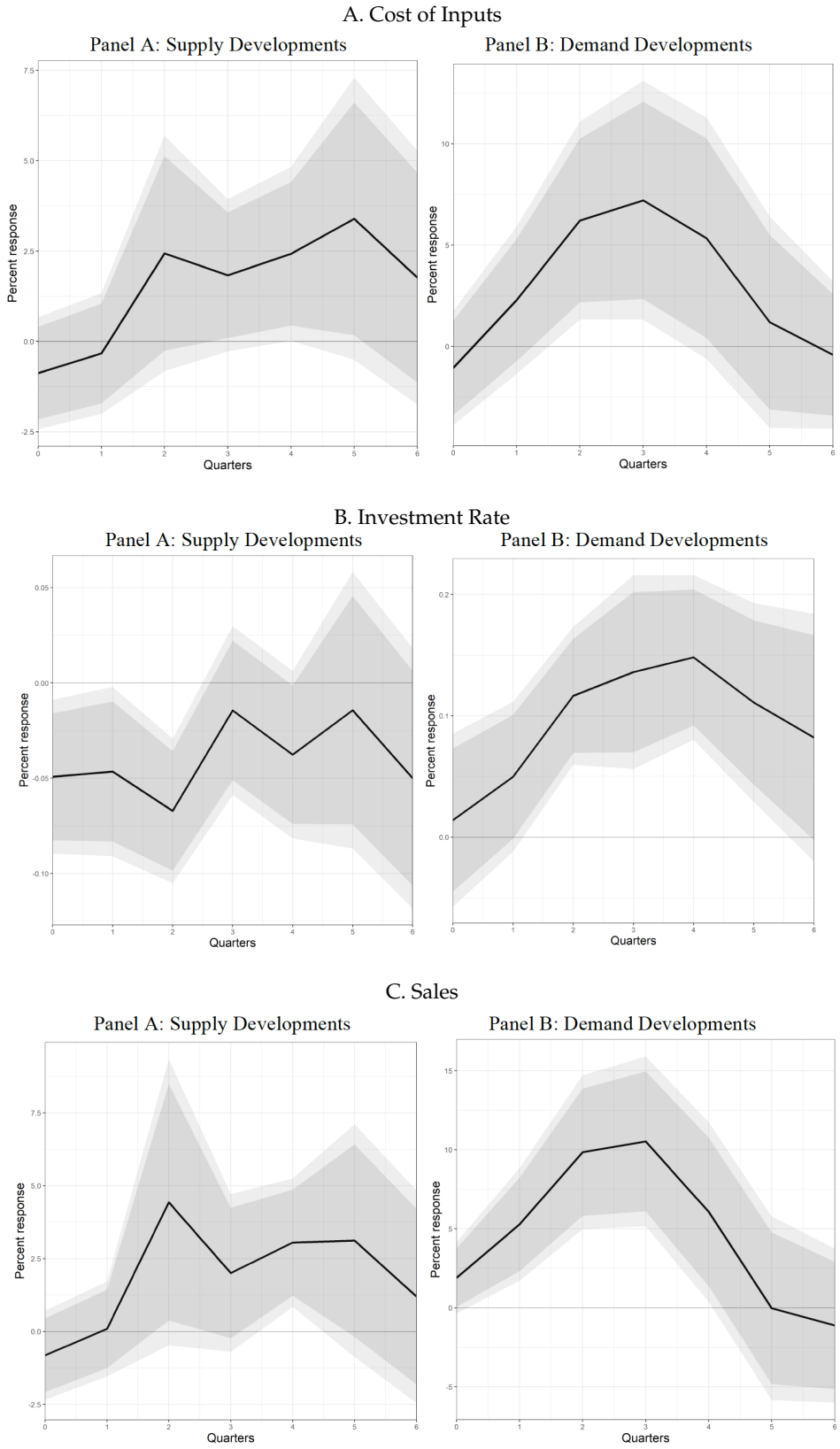
In the subsequent analysis, we examine the heterogeneous effects of our supply and demand indicators on microeconomic outcomes at the firm level. While our empirical strategy does not establish the strict exogeneity of the supply indicator, the resulting estimates provide substantive evidence of qualitatively distinct transmission mechanisms between supply and demand components.

For our microeconomic analysis, we construct a comprehensive firm-level dataset comprising quarterly financial statement information from the universe of publicly-traded U.S. firms spanning 2001-2023, thereby establishing temporal alignment with our textual commodity market indicators.

Figure 16 presents firm-level evidence on the transmission of commodity market developments. Supply contractions exhibit multiple offsetting effects across firm operations. Negative supply developments are associated with increased input costs, consistent with standard price effects in factor markets. These supply disruptions simultaneously correlate with reduced investment rates, suggesting an operational channel whereby heightened uncertainty activates real options mechanisms that incentivize investment deferral. Notably, the revenue impact of supply contractions appears positive, indicating that the scarcity-induced price effect dominates the potentially countervailing recessionary demand effect.

Demand expansions, conversely, demonstrate theoretically consistent unidirectional effects across firm outcomes. Positive demand shocks correlate with elevated input costs, reflecting increased factor demand, enhanced investment rates, consistent with accelerator mechanisms, and expanded sales, capturing the direct effect of increased product demand. The empirical patterns additionally suggest that demand-side indicators capture predominantly systematic factors that exhibit broad-based effects across firms, consistent with common exposure to aggregate demand conditions.

FIGURE 16. Percentage Firm Outcomes Response to Supply and Demand Developments



Note: Percentage cost of inputs (year-on-year), investment rate (logarithmic), and sales (year-on-year) response following a one standard deviation increase in supply and demand developments, contemporaneously, and up to a six-quarter horizon (90% and 95% CI). Controls: tobin's q, book leverage, size, long-term debt, GDP log change, GSCI log returns, and a lag of the cost of inputs. Each specification includes a constant term and firm fixed effects. Standard errors are two-way clustered by firm and year.

8. Concluding Remarks

The longstanding challenge of empirically identifying supply-side disturbances that drive business cycle fluctuations has persisted since the seminal work of Kydland and Prescott (1982). While considerable methodological progress has occurred in the oil market domain, modern economies depend on diverse commodity inputs whose supply disruptions constitute plausible sources of macroeconomic fluctuations. This paper addresses the notable gap in measuring non-oil commodity market disturbances by developing a comprehensive textual approach to identifying supply and demand shocks across the full commodity spectrum.

Our empirical results demonstrate that commodity supply disruptions generate significant macroeconomic effects. The macroeconomic responses to our supply disturbances confirm theoretical predictions: supply contractions generate stagflationary pressure (higher prices, reduced output, lower employment), while demand expansions increase both prices and economic activity. At the firm level, supply contractions associate with higher input costs, reduced investment rates–consistent with real options theory–and higher sales as scarcity effects frequently dominate recessionary pressures.

More importantly, we show that disturbances originating in non-petroleum commodity markets–despite being historically overlooked in the literature–exhibit more pronounced stagflationary impacts than those originating in petroleum markets. This finding carries important policy implications as underestimating the magnitude, frequency, and persistence of commodity supply disruptions can lead to several substantive distortions, including misattribution of inflationary pressures, biased estimation of structural parameters, inaccuracies in output gap measurement, and suboptimal resource allocation.

The decomposition of fundamental drivers across commodity categories further reveals systematic patterns: business cycle fluctuations predominantly affect energy and industrial metals; geopolitical risks disproportionately impact energy and precious metals; natural disasters primarily disrupt agricultural commodities with spillovers to energy markets; and climate-related concerns increasingly affect both energy and industrial metals markets.

This comprehensive framework enhances our understanding of commodity market dynamics and their macroeconomic implications, providing a valuable tool for economic analysis that extends well beyond the traditional focus on oil markets. By mapping the multidimensional sources of commodity price movements, our approach offers valuable signals for economic analysis while documenting both persistent patterns and emerging trends in global commodity markets.

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Appendix A. Article Handling

We sampled articles from Reuters via the Factiva Snapshots API.

Appendix B. Dictionaries

In this Appendix we provide the list of supply and demand words used for the creation of the "global" commodity index and the indices for crude oil, natural gas an wheat. We also present the standard list of increase and decrease words which is common across commodities.

Table B1 to Table B4 present the list of roots of words we use to search for supply and demand related expressions for the construction of the "global" commodity index as well as the indices that aim to capture individual commodities. Our results our robust to using both words and lemmas.

Table B5 and Table B6 present the list of roots of increase and decrease words.

Table B1. Supply and demand words: Global Commodity Index

Supply		
suppl*	produc*	output

Demand			
demand*	consum*	buy*	purchas*

Table B2. Supply and demand words: Crude Oil

Supply				
suppl*	produc*	output	discovery	glut*
reserv*	surplus*	rig*		

Demand				
demand*	consum*	buy*	util*	drain*
deplet*	refin*			

Table B3. Supply and demand words: Natural Gas

Supply				
suppl*	produc*	output	capacity*	inject*
explor*	extract*	rig*	drill*	

Demand				
demand*	consum*	buy*	plant*	util*
emission*	costumer*	electric*	heating*	

TABLE B4. Supply and demand words: Wheat

Table B4: Supply and demand words
Wheat

Supply

suppl*	produc*	output	crop*
planting*	farm*	harvest*	

Demand

demand*	consum*	buy*	purchas*
flour*	feed*	miller*	

TABLE B5. Increase words

accru*	climb*	improve*	rais*	soar*
accumulat*	elevat*	increas*	rall*	spik*
add*	enlarg*	inflat*	reach*	spring*
advanc*	escalat*	jackup*	rebuil*	spurt*
augment*	expand*	jump*	recoup*	strengthen*
bolster*	firm*	leap*	recover*	surg*
boom*	gain*	lift*	regain*	surpass*
boost*	grow*	perk*	resurgenc*	swell*
buil*	heigh*	pickup	reviv*	up*
bullish*	high*	pop*	ris*	
buoyant*	hik*	propell*	*rocket*	

TABLE B6. Decrease words

abat*	dent*	evaporat*	pullback*	slump*
bearish*	depress*	fad*	reced*	small*
below	deteriorat*	fall*	reduc*	squeez*
collaps*	diminish*	falter*	restrict*	stumbl*
compress*	dip*	halt*	retre*	sub*
contract*	disappear*	landslid*	sink*	suppress*
crash*	disappoint*	less*	short*	suspend*
crimp*	disrupt*	los*	shrink*	tank*
crush*	div*	low*	shut*	tap*
curtail*	down*	meltdown*	slack*	tight*
cut*	drawdown*	nosediv*	slash*	
dampe*	drop*	outage*	slid*	
declin*	dwindl*	plummet*	slip*	
decreas*	ebb*	plung*	slow*	

APPENDIX C. AUDIT PROCESS BASED ON HUMAN READINGS

We first randomly sample (without replacement) a fixed number of articles per month. The idea is to insulate the sample from changes in the number of articles that result from increasing trends in coverage, as well as from the differential effect of supply and demand developments. We further randomize the order in which a given auditor reviews and codes assigned articles in order to make

sure that the auditors' "learning" does not bias the assessment of differences over time. We assign the same sample to, at least, two auditors trading off the coverage of a larger sample for accuracy and confidence about our human measurement.

When it comes to the information we retain, we, first, assess whether the article indeed refers to and provides details regarding the commodity-in-question; we code the different outcomes accordingly [if yes, 2; if only to a limited extent, 1; else, 0]. Next, we verify whether the article is about supply and demand market developments [if yes, supply_demand = 1, else supply_demand = 0], and if so, we, subsequently, identify these developments as supply increase, supply decrease, demand increase, and or demand decrease. We also count the number of supply, demand, increase, decrease words as well as combinations and examine whether the supply and demand words actually imply the right market developments (e.g. increased number of planted crops (supply increase) vs pasta plants boosted orders (demand increase)). At this stage we additionally examine if any relevant demand or supply words are missing from the current dictionaries.

The auditing results also serve as a performance benchmark for our computer-based indices. The correlation between our human- and computer-built indices is high; it ranges between 0.64 (demand decrease) and 0.85 (demand increase) in quarterly data. In particular, to dynamically assess the time-series performance implied by our machine-generated process, we examine the co-evolution of the human- and computer-generated indices. Figure C1 to Figure C4 plot the quarterly comparison for each of the supply and demand components along with the net index performance of the two methods.

FIGURE C1. Human and Computer Increase indices

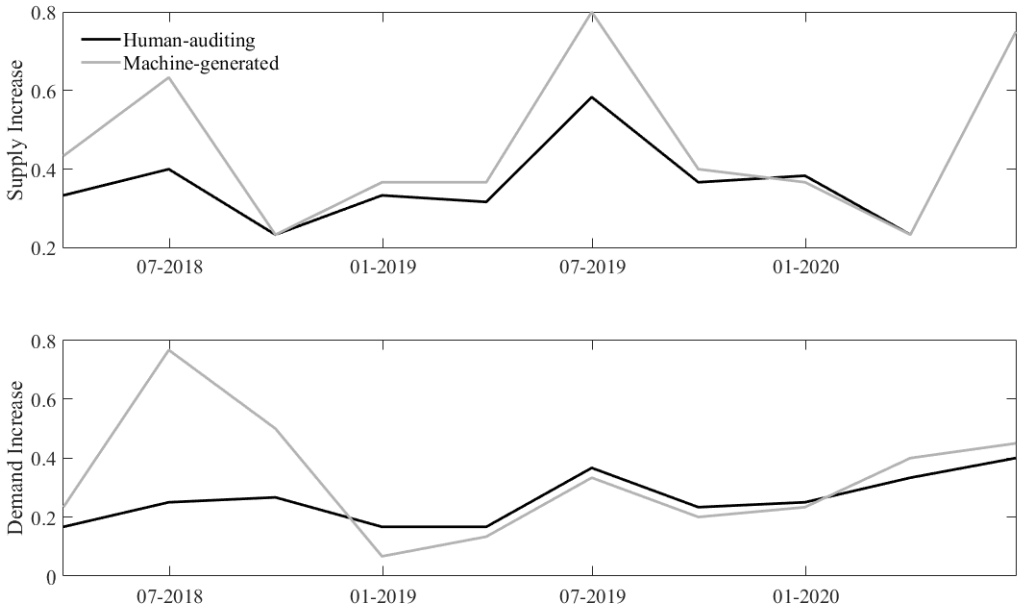


FIGURE C2. Human and Computer Decrease indices

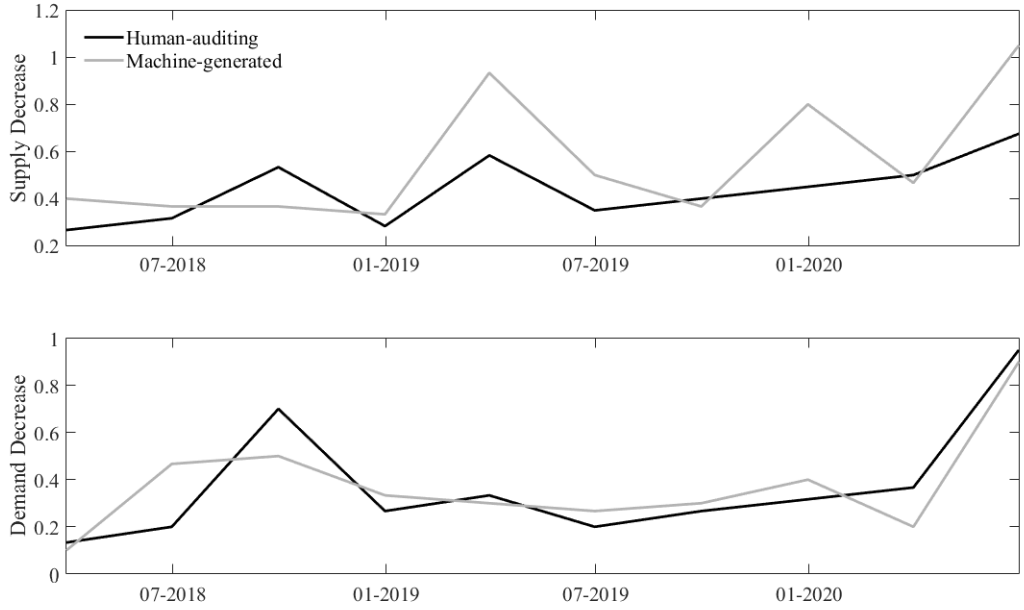


FIGURE C3. Human and Computer Net indices

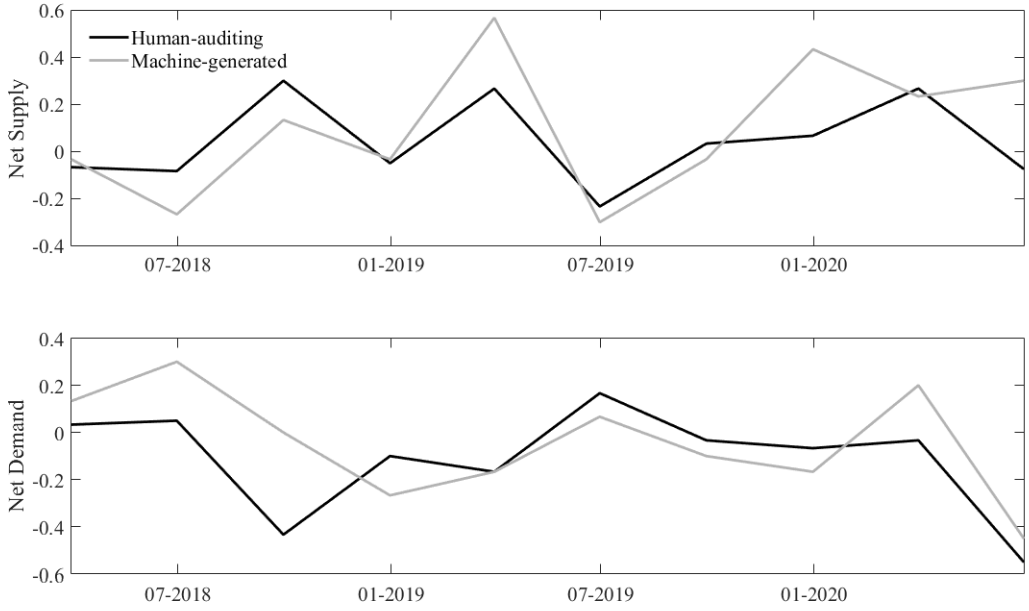
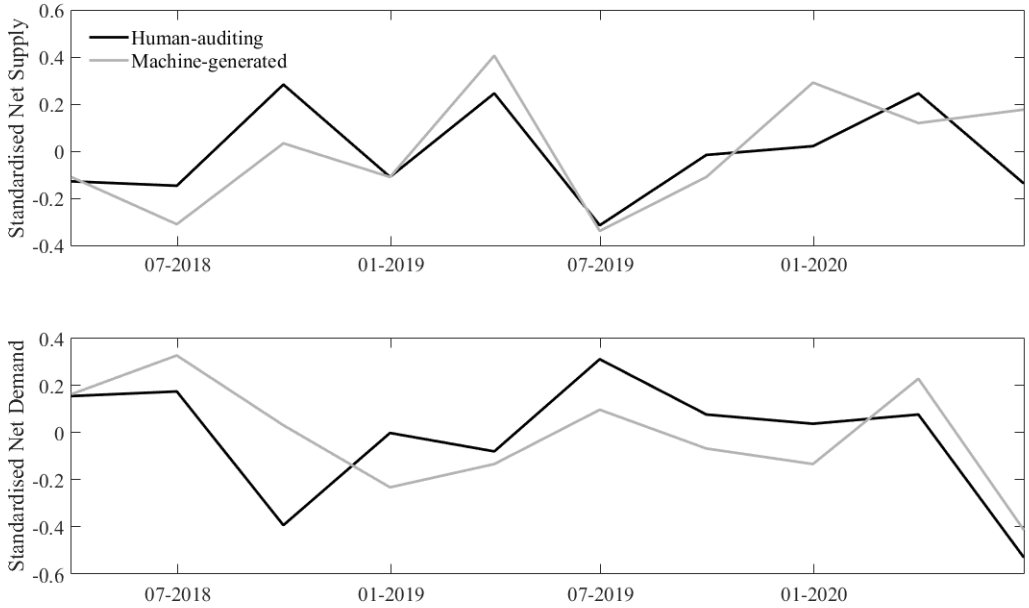
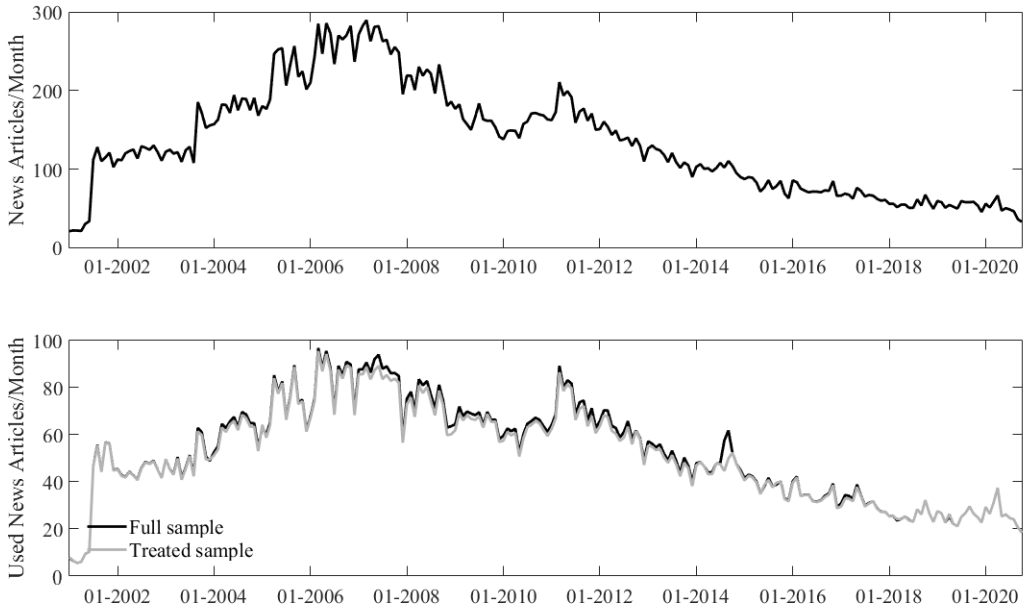


FIGURE C4. Human and Computer Standardized Net indices



C.0.1. *Auditing the Article Selection.* An important consideration for the construction of the supply and demand indices is that the news outlets' change in policies could artificially inflate, and generally distort news coverage and our commodity indicators as a result. We control for this caveat by dividing the net supply and demand indicators with the number of articles published per day. An additional consideration is that a large number of price updates and other technical reports gets published for a limited period of time and subsequently discontinues. To further address this issue we treat the original article sample by removing technical reports that display a hump-shaped distribution and eventually disappear from the sample. Figure C5 plots the average number of news articles per month for the original and the treated sample used for the construction of the composite index. The two curves are identical which lends further support to the ability of our algorithm to correctly select informative articles, successfully discarding irrelevant content.

FIGURE C5. News Coverage of the Global Commodity Index – Average Number of News Articles per Month



C.0.2. *Duplicates and Exceptions.* We follow two approaches to identify similar duplicates. The first method exploits Reuters' editorial title policy while the second method, which can be applied to other news outlets, relies on the percentage of identical sentences across articles. We combine both methods for the construction of the composite index as well as for all articles that we retrieve from Reuters.

The first method consists in removing articles whose title contains the acronym "RPT" (i.e. repeat) or "UPDATE" if another article with the same title except "RPT" or "UPDATE" is published within 24 hours. The second method computes the percentage of identical sentences across articles. The general idea is to remove one article of the identified pair of similar duplicates according to a percentage of identical sentences across articles within a specific time window.

The combination of the two approaches is effective even if the title of a recurring article is modified; also, when several articles re-appear in a merged format. For the construction of the composite index we remove 75,290 duplicate articles (7.2% of total articles).