BEYOND OIL: THE ORIGINS OF COMMODITY PRICE FLUCTUATIONS

ALVIN LUMBANRAJA, SARAH MOUABBI, EVGENIA PASSARI AND ADRIEN ROUSSET PLANAT

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 business cycle transmission of these supply-side disturbances is often larger and more persistent than those arising in oil markets in our sample.

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

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

1. INTRODUCTION

Ever since the fundamental work of Kydland and Prescott (1982) that 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 on this front comes from oil markets (Hamilton, 1983, 2003).[1] However, 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—beyond oil—that extend far beyond petroleum, whose supply is subject to varied shocks that could plausibly drive fluctuations in quantities and prices. Despite their importance for production, much less attention has been devoted to these other key commodities, whose

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[1] Additional work focusing on the importance of oil for business cycle fluctuations includes Kilian (2009); Antolín-Díaz and Rubio-Ramírez (2018); Baumeister and Hamilton (2019); Caldara, Cavallo, and Iacoviello (2019) and Känzig (2021).

importance has only grown in light of the COVID-19 pandemic, Russia's invasion of Ukraine, and ongoing geopolitical tensions with China.

Our goal is to fill this gap by constructing broad measures of supply-side disturbances originating in commodity markets, derived from news coverage of commodity developments. 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. Because commodities are essential inputs across most production sectors, shocks to their supply represent a plausible source of business-cycle fluctuations. Using our measures, we show that commodity-driven supply disturbances that originate outside the oil market have sizable effects on both prices and output. In fact, supply-driven fluctuations in non-oil markets are cumulatively more stagflationary than those originating in oil markets and are often more persistent.

The key identification challenge is to separate supply-driven from demand-driven fluctuations in commodity prices. We address this problem in three steps. First, we read the news systematically. We construct an audited, taxonomic dictionary that captures the words and phrases journalists use to describe the forces behind commodity prices. We then count how often these terms appear with directional modifiers and standardize the counts by the total number of articles we use in our exercise. This procedure yields clean, comparable measures of supply and demand pressure. Second, we decompose the sources of these pressures. We assemble training libraries of authoritative texts covering business cycles, geopolitical shocks, natural disasters, and climate change. We compute how often these topical patterns appear within supply- and demand-related news. This step allows us to trace commodity price movements back to their underlying origins. Last, we 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 measures. The correspondence between the human-coded and machine-generated indices is strong, with correlations reaching up to 85% in quarterly data. 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.

Our narrative-based identification strategy is successful in isolating supply from demand side disturbances. We validate our methodology along two dimensions. First, we examine the correlation between our daily supply and demand indicators with commodity returns. We see that, a reduction in our supply indicators is associated with an increase in commodity spot prices; similarly, an increase in our demand indicator coincides with higher commodity spot prices. Most importantly, these relations hold not only at the level of the index, but also at the level of individual commodities. Exploiting the high-frequency nature of our indicators, we demonstrate that they capture genuine informational content that is largely unanticipated by commodity markets. Second, for the subset of supply disturbances (i.e. oil) for which alternative measures are available, we validate our oil measure of supply using structurally estimated oil supply shocks as a benchmark.

Examining our indices, we see that they 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 identifies 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 and copper, 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 measure.

Armed with our measures of supply-side disturbances, we next examine their implications for aggregate quantities and prices. 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 to increased input costs, increased investment, and higher sales volumes, reflecting standard economic intuition about firm responses to strengthening market conditions.

A key contribution of our work 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 and heavily affects demand. 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 elasticities outside episodes of trade conflict. Our decomposition of drivers across commodity categories reveals systematic patterns. Fluctuations in the business cycle mainly affect energy, industrial metals, precious metals, and soft commodities related to biofuels. Geopolitical risks disproportionately impact energy, precious metals, and soft commodities. Natural disasters mainly disrupt grains and soft commodities with secondary spillovers into energy markets. Climate-change-related concerns are most pronounced in energy markets and increasingly relevant for industrial metals.

Our methodology also extracts demand signals across 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 provides narratively identified demand signals, enabling direct tests of New Keynesian predictions about the propagation of demand disturbances through the economy (Christiano, Eichenbaum, and Evans, 2005; Galí, 2015; Kaplan, Moll, and Violante, 2018). It also offers a novel perspective on the channels through which these disturbances are transmitted.[2]

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. The recent experience of COVID-19 has also revived 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 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,

[2]See also Nakamura and Steinsson (2014) on the importance of identifying demand shocks.

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.

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.

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, only a

few papers derive structurally estimated supply measures outside the energy sector. Notable exceptions include studies 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 that leverage 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 approach develops robust proxies for supply and demand disturbances that span the commodity universe in a consistent and comparable manner.

The remainder of the paper is organized as follows. Section 2 presents our methodology and introduces the methodology for developing our supply- and demand-side indicators in commodity markets. In Section 3 we perform a series of validation exercises for our indicators. Section 4 compares the macroeconomic responses to oil and non-oil disturbances and reveals that the latter are quantitatively larger. Section 5 decomposes the indices into factors driving commodity price fluctuations and documents the time-varying importance of these factors. In Section 6, we examine the differential effects of our commodity indices on firm-level outcomes. Section 7 concludes.

2. Building Supply and Demand Commodity Measures

In this section, we introduce our news-based narrative strategy for identifying supply- and demand-side fluctuations in commodity prices. The approach is flexible and applies across all major commodity groups, including energy, metals, agriculture, and livestock. Our indices clearly differentiate between supply and demand drivers, and their peaks coincide with major episodes such as the post-crisis collapse in commodity markets, market-specific disruptions, and the COVID-19 shock. The richness of the news data also allows us to pinpoint the fundamental forces shaping commodity dynamics, including business-cycle conditions, geopolitical risks, natural disasters, and climate change.

2.1. General Methodological Overview.

Our methodological approach rests on the premise that financial news provides timely and economically meaningful information about the shocks that drive commodity markets. Two assumptions guide our approach. First, news outlets report economically significant developments with minimal delay. Second, the magnitude of a shock is positively associated with the breadth and intensity of coverage. Motivated by these assumptions, we construct text-based indices that simulate a systematic news-reading protocol. These indices measure supply and demand developments through a narrative econometric framework that quantifies both the frequency of commodity-related reporting and its directional content. In doing so, we build on existing measures of aggregate commodity sentiment and extend the methodology across all major commodity categories—energy, industrial and precious metals, agricultural commodities, and livestock—within a unified analytical framework.

We construct our supply- and demand-side disturbances based on news articles using a two-stage text-analysis procedure. First, we identify words and phrases that signal supply- and demand-side developments at the sentence level. Second, we refine these signals with algorithms that remove ambiguous contexts, adjust for negations, and incorporate commodity-specific exceptions, reducing classification errors from linguistic variation across markets. We construct supply and demand vocabularies by identifying the most frequent terms in the corpus and classifying them according to their economic meaning, with human validation for accuracy (see Appendix D). To incorporate directional information, we combine these vocabularies with standard dictionaries of increase- and decrease-related terminology.

Our indicators count how often supply- or demand-related terms appear near directional language within a sentence. The net supply measure equals supply contractions minus expansions, and the net demand measure equals demand expansions minus contractions. These indicators can be aggregated at any time frequency. We further improve accuracy by correcting cases where verbal descriptions do not align with their economic meaning, such as "high temperature" in agriculture or "long maintenance" in energy, which both signal supply disruptions. Commodity-specific rules ensure consistent interpretation across markets. Using additional identifier terms, we also classify supply and demand developments by underlying drivers, including global activity, consumption, geopolitical events, and natural disasters. Our approach produces simple, transparent, and comparable measures across commodity classes, supported by a concise dictionary and targeted adjustments for ambiguous terms (e.g., "plant").

2.2. **News Outlets and Article Selection.** Our empirical analysis relies on Reuters news articles as the primary source for constructing commodity-market indicators. The dataset comprises more than 1,100,000 articles published between May 2000 and May 2023, offering extensive coverage across multiple commodities. All textual data are sourced through the Factiva database, ensuring consistent formatting and comprehensive coverage of market-relevant information. Our data preparation protocol employs a multi-stage filtering process to ensure that the corpus includes only relevant and non-redundant articles. We first remove identical and near-duplicate articles from the raw Factiva sample to avoid double-counting information. To ensure textual fidelity, we verify that scraped article content precisely matches the original published documents. Additional data-integrity steps include confirming the accuracy of sentence segmentation, disambiguating proper nouns that could otherwise be mistaken for dictionary terms through capitalization checks, and systematically handling negations that may distort measurement.

When constructing our commodity-specific indicators, we apply a commodity-specific relevance filter to exclude sentences whose primary focus is on substitute commodities, thereby reducing the

risk of measurement error. For instance, when constructing wheat market indicators, we filter out articles in which terms such as “corn”, “soybean”, “barley”, “rice”, “maize”, “coffee”, “cocoa”, “sugar”, “cotton”, “palm”, “oilseed” or other competing agricultural commodity terminology appear in the sentence. In contrast, construction of the aggregate commodity index follows an inclusive approach, incorporating all articles containing commodity-related terminology (refer to Appendix C for further details).

2.3. **Disentangling Supply and Demand.** We construct a simple, transparent methodology for extracting economically meaningful supply and demand signals from financial news. Before implementing the text-reading algorithms, we standardize the structure of the news articles through a set of pre-processing steps. We begin by segmenting each article into sentence-level units, which serve as the fundamental semantic domains for subsequent analysis. This granularity provides the appropriate contextual boundaries for detecting economically relevant lexical patterns. Following the standard practice in textual analysis, we remove stop words and punctuation from the sentences of our corpus. This normalization step mitigates stylistic variation across journalists. Although stop-word inventories differ across Natural Language Processing applications, they uniformly contain high-frequency functional terms (e.g., "the", "is", "at", "which", "and", "on") that carry minimal informational content for economic analysis. Excluding these elements enables the algorithms to focus on content-bearing terms that convey substantive economic information.

Our dictionary development follows a data-driven approach. We first identify high-frequency terms in commodity news articles. Each high-frequency term is evaluated individually and classified as supply-related or demand-related according to its economic significance. This computational classification 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. When building the dictionaries that will capture the shocks to the commodity market as a whole (for more details regarding the core dictionaries see Appendix Table A3), we include few words that unambiguously refer to supply and demand. These include *supply*, *production*, and *output* for the supply category and *demand*, *consumption*, *buy* and *purchase* for the demand category. When constructing indices for individual commodities, we augment the core dictionaries used in the aggregate index with commodity-specific terms that capture the distinct supply and demand conditions of each market. Tables A4, A5, and A6 in the Appendix present the specialized dictionaries for crude oil, natural gas, and wheat. These lexicons are designed to remain parsimonious and structurally simple to limit classification errors and attribution inaccuracies. The algorithm applies additional contextual filters to ensure accurate attribution of market developments. It identifies sentences that explicitly reference the focal commodity while excluding content centered on competing commodities. To incorporate directional information,

we employ standardized dictionaries of increase- and decrease-related terminology that have been validated in the economic textual-analysis literature. Operationally, the supply and demand vocabularies are combined with these directional indicators to create compound semantic units that capture both the market dimension (supply or demand) and the direction of change (expansion or contraction) in commodity market developments.

Our methodology quantifies the lexical co-occurrence of market-dimension terms (supply and demand) with directional words within defined sentence-level proximity windows. Specifically, we count instances in which supply- or demand-related words and expressions appear alongside directional indicators within a specified word-distance threshold on either side of the focal market term. These co-occurrence counts are then used to construct directionally sensitive market indicators. The net supply indicator is defined as the difference between supply contractions and supply expansions, while the net demand indicator reflects the excess of demand expansions over demand contractions. Together, these net measures yield continuous indicators of directional market pressure that can be examined at various time frequencies.

To enhance measurement precision, we supplement our baseline approach with contextual refinement algorithms designed to account for semantic negation and commodity-specific linguistic idiosyncrasies. This refinement is essential for ensuring that paired market-dimension and directional terms accurately capture the underlying economic meaning of news content. Several commodity groups exhibit systematic semantic inversions that would otherwise introduce measurement error. For agricultural commodities, combinations of positive directional terms with supply-related words may in fact signal supply contractions–for example, high temperature" denotes adverse growing conditions and reduced supply rather than expansion. In energy markets, long maintenance" similarly indicates supply disruption rather than increase. Our algorithm also incorporates commodity-specific exception rules to correct such inversions, maintaining consistent economic interpretation across heterogeneous commodity classes.

2.4. **Narrative Drivers of Supply and Demand.** In addition, we construct a separate classification of the key events that drive commodity markets. Drawing on the IMF's *Commodity Special Feature* and the World Bank's *Commodity Markets Outlook*, we organize the potential sources of commodity-market shocks into four primary drivers: business-cycle developments, geopolitical risk, natural disasters, and climate change. To identify language associated with each driver, we develop dictionaries derived from authoritative sources, following the methodology of Engle et al. (2020) for contexts in which predefined dictionaries are unavailable. For business-cycle terminology, we use the complete historical record of announcements issued by the NBER Business Cycle Dating Committee (1979-2020). To capture geopolitical risk, we rely on the full set of press statements from the President of the United

Nations Security Council. For natural disasters, we draw on the EM-DAT International Disaster Database. For climate-change terminology, we adopt the same authoritative texts used by Engle et al. (2020).

2.5. **Supply and Demand Indicators.** We next create indicators of supply-side and demand-side disturbances. We construct both aggregate indicators but also indicators for specific commodities. For the aggregate commodity market indicator, we employ an inclusive sampling strategy that captures all articles referencing any commodity included in the Standard & Poor's Goldman Sachs Commodity Index (GSCI) spot price series excluding lead. This criterion ensures broad coverage of economically significant commodity markets, as the GSCI comprises major physical commodities with active and liquid futures markets, providing a representative measure of broad commodity market developments. Table 1 lists the individual commodity constituents considered in our analysis, which encompasses the full range of major tradable commodities across energy, metals, and agricultural markets.

TABLE 1. Keywords for the global commodity supply and demand index

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	
Gasoil	Zinc			Cotton	
Gasoline					

Note: This table lists the constituent commodities of the S&P GSCI composite index. These items serve as the keyword set used to construct the Global Commodity Supply and Demand Index series.

For each commodity i, we begin by constructing distinct measures of supply- and demand-driven directional market pressure. Specifically, we create four indicators (capturing increases and decreases in supply and demand) by counting, for each day t, the number of articles that mention supply or demand in market i together with a directional qualifier (+/-). Accordingly, the indicator for a supply increase is defined as:

$$S^{+}_{i,t} \equiv \frac{\#\text{ of Articles Indicating Commodity Supply Increase}_{i,t}}{\#\text{ of Articles Read}_{t}}. \tag{1}$$

The remaining indicators–supply decreases S^{-}_{t} and demand increases D^{+}_{t} and decreases D^{-}_{t}–are defined analogously. To account for shifts in publication volume, all indicators are normalized by the number of retained articles on day t. We also develop aggregate indices that pool information across markets. Thus, the aggregate net-supply indicator is given by:

$$S^{+}_{t} \equiv \frac{\#\text{ of Articles Indicating Commodity Supply Increase}_{t}}{\#\text{ of Articles Read}_{t}}. \tag{2}$$

Next, we derive net supply and net demand measures by taking the difference between opposing directional indicators: net supply as supply contractions minus supply expansions, and net demand

as demand expansions minus demand contractions. Thus, for the aggregate indices, we define

$$S_t \equiv S_t^- - S_t^+ \qquad \text{and} \quad D_t \equiv D_t^+ - D_t^-. \tag{3}$$

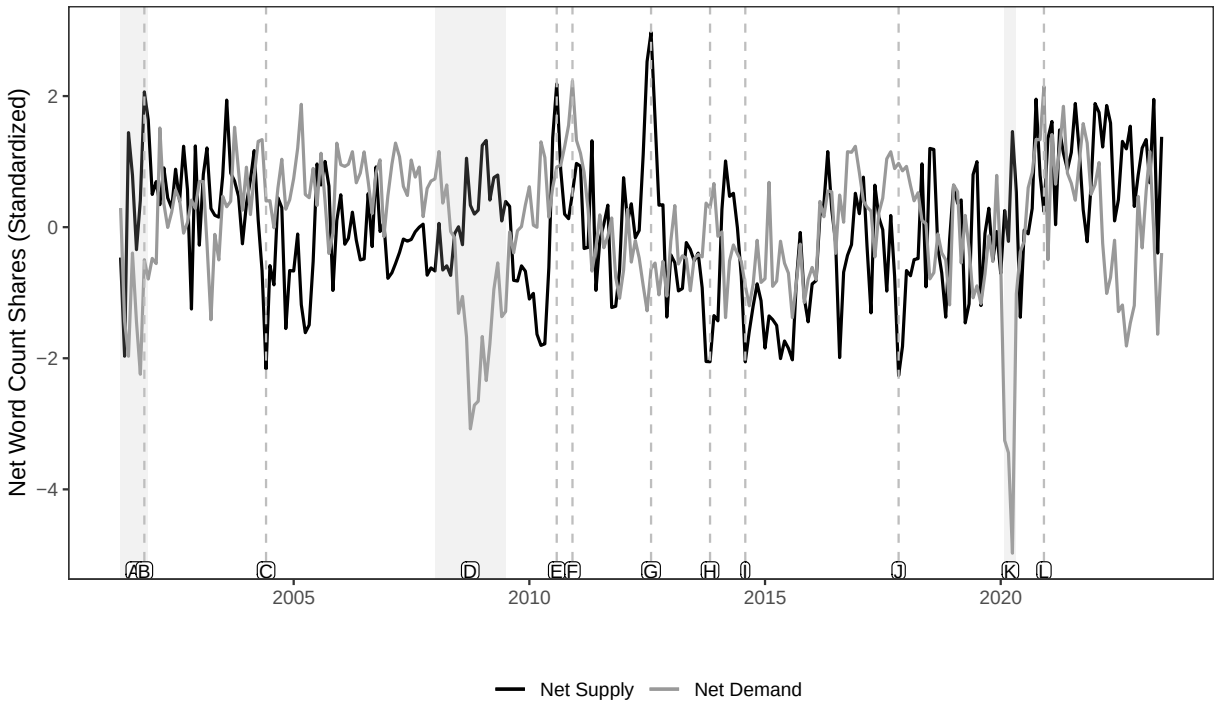
We construct analogous indices for each commodity market i.

Figure 1 displays the standardized monthly net supply and net demand indicators. To mitigate distortions arising from changes in publication volume over time, these indicators are normalized by the daily count of retained articles. The resulting time series align closely with well-documented commodity market dynamics. Major turning points in the demand indicator coincide with systemic economic events, including the 2001 US Recession, the global financial crisis (2007-2009), the COVID-19 pandemic (2020-2021). The supply-side indicator exhibits pronounced volatility during episodes of significant production adjustments, such as OPEC interventions following the 2001 recession and the September 2001 terrorist attacks, as well as during subsequent quota revisions. The supply measure additionally shows marked contractions during severe drought episodes that significantly impaired global grain production.

Figure 2 presents the decomposition of the net supply and net demand indicators into their underlying drivers across major commodity categories. The cross-sectional patterns highlight clear differences in both the incidence and synchronicity of market developments. Supply disturbances arise primarily in grains, softs, and energy markets, and exhibit limited temporal alignment across categories, indicating that supply-side pressures tend to be commodity-specific rather than systemic. In contrast, demand fluctuations show a high degree of cross-sectional co-movement, with pronounced cyclical patterns evident across most commodity groups. This synchronicity aligns with the influence of shared macroeconomic forces shaping global demand conditions. Grain markets represent a notable exception: they demonstrate comparatively muted demand elasticity outside episodes of trade conflict, reflecting the inherently inelastic consumption characteristics of staple agricultural goods.

Overall, the commodity-level indicators for crude oil, wheat, corn, sugar, and copper reveal marked heterogeneity in the drivers of price dynamics. Energy and metal markets are highly responsive to the business cycle, with demand movements closely aligned with broader macroeconomic conditions. Agricultural commodities, by contrast, are more heavily affected by natural-disaster shocks and show more inelastic demand due to their specific production processes and consumption profiles.

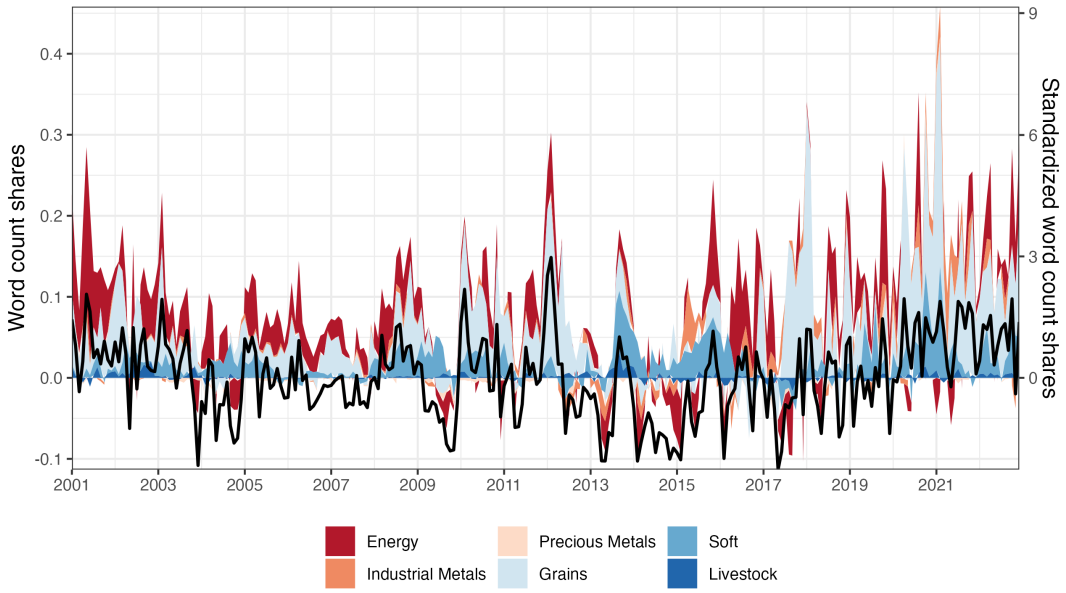
FIGURE 1. Net supply and net demand indices across all commodity-related news articles



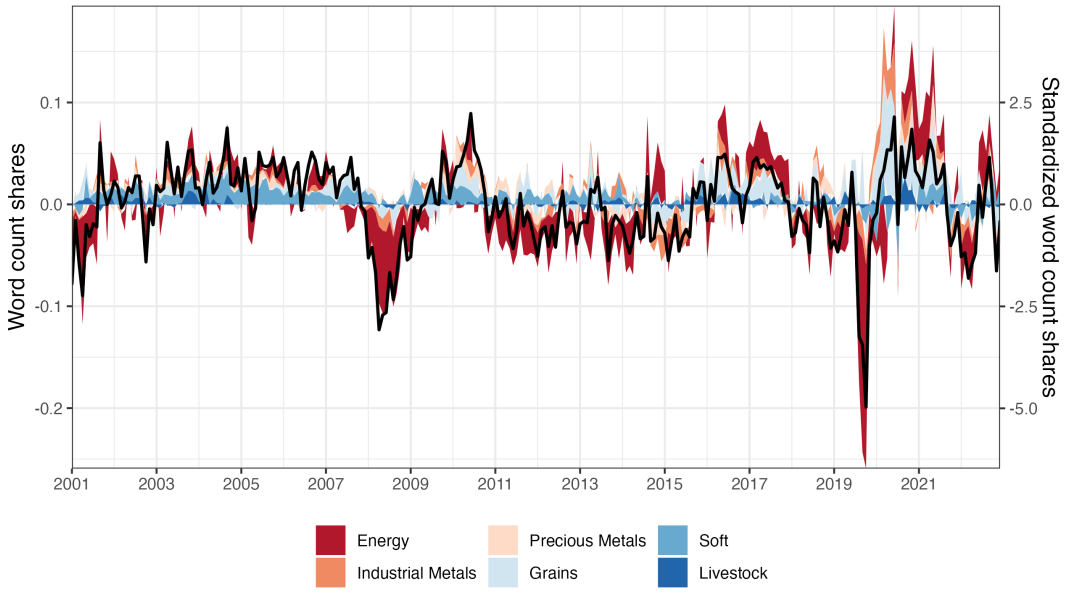
Note: This figure plots the standardized net supply and net demand indicators from 2001 to 2023, constructed using all commodity-related news articles in the Reuters corpus. The bars and lines map a number of well-known commodity-wide developments that exceeded ±2 S.D. These events are: [A] US Recession and 9/11, [B] OPEC 118th Extraordinary Meeting (production cut by 1mbpd following US Recession and 9/11), [C] OPEC 131st Extraordinary Meeting (production increase by 2mbpd), [D] 2008 Global Financial Crisis, [E] Multiple natural disasters in Pakistan, Russia, China, and India, [F] Positive outlook on global recovery increased global demand, [G] Worst drought in more than 50 years in the U.S. severely cut corn and soybeans productions, [H] Record US corn harvest, third-largest US soybean harvest, [I] Record grain harvest in US, Brazil, and South Africa, [J] Record-high US crude production, 5-year high crude production in Libya, [K] Onset of Covid-19 Pandemic, US Recession, [L] Covid vaccine approval increases broad-based demand for commodities

2.5.1. *Energy Commodities: Crude Oil.* Our crude oil indicators capture well-documented market dynamics, particularly production adjustments following OPEC ministerial meetings. OPEC's supply management decisions remain the dominant source of supply-side variation in global oil markets. Additional supply disruptions arise from weather-related production impairments (e.g., hurricanes), the structural expansion of US production capacity during 2014-2016, and the acute oversupply conditions of April 2020, when pandemic-induced demand collapses triggered both a price breakdown and severe physical storage constraints. The demand for petroleum products displays pronounced cyclicality, with major contractions aligning with key macroeconomic downturns: the 2001 US recession, the 2007-2009 global financial crisis, and the early phase of the COVID-19 pandemic. Figure 3 further illustrates the rapid demand recovery observed in 2021, after the global roll-out of vaccines, and in

FIGURE 2. Decomposition of composite indices across categories



Panel A: Net supply



Panel B: Net demand

early 2023, after China's economic reopening. These episodes underscore the sensitivity of petroleum consumption to mobility restrictions and broader economic activity.

2.5.2. *Agricultural Commodities: Wheat, Corn and Sugar.* Figure 4 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 disturbances corresponding to bilateral trade agreements between major market participants (notably US-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 5 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.

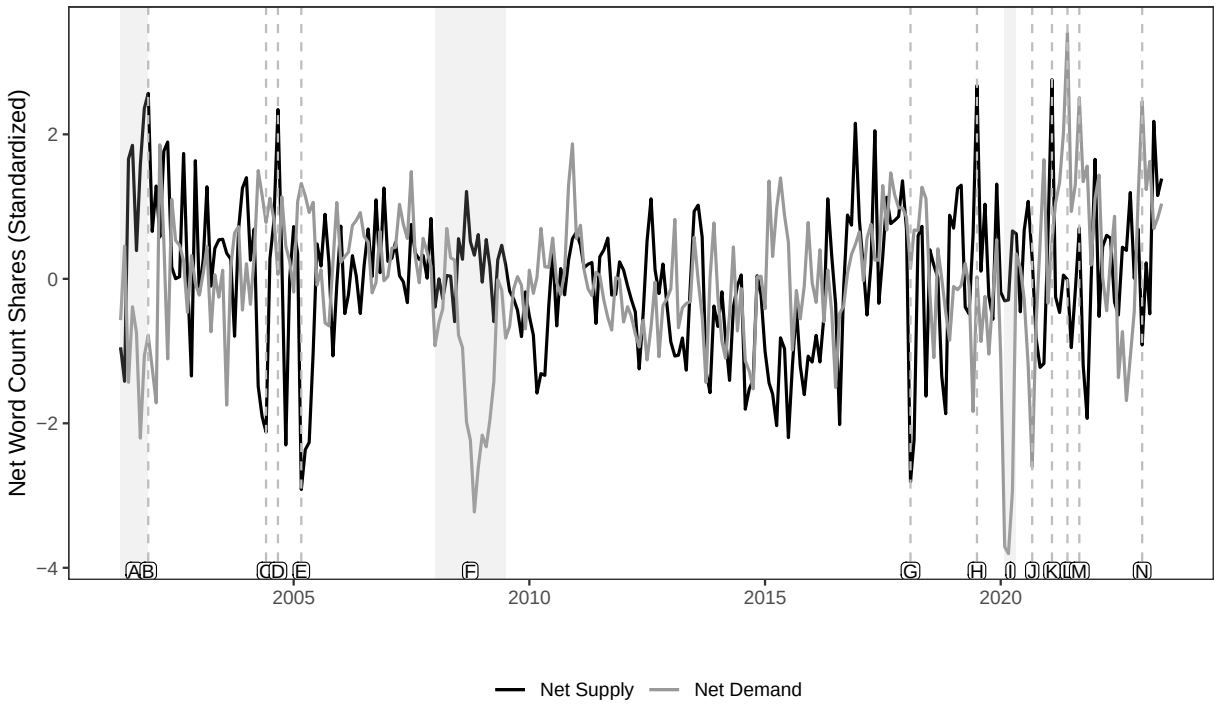
Figure 6 displays the standardized net supply and demand indicators for sugar markets from 2001 through 2023. Sugar demand exhibits distinctive temporal patterns, with pronounced seasonality driven by international holidays and festivals that generate systematic consumption peaks. Additionally, discrete 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.

2.5.3. *Industrial Metals: Copper.* Figure 7 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.

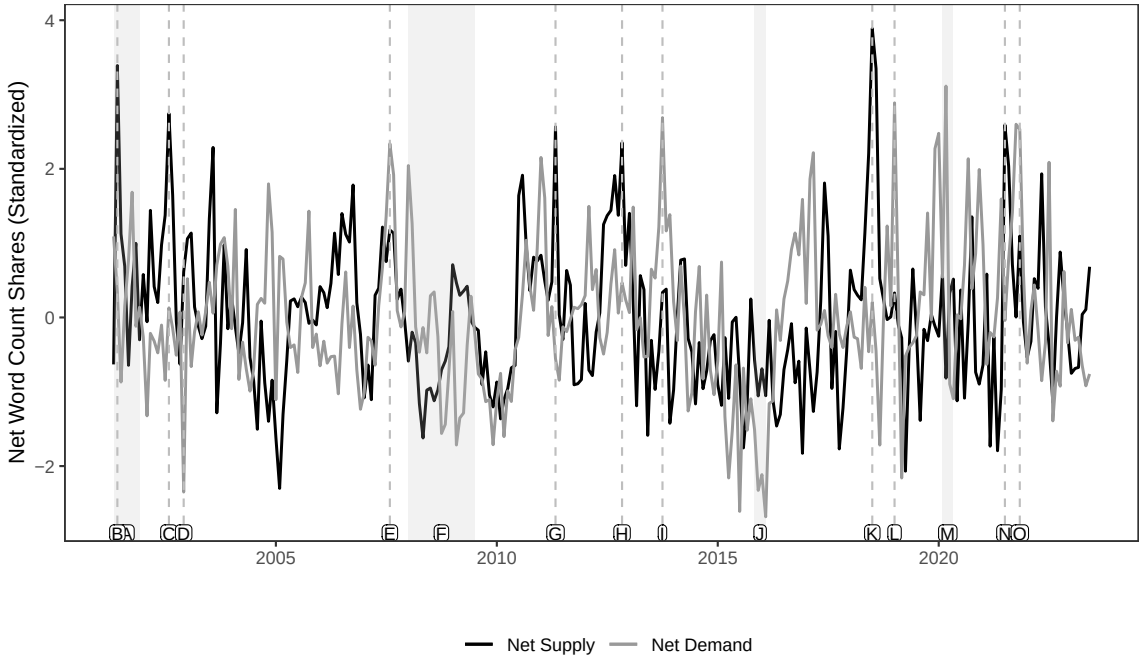
Taken together, the commodity-level indicators–constructed for crude oil, wheat, corn, sugar, and copper–reveal substantial heterogeneity in the forces driving market developments across commodity groups. Energy and metal markets show pronounced sensitivity to the business cycle, with demand fluctuations closely tracking broader macroeconomic conditions. In contrast, agricultural commodities, including both grains and softs, are more strongly shaped by natural-disaster shocks and exhibit characteristically inelastic demand, reflecting their distinct production technologies and consumption patterns.

FIGURE 3. Crude oil index: Net supply and net demand



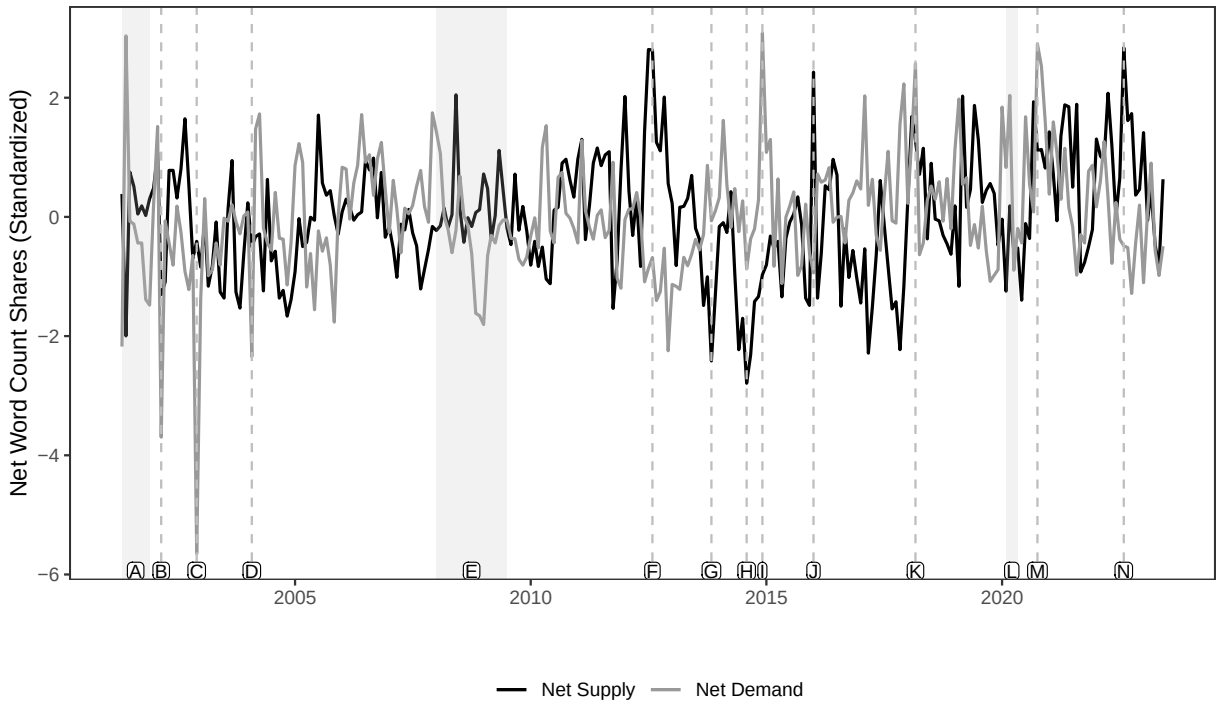
Note: This figure plots the standardized net supply and demand indicators for the period between 2021 and 2023. The bars map a number of well-known oil sector developments that are in the top 1% (two-tailed) of events. These events are: [A] US Recession, [B] OPEC 118th Extraordinary Meeting (production cut by 1mbpd following US Recession and 9/11), [C] OPEC 131st Extraordinary Meeting (production increase by 2mbpd), [D] Niger Delta conflict affecting Nigeria oil output, [E] OPEC 135th Meeting (production increase by 0.5mbpd, production at record high), [F] Global Financial Crisis, [G] U.S. record oil production (above 10 million bpd for the first time since the 1970's) fed worries about oversupply, [H] OPEC+ extended production cut, US imposed sanction on Venezuela, Iran, [I] Onset of Covid-19 Pandemic, US Recession, [J] Bad US unemployment data and strong dollar depressed oil demand, [K] Saudi announced 1mbpd voluntary cut, winter storm in Texas cut U.S. production by more than 10%, [L] Very positive global demand forecast due to vaccine rollout and expected recovery, [M] Global oil demand jumped by 1.4mbpd (mtm) on continued recovery, [N] Major economies started to reopen borders and China lifted strict COVID-19 restrictions, boosting demand growth expectations

FIGURE 4. Wheat index: Net supply and net demand



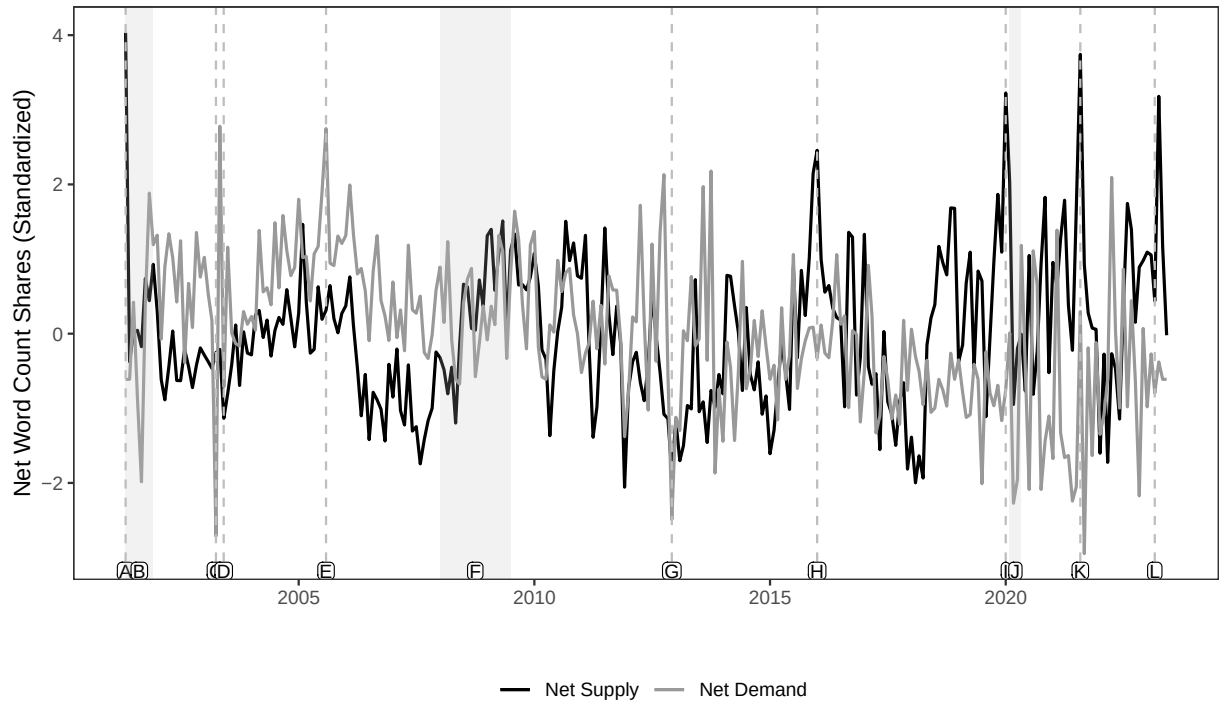
Note: This figure plots the standardized net supply and demand indicators for the period between 2001 and 2020. The bars map a number of important developments in the wheat sector that are in the top 1% (two-tailed) of events. These events respectively are: [A] US Recession and 9/11, [B] US wheat production declined by 10% from previous year, [C] Severe drought in Canada cut spring wheat production by more than 25%. Worrisome dry weather in Australia and U.S. Northern Plains area threatened yields' prospects, [D] Decline in global wheat import putting pressure on price, [E] Strong global growth drives prices to record high, Ukraine imposes export restriction, [F] Global Financial Crisis, [G] Dry weather stressed the hard red winter wheat crop in the Plains, while wet weather slowed spring wheat seeding in the northern Plains. Dry weather in France led to concerns about harm to the wheat crop, [H] Expectations of smaller wheat crops in Argentina and Australia, dry conditions in the US Midwest, and low supply in the Black Sea region sparked worries about world supply, [I] Prospect of strong demand from China, [J] Sluggish demand for U.S. supplies, partly due to appreciating USD, China's policy shift that favoured other grains, tensions with traders over Egyptian policy on grain fungus ergot,[K] Widespread severe drought developed over Northern and Central Europe in summer 2018 led to a significant drop in harvests, [L] Resuming trade talks between China and the U.S. boosted hopes for higher wheat demand, [M] Covid-19 Recession, global shutdown induced panic buying of essential goods, [N] Adverse hot weather in North America, torrential rain in western Europe and reduced expectations for Russia's harvest created concern about global supply, [O] Ongoing supply chain disruption and robust demand after global reopening drives wheat to 9-year high.

FIGURE 5. Corn index: Net supply and net demand



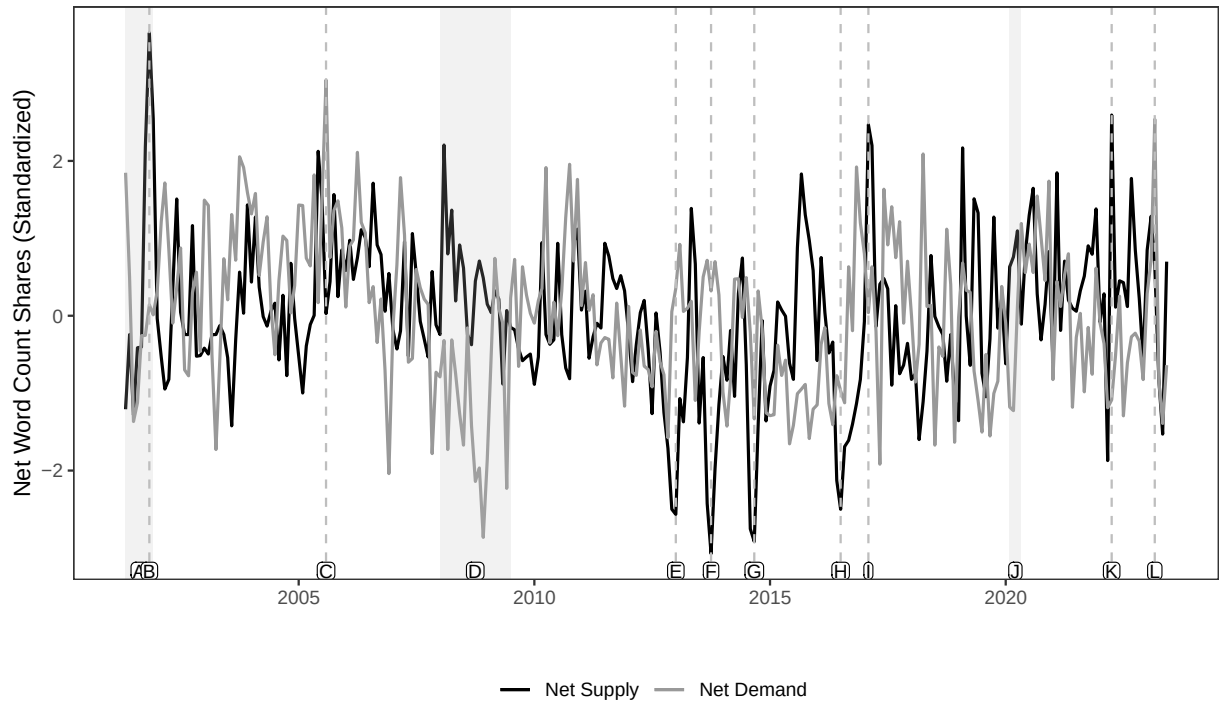
Note: This figure plots the standardized net supply and demand indicators for the period between 2001 and 2023. The bars map a number of important developments in the corn sector that are in the top 1% (two-tailed) of events. These events respectively are: [A] US Recession and 9/11, [B] Weak US export demand and abundant supply put pressure on corn price, [C] Persistent weakness in demand prompted reduction in US corn export forecast, [D] Concern over bird flu in East Asia depress demand for corn feed, [E] Global Financial Crisis, [F] Worst drought in more than 50 years in the US severely cut corn and soybeans productions, [G] Record US corn harvest, third-largest US soybean harvest, [H] Record US grain harvest in US, Brazil, and South Africa, [I] Strong global demand for U.S. corn from traditional buyers, including Mexico, Japan and South Korea, [J] El Niño induced drought and hit corn production in Southern Africa, [K] Strong export demand for U.S. corn, [L] Covid-19 Recession; global shutdown induced panic buying of essential goods, [M] China's recovery from swine fever boosted demand for corn, [N] Lower U.S. and EU corn crops amid dry weather

FIGURE 6. Sugar index: Net supply and net demand



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 that are in the top 1% (two-tailed) of events. These events respectively are: [A] EU permanent production quota reduction and adverse weather in key producers (e.g. Brazil, China) reduced sugar production, [B] US Recession and 9/11, [C] 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, [D] Notable uptick in sugar futures driven by trade (Libya, Taiwan, Russia) and speculative buying, buoyed the market from a recent low, [E] Robust consumer buying from Russia, Pakistan and the Middle East, [F] Global Financial Crisis, [G] Sluggish demand due to winter season and rising supplies amid ongoing cane crushing in India [H] Lower-than-expected sugar output worldwide, with drought affecting India, slow start in Central America, disappointing yields in Thailand, and lowest EU beet crop in 40 years, [I] Poor growing conditions in US and India resulted in poor sugar harvest, [J] Onset of Covid-19 Pandemic, US Recession, [K] Lower production in Brazil due to the earlier drought and recent waves of frost, [L] Concerns on lower output from droughts in key producing regions (Thailand, India)

FIGURE 7. Copper index: Net supply and net demand



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 that are in the top 1% (two-tailed) of events. These events respectively are: [A] US Recession and 9/11, [B] roducers in North and South America and Asia announced production cuts to battle steep mining and processing costs and historically low metal prices, [C] Strong demand from China and good U.S. manufacturing-related news indicated demand for copper would remain sustained, [D] Global Financial Crisis, [E] Well-supplied market amid higher output from mining groups (such as BHP Billiton) and China's domestic production, [F] Higher copper output in China (jumped by 21 percent y.o.y) and Chile (copper mine's output surged back after tough 2012), [G] Concerns about rising supply as Newmont Mining Corp raised its full-year copper production forecast, [H] The global copper market is expected to move into surplus as boom time-driven new mine supply ramps up mostly from Peru, [I] Concerns about supplies after disruptions in top producer Chile (strikes), Indonesia (dispute with the government over mining rights) and Peru (strikes), [J] Onset of Covid-19 Pandemic, US Recession, [K] 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, [L] Signs of improving copper demand from China amid the easing of COVID-19 restrictions

3. VALIDATION

In this section, we conduct several validation exercises to assess the reliability of our commodity indicators. First, we illustrate how major supply shocks are reflected in contemporaneous news coverage. Second, we implement human-based auditing to evaluate the accuracy of our article classification procedure. Third, we test whether the signed demand and supply disturbances produce price responses consistent with economic theory, and we employ a placebo experiment to confirm that these

correlations are not spurious. Finally, we compare a subset of our indicators–specifically, supply-side disturbances in the oil market–with established measures of oil supply shocks.

3.1. **Illustrative example.** To assess the empirical validity of our key assumption–that shocks with substantial effects on commodity markets generate immediate news coverage–we examine a setting in which market disruptions stem from exogenous and unexpected events. We focus on seismic activity in Chile, a major copper producer, to evaluate the temporal correspondence between actual supply disturbances and their media footprint. These episodes offer a clean environment for testing whether market-relevant information is reflected in news coverage without delay.

TABLE 2. Major earthquakes in Latin America and change in copper net supply indices

Country	Date	Magnitude	Total Affected	Supply Decrease (Copper, All)	Supply Decrease (Copper, Nat. Dis.)
Chile	2007-11-14	7.7	25,155	1.53	5.40
Chile	2010-02-27	8.8	2,671,556	0.72	4.58
Chile	2014-04-01	8.2	513,387	1.15	4.13
Chile	2015-09-16	8.3	681,499	1.90	3.50

Note: This table reports four large seismic episodes in Chile. The second and third columns report the date and magnitude of the event. The fourth column reports the EM-DAT human impact, as the sum of the number of injured, number affected and number homeless. The fifth and sixth columns report daily the values of the copper supply decrease index and the natural disaster component of the copper supply decrease index, respectively, on the day following the event.

Table 2 documents the correspondence between major seismic events in Chile's copper-producing regions and our textual supply indicators. Using seismic data from EM-DAT merged with our daily indicators, we report standardized values of both the aggregate copper supply-decrease measure and its natural-disaster component on the trading day following each earthquake. The results reveal a clear and systematic relationship between large seismic events (magnitude above 7.5) and our indicators, with particularly strong responses for earthquakes occurring near mining sites where production capacity is directly affected. This high-frequency alignment provides compelling validation that our textual methodology captures exogenous supply disruptions with appropriate temporal precision. Post-event dynamics show acute increases in the copper supply-decrease indicator, with amplitudes of 1-2 standard deviations above the mean on the first trading day after the shock. This magnitude is economically meaningful, especially given the wide range of other supply-side disturbances–such as labor disputes, logistical bottlenecks, regulatory changes, energy shortages, mechanical failures, and safety incidents–that routinely generate production losses, operational suspensions, or project delays in copper markets.

To isolate the effects of geological disturbances, we decompose the supply-decrease indicator and analyze the natural-disaster component separately. This more granular measure exhibits markedly stronger reactions, with peaks of 3.5-5.4 standard deviations above baseline levels on the day following major earthquakes. The pronounced responsiveness of this sub-indicator provides strong evidence

that our textual methodology not only detects commodity market disruptions but also classifies them with appropriate specificity and temporal accuracy.

Taken together, these results show that financial news coverage incorporates major supply shocks rapidly and with precise characterization. This validation supports the construct validity of our textual indicators as timely and reliable measures of supply-side disruptions in commodity markets.

3.2. **Human Auditing.** We validate our algorithmic classifications using a structured human-audit protocol designed to minimize bias. Each month, we draw a fixed sample of articles and randomize their evaluation order to reduce exposure to temporal coverage patterns and learning effects. Two independent auditors review each article, assessing commodity relevance, identifying market developments, and evaluating the completeness of dictionary-based classifications.

The correspondence between human- and algorithm-generated indicators is strong. Quarterly correlations reach 0.85 across market dimensions, indicating substantial agreement between the two approaches. Time-series comparisons show similarly tight alignment between human-coded and algorithmic measures. The audit procedure is described in detail in Section E of the Appendix. Figures A1 through A4 display the evolution of human- and algorithm-derived indicators for supply, demand, and composite indices, visually confirming the robustness of our classification methodology.

3.3. **Relation to Commodity Price Fluctuations.** We next examine the relationship between our supply- and demand-side disturbances and high-frequency movements in commodity prices. Conceptually, commodity price increases should coincide with supply contractions or demand expansions. We provide supporting evidence for this prediction using a panel specification that exploits cross-commodity variation.

3.3.1. *Panel Evidence.* We focus on the analysis of individual commodities. Specifically, we estimate:

$$R_{i,t} = \beta\, S_{i,t} + \gamma\, D_{i,t} + c\mathbf{Z}_{i,t} + u_{i,t}. \tag{4}$$

Our main coefficients of interest are β and γ that capture the impact of a one-standard deviation reduction in supply (an increase in $S_{i,t}$) and increase in demand $D_{i,t}$, respectively, on the daily (log) returns of commodity i. We focus on twenty distinct commodity markets, including energy products (crude oil, gasoil, gasoline, heating oil, natural gas), industrial metals (copper, aluminum, zinc, nickel), precious metals (gold, silver), grains (corn, wheat, soybean), softs (sugar, cocoa, cotton, coffee), and livestock (hogs, live cattle). The vector of controls $\mathbf{Z}$ includes fixed effects for individual commodities and calendar time (day). The dependent variable is the return on spot GSCI component commodity prices between day $t-1$ and t. We cluster the errors by day and commodity.

Columns (1) to (6) of Table 3 report the estimated coefficients β and γ. These panel estimates reveal a statistically and economically significant relation between our narrative-based supply and demand

indicators and individual commodity (log) returns. In columns (1) to (3) the main dependent variables are the net supply and demand indicators while in columns (4) to (6) we replace them with the residualized net supply and demand indicators. Specifications in columns (1) and (4) control for global risk aversion (VIX), monetary conditions (the Fed Funds Rate) and exchange rate movements (the trade-weighted USD index) and include daily fixed effects. Specifications in columns (2) and (5) include include both commodity and daily fixed effects and in columns (3) and (6) we also add one lag of the dependent variable.

Overall, a unit standard deviation decline in the residualized supply-side indicator leads to a 7-8 basis point increase in the price of the commodity on the same day; for the demand-side indicator, a one-standard deviation increase in demand leads to a 12-15 basis point increase depending on the specification. The estimated effects on the supply side are approximately half the size of the demand-side coefficients–suggesting asymmetric price responsiveness to supply versus demand innovations. These relationships remain robust across alternative specifications.

Table A1 in the Appendix reports the estimation results for the eighteen commodity markets based on individual time-series regressions. The estimated coefficients on the net supply indicator are uniformly positive and statistically significant at conventional levels for fourteen of the eighteen commodities; only natural gas, nickel, silver, and gold show insignificant supply effects. The net demand indicator exhibits consistently positive and statistically significant effects across all commodities (except aluminum for which the coefficient is statistically insignificant), in line with theoretical predictions.

The robustness of these relationships across heterogeneous commodity markets provides strong evidence for the broad applicability of our text-based methodology. The estimation results in Table 3 and Table A1 show that our commodity-specific supply and demand indicators have significant explanatory power for S&P GSCI single-commodity index returns, even after controlling for global risk aversion (VIX), monetary conditions (the Fed Funds Rate) and exchange rate movements (the trade-weighted USD index). This consistent pattern across diverse commodity classes suggests that our textual indicators capture economically meaningful variation in the fundamental supply-demand dynamics that drive individual commodity price formation.

TABLE 3. Panel Regression of commodity futures daily returns on commodity-level supply & demand indicators

Commodity Returns (%)	Narrative Indices (Raw Series)			Narrative Indices (AR20 residuals)		
	(1)	(2)	(3)	(4)	(5)	(6)
Net Supply	0.087***	0.079***	0.080***	0.077***	0.079***	0.080***
	(5.71)	(6.19)	(6.21)	(4.69)	(5.70)	(5.74)
Net Demand	0.153***	0.128***	0.130***	0.127***	0.126***	0.127***
	(8.53)	(8.13)	(8.39)	(6.60)	(7.96)	(8.17)
Observations	106,880	111,940	111,920	106,480	111,540	111,540
Controls:						
Commodity Fixed Effects	Y	Y	Y	Y	Y	Y
VIX, FF, USD	Y			Y		
Time Fixed Effects		Y	Y		Y	Y
Lagged Return			Y			Y

3.3.2. *Placebo Test.* Thus far, we have shown that our supply- and demand-side disturbances are significantly related to commodity returns–and, crucially, that the signs of these relationships align with our text-based classification of supply and demand. These relationships remain robust even after controlling for standard financial market variables. The consistent statistical association between our indicators and market-wide investable commodity index returns suggests that our approach captures economically meaningful variation in global commodity market conditions. We next implement a series of falsification tests to verify that these relationships are not spurious. Specifically, we re-estimate equation (4) for the daily GSCI component returns of commodity i, but replace the commodity-specific supply and demand indicators with those constructed for commodity $j \neq i$. This cross-commodity specification serves as a placebo test, allowing us to assess whether the relationships documented in the columns of Table 3 reflect genuine commodity-specific information rather than spurious correlations or omitted variables that might produce artificial statistical significance.

Examining Table 4, we find that none of the cross-commodity supply indicators exhibit statistically significant coefficients at conventional levels. The absence of significant effects provides strong evidence against the concern that our baseline results are driven by common shocks, measurement error, or statistical artifacts. Instead, these null findings support the interpretation that our commodity-specific textual indicators capture genuinely idiosyncratic information relevant to their corresponding markets, thereby reinforcing the credibility of the baseline estimates. In specifications that omit daily

temporal fixed effects, demand indicators remain statistically significant, but with markedly attenuated coefficient magnitudes. This systematic reduction in estimated elasticities is consistent with the presence of substantial common components in demand innovations across commodity markets (see Chiaie, Ferrara, and Giannone, 2022). The attenuation pattern provides empirical support for the theoretical expectation that demand shocks are more correlated across commodities than supply shocks, which tend to be more idiosyncratic and commodity-specific. Once temporal fixed effects absorb the shared variation in commodity markets, the remaining identifying variation in demand indicators reflects primarily idiosyncratic components, resulting in diminished coefficients. This empirical regularity aligns with macroeconomic theories that view aggregate demand as a key common factor across commodity classes, typically linked to global business cycle fluctuations, monetary conditions, and broad-based shifts in risk appetite that simultaneously influence multiple commodity markets through parallel channels.

TABLE 4. Placebo panel regression of commodity futures daily returns on commodity-level supply & demand indicators

	(1)	(2)	(3)	(4)	(5)	(6)
Net Demand (Standardized)	0.0180***		0.0180***	0.0180***	0.0066*	-0.0063
	(0.0029)		(0.0029)	(0.0029)	(0.0030)	(0.0033)
Net Supply (Standardized)		0.0047	0.0046	0.0046	-0.0010	-0.0046
		(0.0032)	(0.0032)	(0.0032)	(0.0030)	(0.0027)
Within R^2	0.000	0.000	0.000	0.000	0.000	0.000
N	100,746	100,746	100,746	100,746	100,746	100,746
Time FE	No	No	No	No	Weekly	Daily
Commodity FE	No	No	No	Yes	Yes	Yes

Note: This table reproduces columns (4) to (6) of Table 3 but this time we estimate Equation (4) for the daily GSCI component returns of commodity i, but replace the commodity-specific supply and demand indicators with those constructed for commodity $j \neq i$.

3.4. **Do our news-based indicators contain actual news?** So far, we have seen that our supply and demand indicators are correlated with (contemporaneous) changes in commodity prices in a manner consistent with theory: decreases in supply, or increases in demand, are associated with higher commodity prices. However, part of that effect can be anticipated in advance; in that case, the daily increase in commodity prices can underestimate the full effect. To investigate the extent to which our narrative supply- and demand news-based indicators are indeed *news*, we explore the extent to which commodity prices respond in advance of the news releases.

We proceed in two steps. First, our narrative-based indicators have some serial correlation at the daily frequency; to remove that serial dependence, we compute residuals from an AR(p) process,

$$S^r_{i,t} \equiv S_{i,t} - B(L)S_{i,t} \qquad \text{and} \quad D^r_{i,t} \equiv D_{i,t} - B(L)D_{i,t}. \tag{5}$$

We set the lag length to $p = 20$ days, though we obtain quantitatively similar results with longer lag lengths. We standardize these residuals to unit standard deviation.

Second, we re-estimate the response of commodity prices at different horizons,

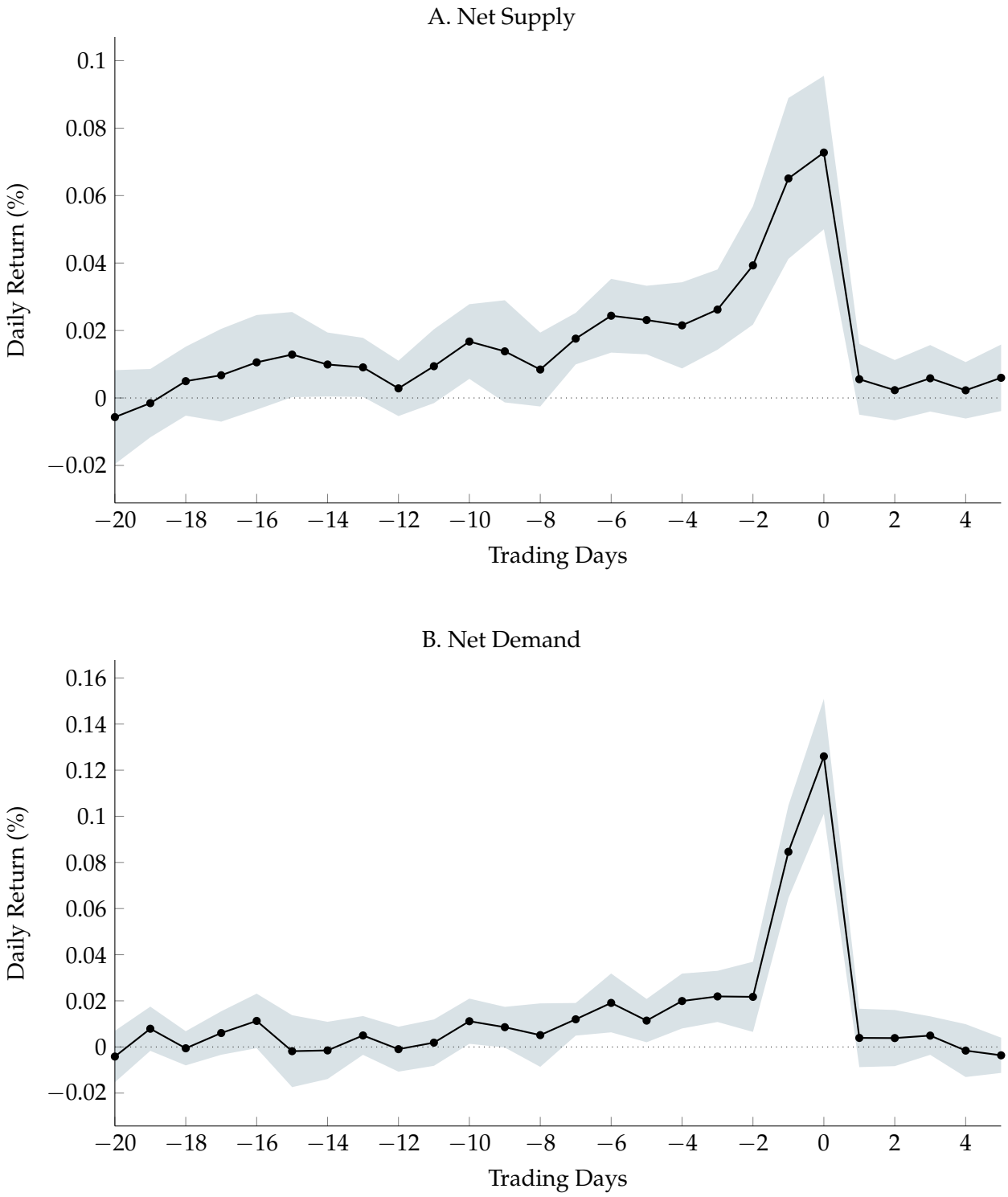
$$R_{i,t+k} = \beta(k)\, S^r_{i,t} + \gamma(k)\, D^r_{i,t} + \alpha_i + \mu_t + u_{i,t}. \tag{6}$$

The dependent variable is the daily (log) return on commodity i in day $t + k$, while the key independent variables are our residualized net supply and demand indicators from (5). We include commodity and calendar date fixed effects, and cluster the errors by day and commodity.

Figure 8 plots the estimated coefficients $\beta(k)$ and $\gamma(k)$ for horizons of $k = -20$ to $k = 5$. Examining the figure, two things become apparent. First, returns spike on the day the news are released ($k = 0$). This supports our assumption that our news-based indicators include actual news that commodity markets respond to. Consistent with our estimates above, a unit standard deviation decline in the residualized supply-side indicator leads to a 7 basis point increase in the price of the commodity on the same day; for the demand-side indicator, a one-standard deviation increase in demand leads to a 12 basis point increase. Second, there is some evidence of prior leakage, especially for our supply indicator in Panel A, but this prior leakage of information seems to be confined to approximately a week or so prior to the news release and is also quantitatively small—approximately 1 or 2 basis points.

Overall, these findings using high-frequency commodity return data support our assumption that our indicators contain actual news that are (mostly) unanticipated by commodity markets. This evidence strengthens our interpretation of these supply and demand indicators as *shocks*, especially at a frequency that is less granular than daily—say at a monthly or quarterly frequency.

FIGURE 8. Are our indicators anticipated?



3.5. **Comparison to Existing Indicators.** As a final validation exercise, we compare our supply- and demand-side disturbances with established indicators. Because the existing literature has predominantly focused on the oil market, this comparison is feasible only for our oil-specific indicators. The

standard approach to disentangling supply- and demand-driven movements in oil prices relies on structural vector autoregressions (SVARs) (see, e.g., Kilian, 2009; Baumeister and Hamilton, 2019). More recently, Känzig (2021) uses high-frequency variation in oil prices around OPEC announcements to identify supply-side shocks. To validate our narrative-based indicators, we focus on two benchmark measures: the oil supply shock series of Baumeister and Hamilton (2019) and the news shock about future oil supply identified by Känzig (2021). We compare the impulse responses of key quantities and prices to these two shocks with those generated by the"surprise" component of our Net Supply Oil Index, defined as the residuals from an AR(1) regression. We implement this comparison using local projections following Jordà (2023):

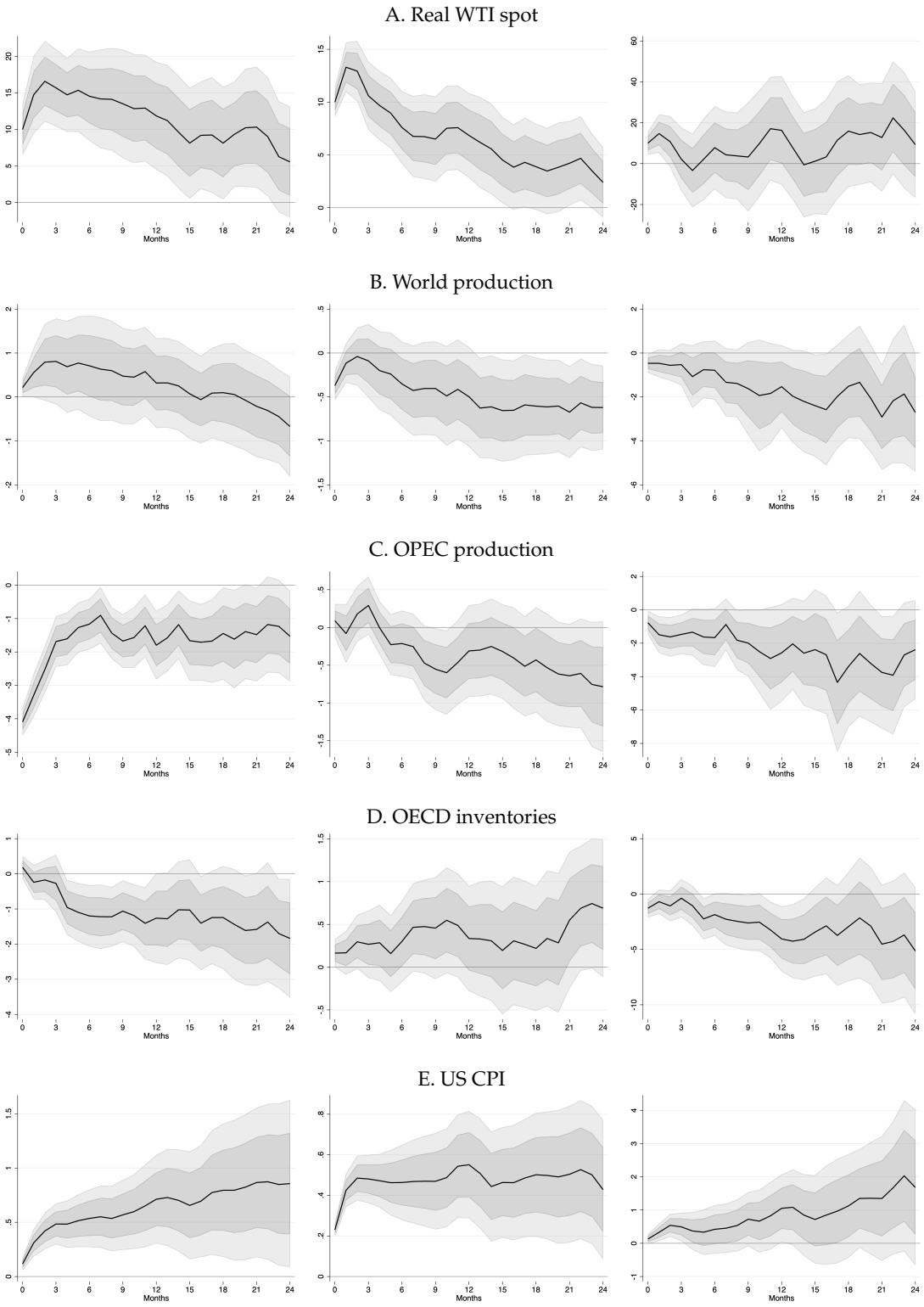
$$x_{t+k} = \beta(k) S_{oil,t} + \sum_{l=1}^{L} c_l(k)\, x_{t-l} + c(k)\mathbf{Z}_t + u_t \tag{7}$$

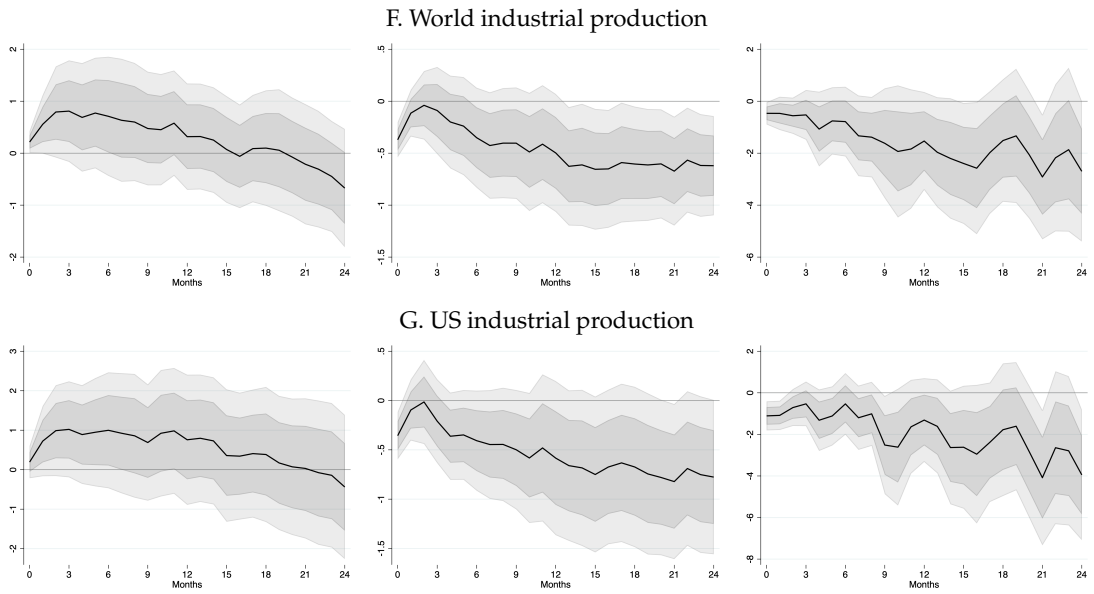
Figure 9 compares the estimated coefficients $\beta(k)$ from the local projections for the two existing measures (Columns one and two) with those obtained from our oil-specific supply disturbance. The top three rows of the figure report the responses of oil-market prices and quantities. The impulse responses associated with our supply-side indicator closely resemble those of the benchmark measures: all three series show that a negative supply shock leads to higher prices and lower quantities. The fourth row presents the response of OECD inventories, where a negative supply shock initially triggers an accumulation of inventories, followed by a gradual depletion over time–except in the case of the middle shock. The final three rows display the responses of US inflation as well as world and US industrial production. Consistent with theoretical predictions, a negative supply shock is associated with higher US prices and lower industrial production both globally and in the US.

In sum, a negative surprise in our net supply index accurately predicts a future increase in the real WTI price, a significant short- and medium-term decline in global and OPEC oil production, a reduction in future OECD inventories over time, an increase in US CPI, and a medium-term decline in world industrial production. Notably, despite excluding price data from our methodology, our approach successfully captures market dynamics comparable to those identified by methods that explicitly incorporate oil prices. This demonstrates that textual sources contain sufficient information to recover the underlying structural factors driving commodity markets without relying on endogenous price signals. We find that our supply-side indicator for the oil market generates responses closely aligned with those produced by established structural measures. This concordance serves a crucial methodological purpose: it validates our textual approach in the one commodity market where credible structural benchmarks exist. Such validation is particularly valuable because analogous structural proxies are generally unavailable for other commodities. With this benchmark in place, we can extend our narrative-based methodology beyond oil, providing new measures of supply and demand

forces in markets such as natural gas and agricultural commodities, where traditional identification strategies face substantial practical limitations.

FIGURE 9. Local projections impulse responses





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

4. Commodity Supply Shocks and the Business Cycle

Armed with our indicators of supply- and demand-side disturbances in commodity markets, we now turn to the main objective of the paper: assessing the impact of commodity supply shocks on the business cycle. Because our indices span the entire commodity market, we are able to complement the existing literature–which has predominantly focused on oil–by examining the contribution of *non-oil* commodity markets to the business cycle.

4.1. **Aggregation.** The first step is to aggregate our daily indicators to a monthly or quarterly frequency. Specifically, we define the supply-increase indicator for commodity market i and month (or quarter) τ as:

$$S^{+}_{i,\tau} \equiv \sum_{d \in D(\tau)} S^{+}_{i,d},$$

where the set $D(\tau)$ includes all calendar days in month or quarter τ for which we have articles. The second step is to aggregate the commodity-level indicators into overall indices that reflect the relative importance of each commodity for the aggregate economy. Unlike our earlier composite index, which implicitly weighted commodities based on news coverage, we now use production-based weights.

The existing literature has largely focused on supply shocks in the oil market. To underscore the role of non-oil supply shocks for the business cycle, we construct two indicators: one specific to the oil

market and another covering all commodities *excluding* oil. Accordingly, our aggregate index capturing supply increases in non-oil commodities is defined as:

$$S^{+}_{non-oil,\tau} \equiv \sum_{i \in \mathcal{I} \setminus Oil} w_{i,\tau}\, S^{+}_{i,\tau},$$

where w_i denotes the production weight for commodity i, obtained from the GSCI Composite construction methodology. These weights, calculated as five-year moving averages, provide a market-based measure of each commodity's relative importance in global production, enabling a more accurate assessment of the aggregate pass-through from commodity supply disturbances to macroeconomic outcomes.[3] The indicators for supply decreases and for demand increases or decreases are defined in an analogous manner. Finally, we construct the net supply and net demand indicators following equation (3).

4.2. **Local projections evidence.** To quantify the macroeconomic impact of our supply indicators, we next estimate local projections following Jordà (2023):

$$x_{t+k} = \beta(k)\, S_{non-oil,t} + \gamma(k)\, S_{oil,t} + \sum_{l=1}^{L} c_l(k)\, x_{t-l} + c(k)\mathbf{Z}_t + u_t. \tag{8}$$

where $S_{non-oil,t}$ and $S_{oil,t}$ denote the net supply indices for the non-oil and oil markets, respectively. The primary coefficients of interest are those associated with these supply-side disturbances. The control vector Z_t includes the corresponding demand-side disturbances for both the oil and non-oil baskets. In a robustness exercise, we also incorporate a vector of macroeconomic and financial controls. Additionally, we include $L = 8$ lags of the dependent variable to account for dynamic effects. For the dependent variables, we focus on key macroeconomic indicators (in logs): the price level, measured by both the CPI and PPI; industrial production; and US unemployment. In addition, we examine the responses of commodity price indices, specifically the real Brent price for oil and a production-weighted average of real spot prices for the non-oil index.

Figure 10 summarizes the estimated impulse responses. Several patterns are apparent. First, both supply indicators lead to higher price levels and a contraction in economic activity–recall that an increase in S corresponds to a *decrease* in supply. To interpret the magnitudes, it is useful to benchmark them against the corresponding changes in commodity price indices. For example, a one-standard deviation decrease in the oil supply indicator results in approximately a 3% increase in oil prices over the following year, accompanied by a 0.4 percentage point rise in CPI inflation and a 1 percentage point rise in PPI inflation. US industrial production and manufacturing decline by roughly 0.5 percent and 0.7 percent respectively over the same horizon. These supply-driven contractions also generate labor

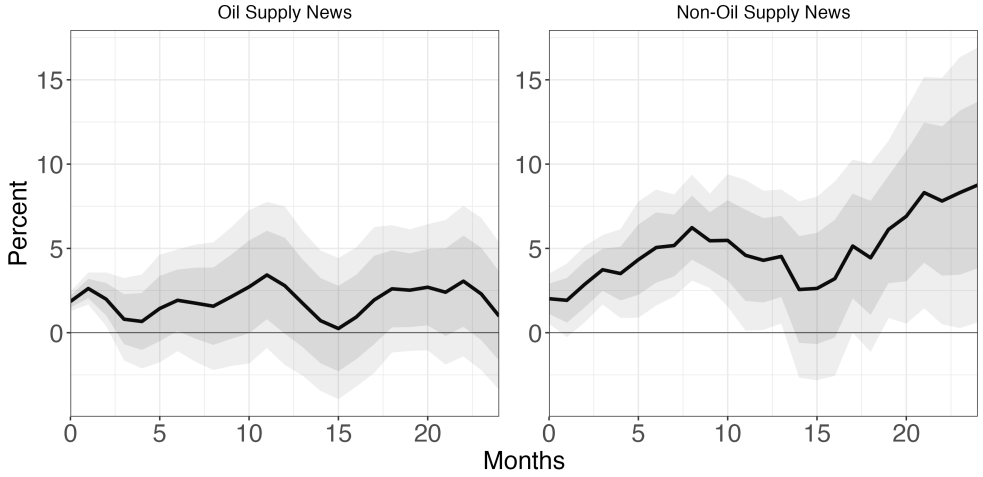
[3]We implement a methodological adjustment to account for the absence of lead from our composite indices. This reweighting ensures that the relative importance of commodities is properly represented in both the aggregate and non-petroleum composite measures, preserving the economic interpretation of the transmission estimates despite incomplete coverage relative to the standard GSCI production-weighted benchmark.

market pressures, with elevated unemployment rates by 1.25 percent. Second, and most importantly, the estimated pass-through of supply shocks from non-oil commodities to both prices and quantities is substantially larger than that observed for oil over the sample period. Specifically, a one-standard deviation decrease in the non-oil supply indicator leads to an approximately 5-7% increase in the commodity price index over the following year, along with an up to 1.2% rise in the CPI and a 2.5% increase in the PPI. US industrial production and manufacturing decline by roughly 0.5-1% over the same horizon. There is also a short-run unemployment rate increase by 1.75 percent.

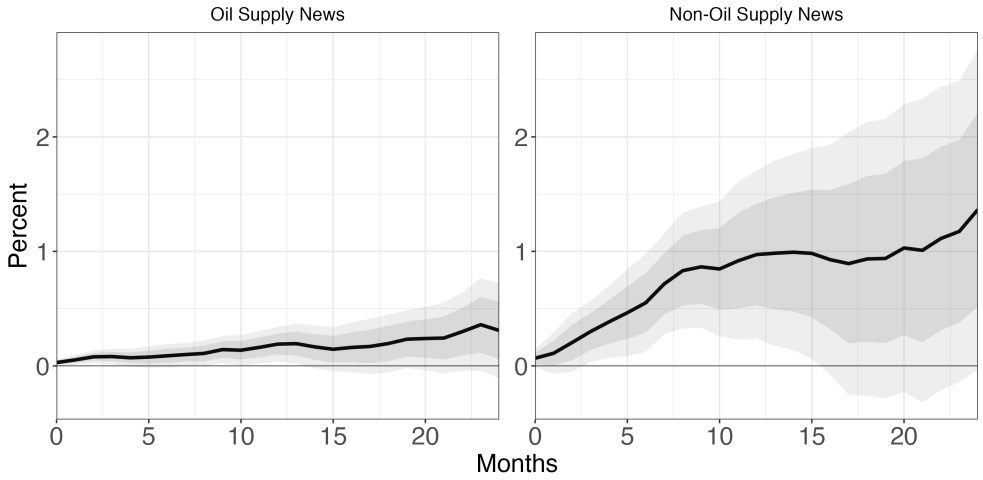
In sum, our empirical results reveal substantial qualitative similarity in the macroeconomic effects of supply contractions across both petroleum and non-petroleum commodity markets. Supply shortfalls generate inflationary pressures, reflected in both consumer and producer price indices, while simultaneously producing contractionary effects on real economic activity, as evidenced by declines in industrial production and manufacturing output.

FIGURE 10. Local projections: Oil and non-oil impulse responses

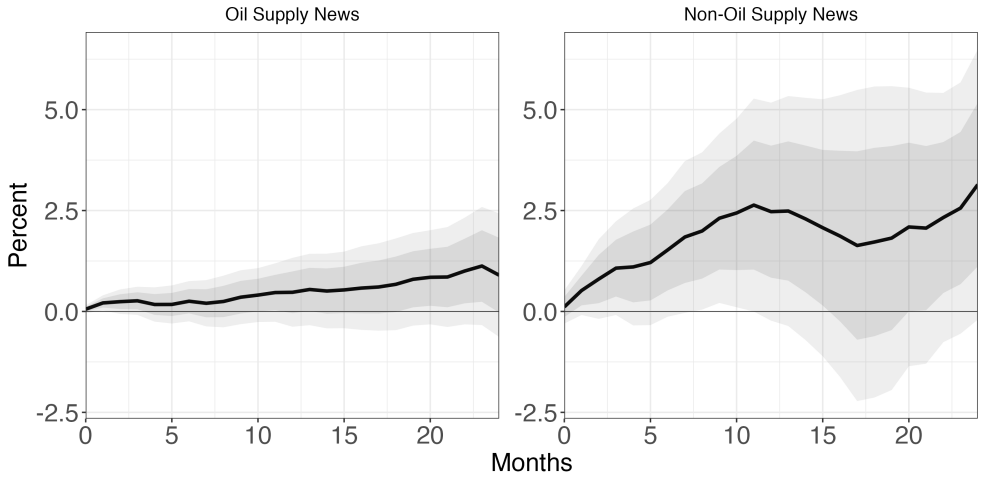
A. Real commodity-specific spot price (left: Brent; right: weighted non-oil commodity basket)



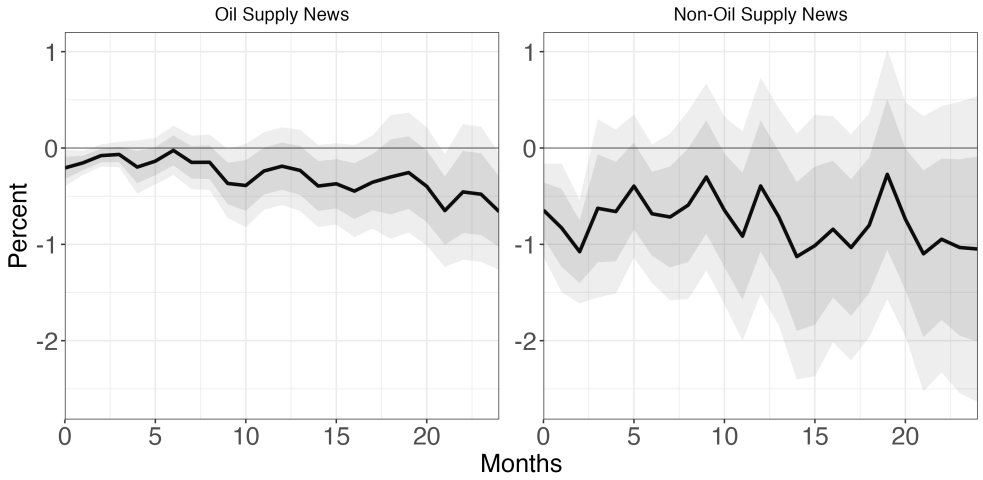
B. US CPI



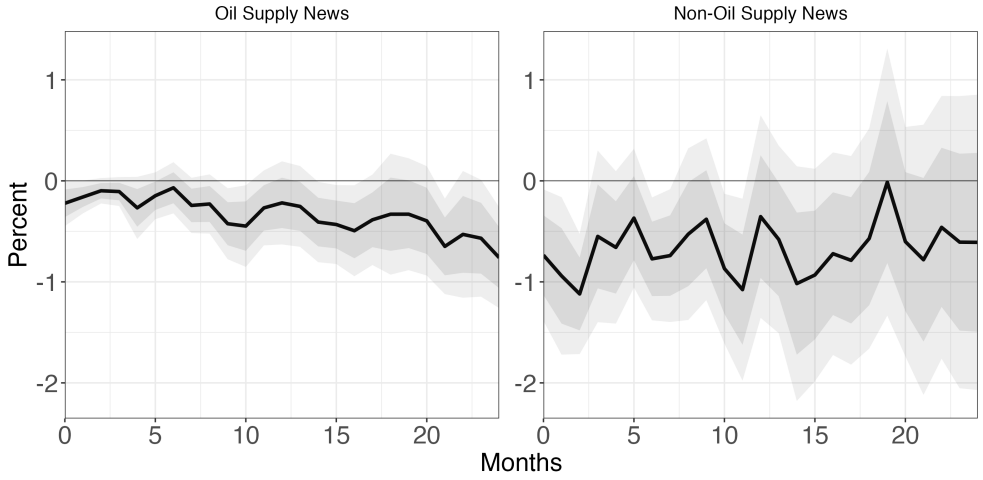
C. US PPI



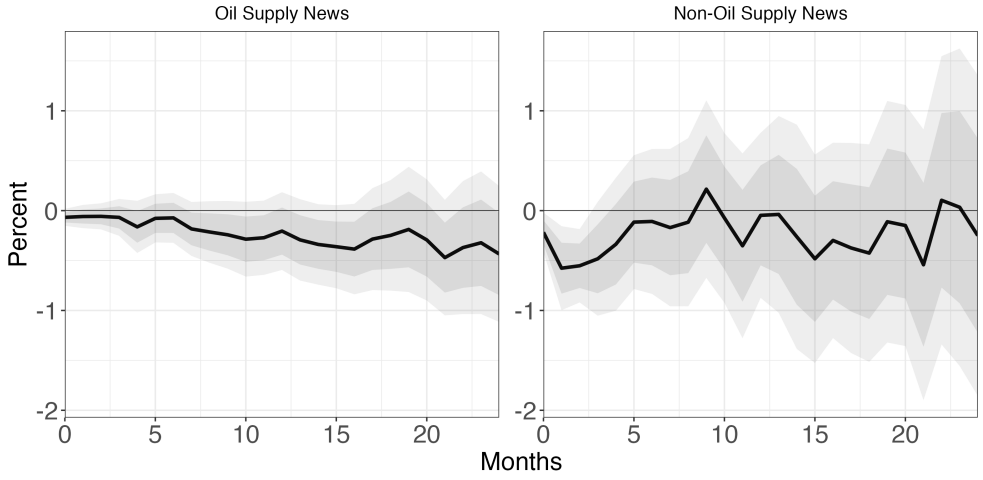
D. US industrial production

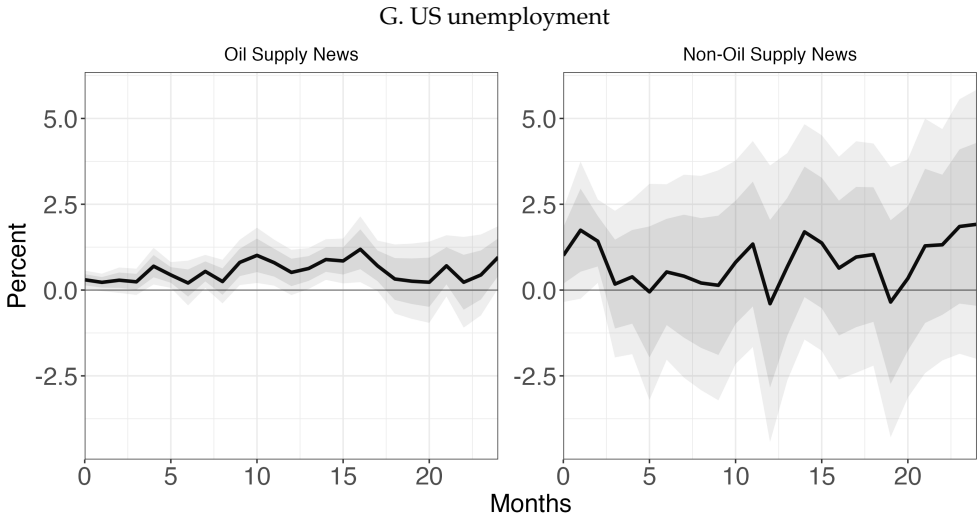


E. US manufacturing



F. World manufacturing





Note: This figure shows the impulse responses to a standard deviation oil supply shock for the Real Commodity-Specific Spot Price (left: Brent; right: Weighted-Commodity Basket), 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.

5. Decomposing the drivers of supply and demand developments

Different types of supply and demand shocks can have distinct implications for macroeconomic outcomes, financial markets, and price stability (e.g., Caballero, Farhi, and Gourinchas, 2008). For example, natural disasters typically affect inflation over the short to medium term, whereas environmental regulations can have a more persistent impact by permanently altering relative prices through expectations. Decomposing commodity price fluctuations into their key drivers allows us to distinguish between short- and long-term effects, and to assess the severity and transmission mechanisms of each shock. In the following, we present the main drivers of commodity supply and demand developments. Drawing on the commodity risk factors highlighted in the *Commodity Special Feature* of the IMF's World Economic Outlook and the World Bank's *Commodity Markets Outlook*, we group these into four broad categories that represent the main drivers of commodity market dynamics: business cycle developments, geopolitical risk, natural disasters, and climate change.

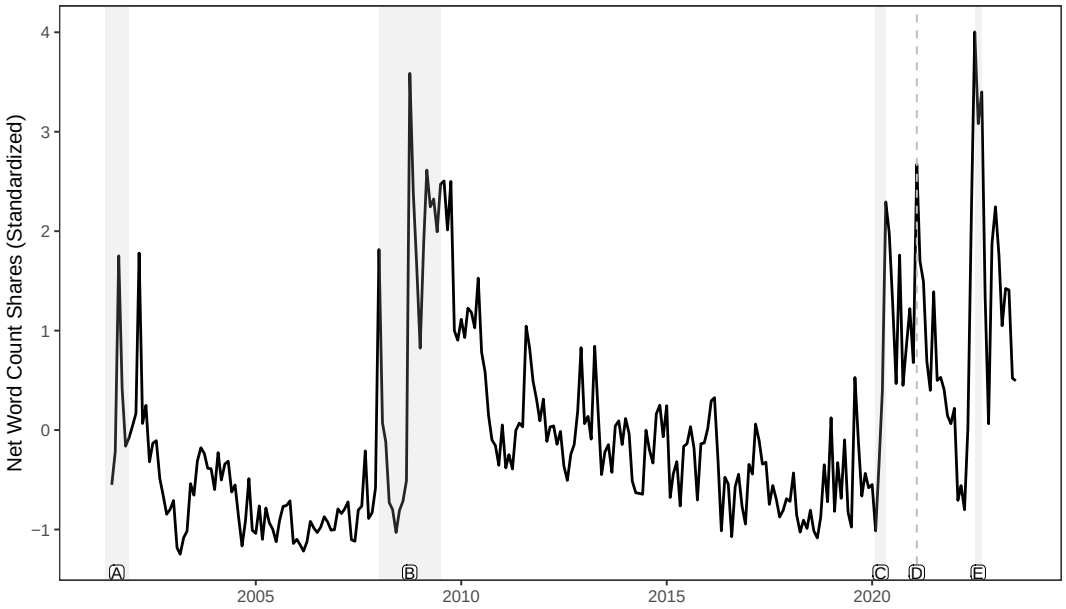
Figure 11 displays the business cycle driver for the period 2001-2023. The series captures major global macroeconomic developments, with the largest spikes corresponding to the 2001 recession, the Global Financial Crisis, the August 2011 stock market decline driven by fears of European sovereign debt contagion, the COVID-19 crisis, and the US debt-ceiling episode. Figure 12 presents the geopolitical risk driver over the same period. The indicator reflects several major geopolitical events, including the 9/11 attacks, the 2003 Iraq invasion, the Arab Spring, the escalation of the US-China trade war, and the Russian invasion of Ukraine. Figure 13 shows the natural disasters driver, highlighting events such as the 2001 Gujarat earthquake, the intense Atlantic hurricane seasons (e.g., Katrina, Emily), the 2012 US summer drought, and the COVID-19 crisis. Finally, Figure 14 plots the climate change driver

for 2005-2023. The series captures key climate-related developments, warnings, and policy initiatives, including European Commission proposals and US Environmental Protection Agency regulations. Decomposing the drivers across commodity categories reveals that: (i) the business cycle is most relevant for energy, industrial metals, and soft commodities that are also used as biofuels, (ii) geopolitical risk events tend to affect energy and soft commodities, with grains becoming important primarily during the trade war period, (iii) natural disasters mainly impact grains and soft commodities, and to a lesser extent, energy, and (iv) climate change effects are concentrated in energy commodities and, more recently, industrial metals.

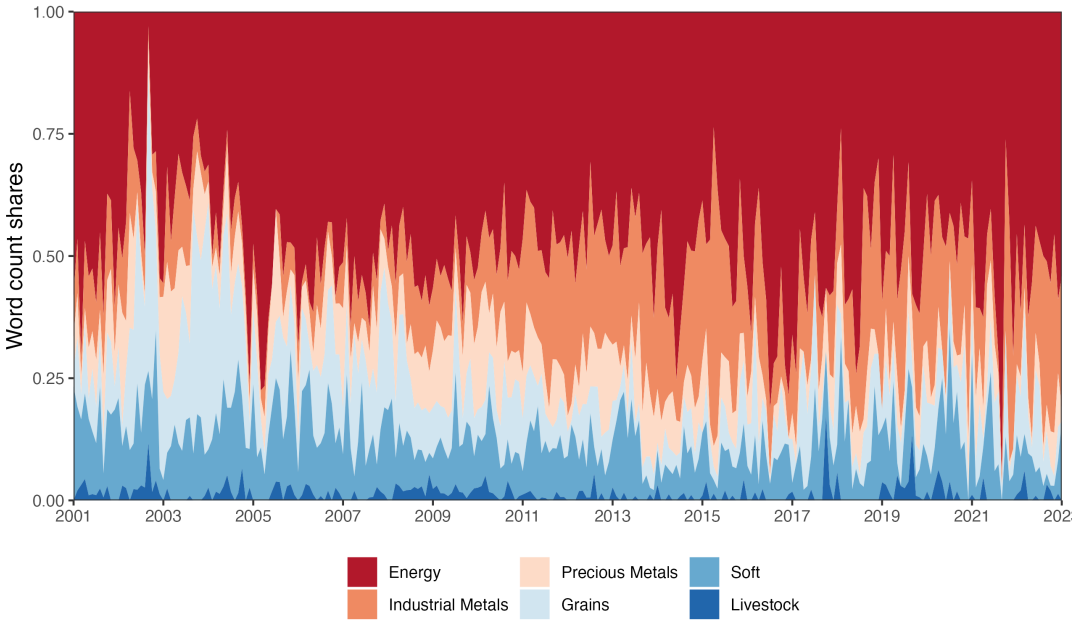
A key methodological contribution of our analysis is the decomposition of commodity supply and demand components into their underlying fundamental drivers. As shown in Figure 15, net supply fluctuations across commodity categories are primarily driven by exogenous events, such as natural disasters. By contrast, net demand variations are largely shaped by endogenous business cycle dynamics, with the notable exception of the COVID-19 pandemic, which manifests as an unusually large exogenous negative natural disaster shock in 2020. This contrasting pattern of driver importance aligns with theoretical expectations regarding the relative exogeneity of supply disruptions versus the endogenous nature of demand fluctuations in commodity markets.

FIGURE 11. Business cycle

A. Occurrence in news articles



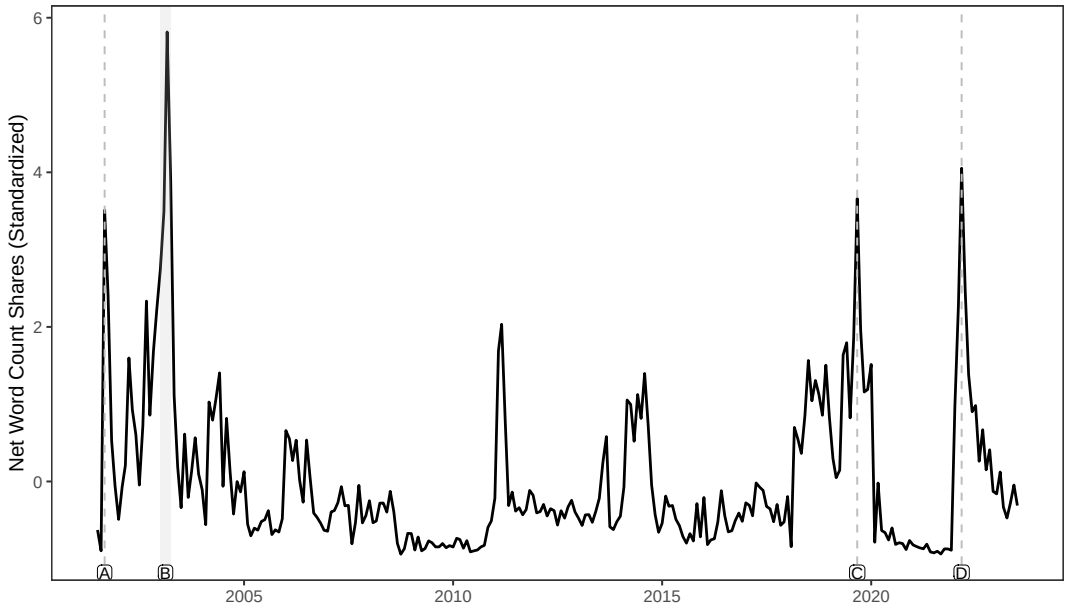
B. Decomposition across commodity categories



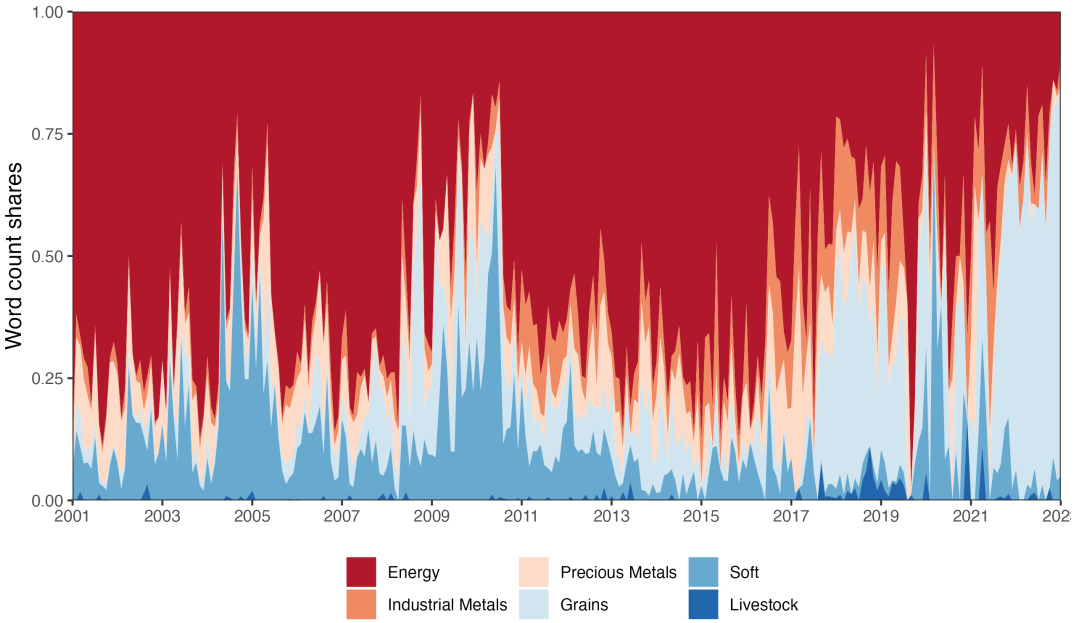
Note: This figure plots the Business Cycle Theme for the period between 2001 and 2023. The bars map a number of important economic developments (i.e. in the top 1% (two-tailed) of events) reflecting the state of the business cycle. These events respectively are: [A] US Recession and 9/11, [B] Global Financial Crisis, [C] Onset of Covid-19 Pandemic, US Recession, [D] Bullish sentiment following signs of recovery and fiscal stimulus, [E] Global central banks' steep monetary tightening induced global market sell-off

FIGURE 12. Geopolitical risk

A. Occurrence in news articles



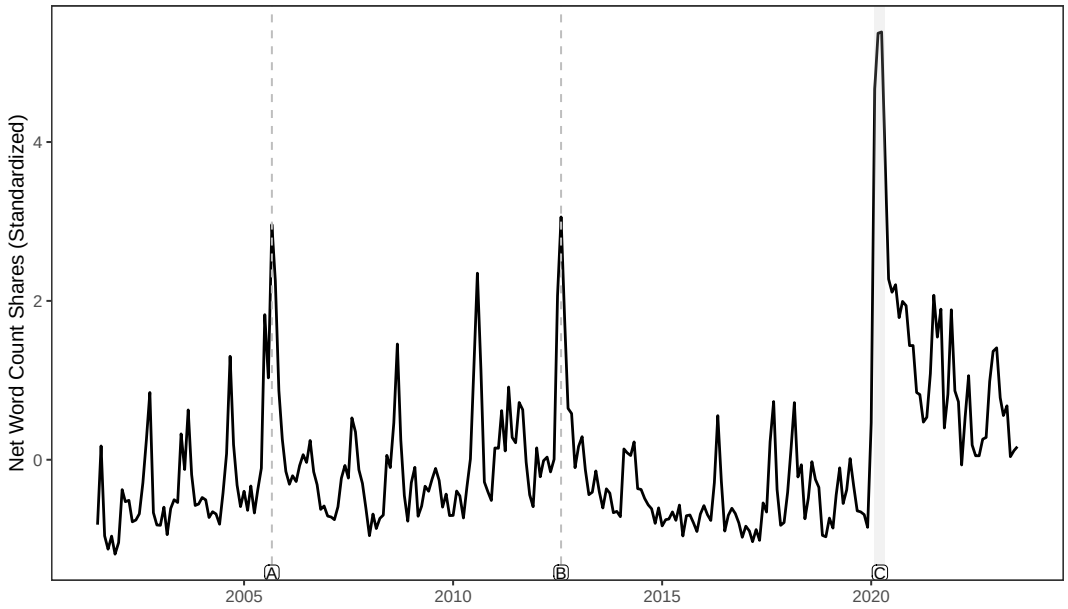
B. Decomposition across commodity categories



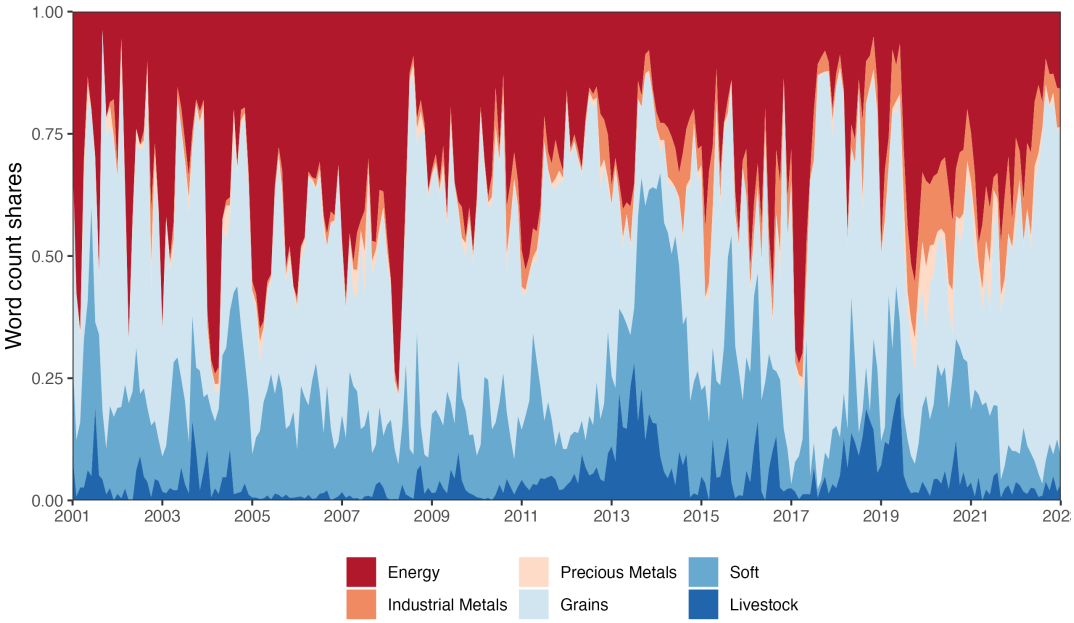
Note: This figure plots the Geopolitical Risk Theme for the period between 2001 and 2023. The bars map a number of important (i.e. in the top 1% (two-tailed) of events) geopolitical events. These events respectively are: [A] 9/11 attacks, [B] 2003 Iraq invasion, [C] China-United States trade war, [D] Russian invasion of Ukraine.

FIGURE 13. Natural disaster

A. Occurrence in news articles



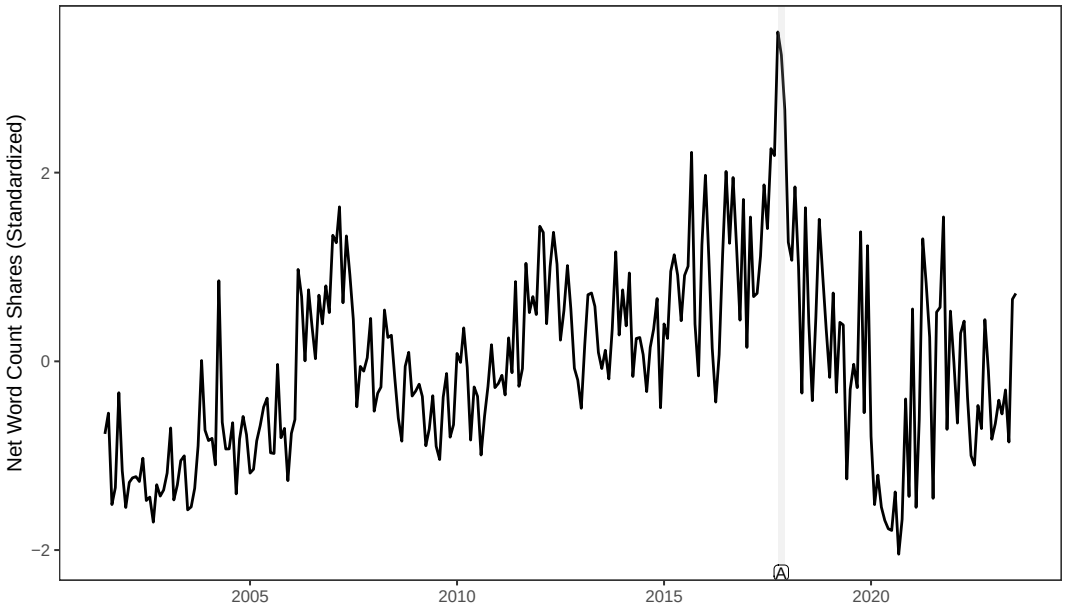
B. Decomposition across commodity categories



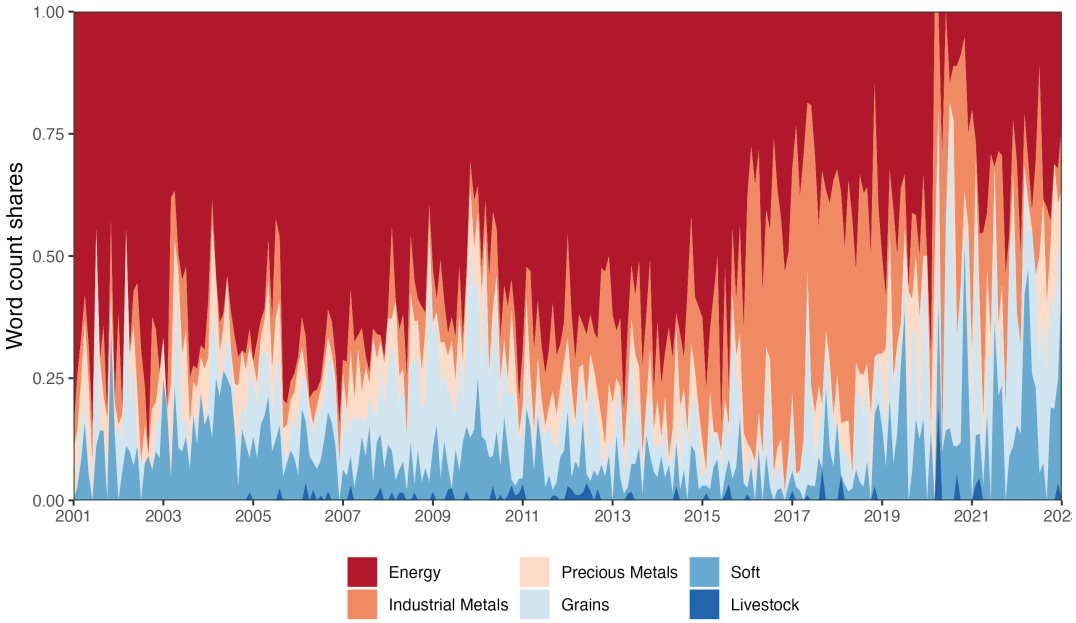
Note: This figure plots the Natural Disasters Theme for the period between 2001 and 2023. The bars map a number of important (i.e. in the top 1% (two-tailed) of events) natural disasters. These events respectively are: [A] 2005 Atlantic hurricane season (Katrina, Emily, Rita, Wilma), [B] US Summer 2012 Drought, [C] Onset of Covid-19 Pandemic

FIGURE 14. Climate change

A. Occurrence in news articles



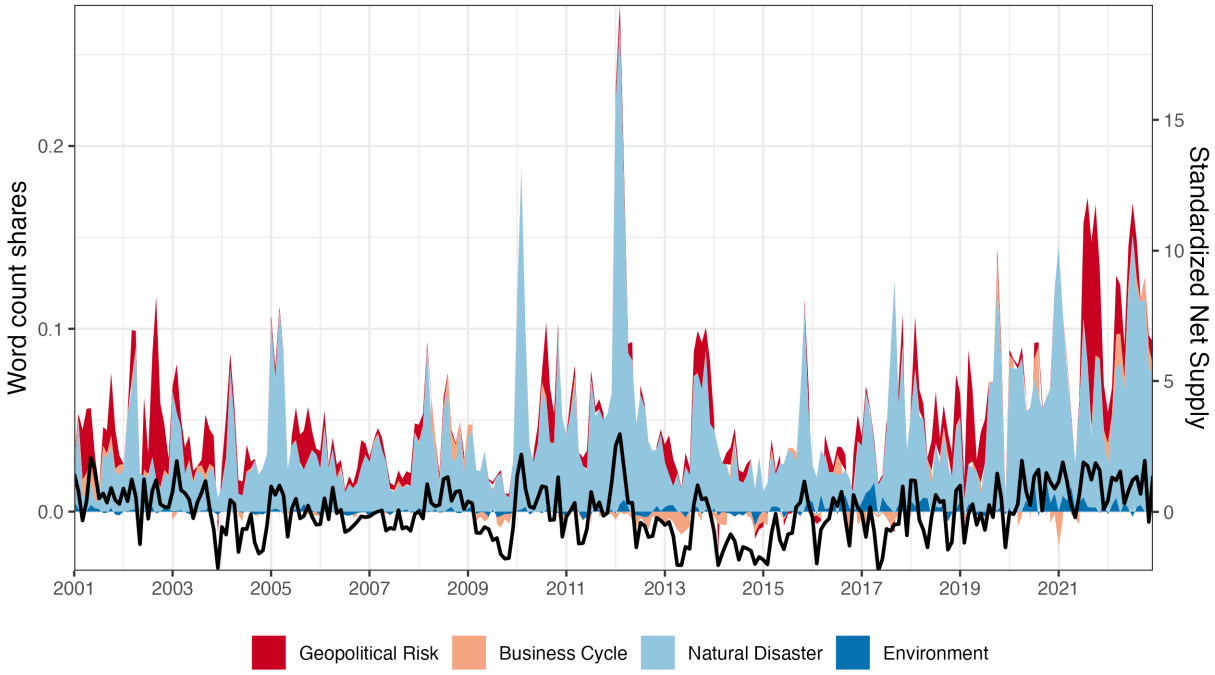
B. Decomposition across commodity categories



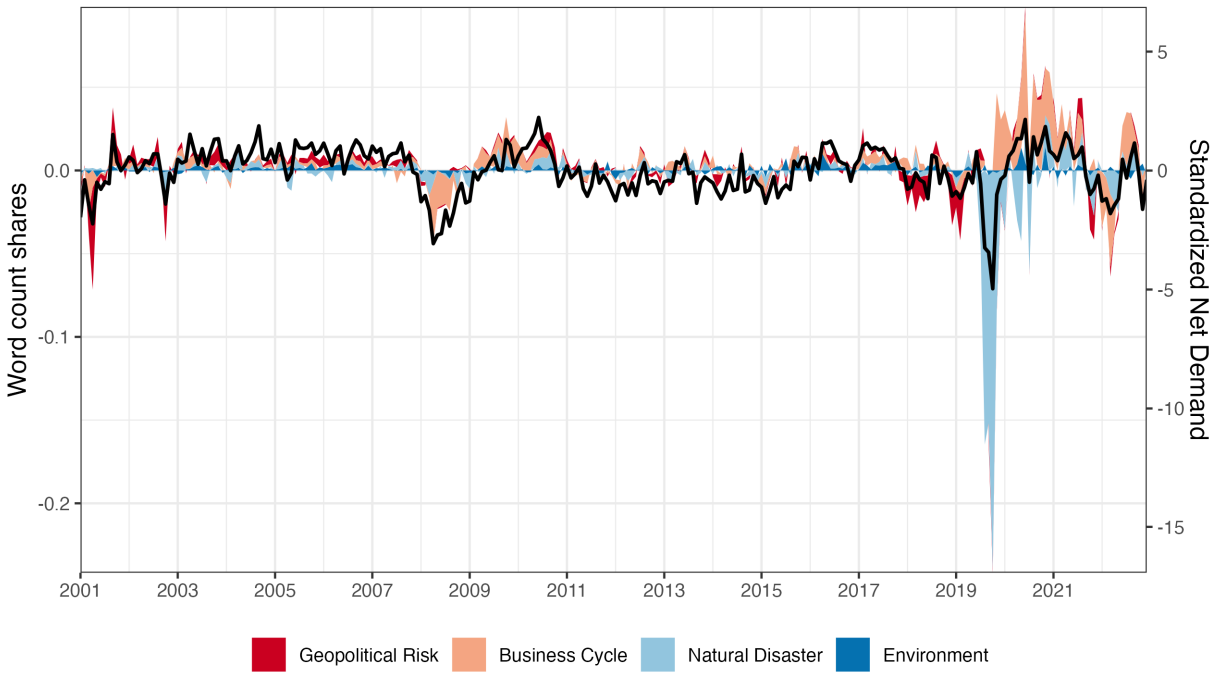
Note: This figure plots the Climate Change Theme between 2001 and 2023. The bars map a number of important (i.e. in the top 1% (two-tailed) of events) climate change events. [A] The U.S. Environmental Protection Agency requires fuel companies to blend slightly more renewable fuels into the nation's fuel supply; major oil spill on the Keystone pipeline in South Dakota sparked environmental debates; China's crackdown on genetically modified (GMO) soybean imports and its intensifying war on smog this winter will boost soymeal prices

FIGURE 15. Factor decomposition: Net supply and net demand

A. Net supply



B. Net demand



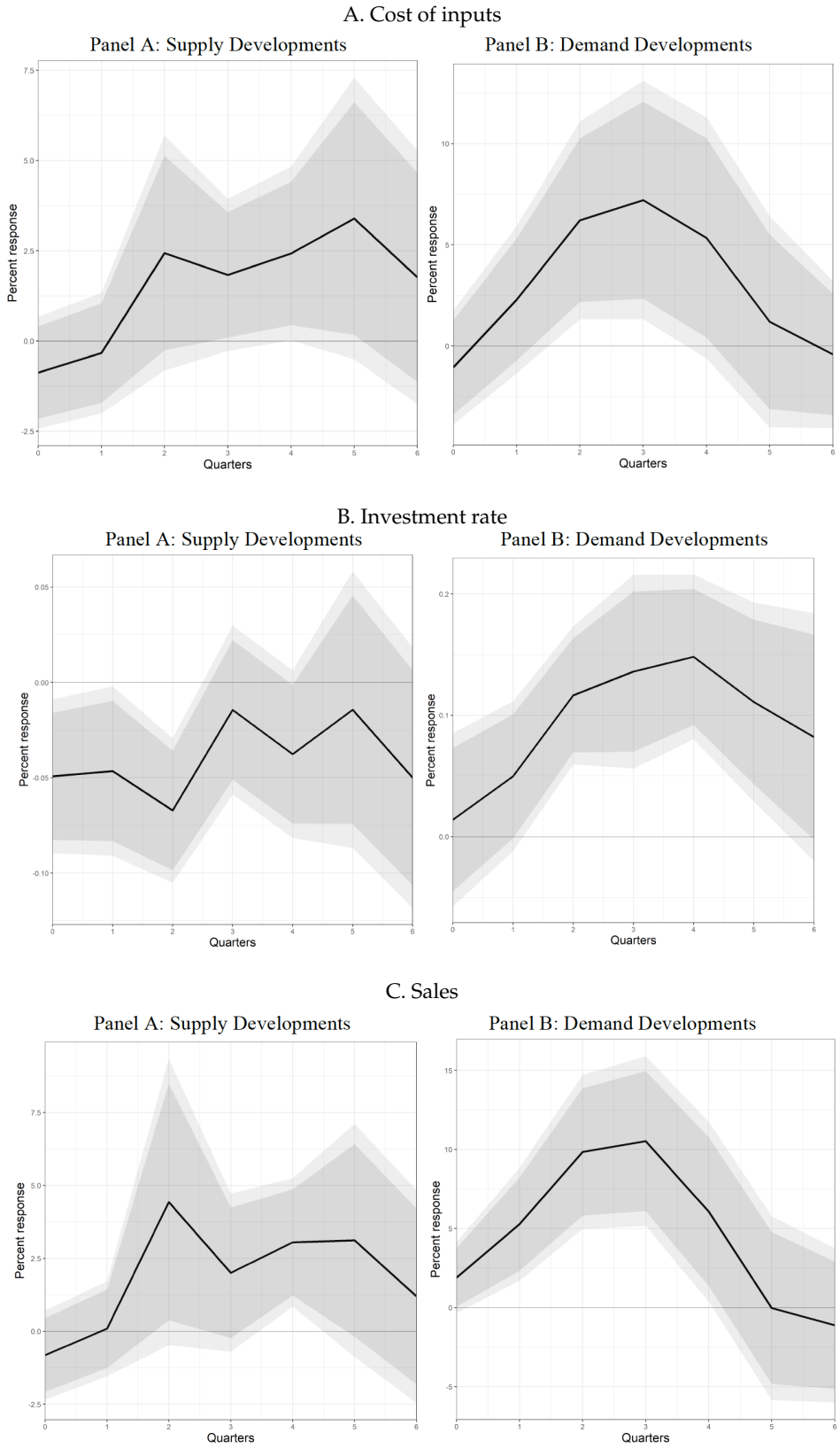
Note: This figure plots the factor decomposition in commodity articles narrating supply and demand events between 2001 and 2023. The factors are: [A] Geopolitical Risk, [B] Business Cycle, [C] Natural Disaster, [D] Environment.

6. Impact on Firm-level Outcomes

In the following analysis, we investigate the heterogeneous effects of our supply- and demand-side indicators on firm-level outcomes. Although our empirical strategy does not guarantee the strict exogeneity of the supply indicator, the estimates provide meaningful evidence of qualitatively distinct transmission mechanisms for supply versus demand components. For our microeconomic analysis, we use Compustat to assemble a comprehensive firm-level dataset of quarterly financial statements for all publicly traded US firms from 2001 to 2023, ensuring 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 on firm operations. Negative supply developments are associated with higher input costs, consistent with standard price effects in factor markets, while simultaneously correlating with lower investment rates, suggesting an operational channel in which heightened uncertainty triggers real options effects that encourage investment deferral. Interestingly, the revenue impact of supply contractions appears positive, indicating that scarcity-driven price effects outweigh any countervailing recessionary demand pressures. In contrast, demand expansions produce theoretically consistent, unidirectional effects across firm outcomes. Positive demand disturbances are associated with higher input costs, reflecting increased factor demand, elevated investment rates, consistent with accelerator mechanisms, and higher sales, capturing the direct effect of increased product demand. These patterns further suggest that demand-side indicators primarily capture systematic factors with broad-based effects across firms, in line 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.

7. Concluding Remarks

The challenge of empirically identifying supply-side disturbances that drive business cycle fluctuations has remained central since the seminal contribution of Kydland and Prescott (1982). Although substantial methodological progress has been made in the context of oil markets, modern economies rely on a broad array of commodity inputs whose supply disruptions represent plausible sources of macroeconomic variation. This paper fills a notable gap by developing a comprehensive textual methodology to identify supply and demand disturbances across the full spectrum of non-oil commodities.

Our empirical findings show that commodity supply disruptions generate economically meaningful macroeconomic effects. The estimated responses align closely with theoretical predictions: supply contractions produce stagflationary dynamics–higher prices, lower output, and reduced employment–whereas demand expansions raise both prices and economic activity. At the firm level, supply contractions are associated with higher input costs, reduced investment rates (consistent with real-options theory), and increased sales, as scarcity-induced pricing effects often outweigh recessionary forces.

More importantly, we show that disturbances originating in non-petroleum commodity markets–despite their historical neglect in the literature–generate more pronounced stagflationary effects than those stemming from petroleum markets. This result carries significant policy implications: underestimating the magnitude, frequency, and persistence of non-oil commodity supply disruptions can lead to misattribution of inflationary pressures, biased estimates of structural parameters, mismeasured output gaps, and suboptimal resource allocation.

Our decomposition of fundamental drivers across commodity groups uncovers clear systematic patterns. Business cycle fluctuations predominantly influence energy and industrial metals; geopolitical risks disproportionately affect energy and precious metals; natural disasters primarily disrupt agricultural commodities with spillovers into energy markets; and climate-related risks increasingly shape both energy and industrial metals markets.

Overall, these findings highlight the value of a comprehensive framework for understanding commodity market dynamics and their macroeconomic consequences–one that extends well beyond the traditional focus on oil. By mapping the multidimensional sources of commodity price movements, our approach provides rich informational signals for economic analysis while documenting both enduring regularities and emerging trends in global commodity markets.

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APPENDIX A. COMMODITY INDICATORS: ADDITIONAL SENSITIVITY CHECKS

TABLE A1. Regression of S&P GSCI commodity-specific daily returns on net supply and demand indices

Panel A: Energy

	Gas	Gasoline	Oil
Net Demand (Standardized)	0.0712***	0.0533***	0.0846***
	(0.0134)	(0.0134)	(0.0136)
Net Supply (Standardized)	0.0129	0.0281*	0.1215***
	(0.0134)	(0.0133)	(0.0134)
Within R^2	0.006	0.010	0.026
N	5,597	5,597	5,597
Controls	Yes	Yes	Yes

Panel B: Industrial metals

	Aluminium	Copper	Nickel	Zinc
Net Demand (Standardized)	0.0269*	0.1509***	0.0575***	0.0321*
	(0.0134)	(0.0132)	(0.0134)	(0.0134)
Net Supply (Standardized)	0.0511***	0.0442***	0.0250	0.0377**
	(0.0134)	(0.0132)	(0.0134)	(0.0134)
Within R^2	0.009	0.030	0.005	0.007
N	5,597	5,597	5,597	5,597
Controls	Yes	Yes	Yes	Yes

Panel C: Precious metals

	Gold	Silver
Net Demand (Standardized)	0.0687***	0.0583***
	(0.0133)	(0.0134)
Net Supply (Standardized)	0.0029	-0.0007
	(0.0134)	(0.0134)
Within R^2	0.005	0.004
N	5,597	5,597
Controls	Yes	Yes

Panel D: Grains

	Corn	Soybean	Wheat
Net Demand (Standardized)	0.0984***	0.1283***	0.1016***
	(0.0133)	(0.0133)	(0.0132)
Net Supply (Standardized)	0.0684***	0.0602***	0.1326***
	(0.0133)	(0.0133)	(0.0132)
Within R^2	0.014	0.021	0.029
N	5,597	5,597	5,597
Controls	Yes	Yes	Yes

Panel E: Softs

	Cocoa	Coffee	Cotton	Sugar
Net Demand (Standardized)	0.0938***	0.0923***	0.1302***	0.0922***
	(0.0134)	(0.0134)	(0.0132)	(0.0133)
Net Supply (Standardized)	0.0534***	0.0513***	0.0726***	0.0781***
	(0.0133)	(0.0134)	(0.0132)	(0.0133)
Within R^2	0.012	0.011	0.024	0.014
N	5,597	5,597	5,597	5,597
Controls	Yes	Yes	Yes	Yes

Panel F: Livestock

	Cattle	Hog
Net Demand (Standardized)	0.2151***	0.1622***
	(0.0131)	(0.0132)
Net Supply (Standardized)	0.0469***	0.0504***
	(0.0130)	(0.0132)
Within R^2	0.051	0.030
N	5,597	5,597
Controls	Yes	Yes

APPENDIX B. DATA SOURCES AND VARIABLE DEFINITIONS

TABLE A2. Data Sources and Variable Definitions

Variable	Description	Source
Energy		
WTI Crude Oil	S&P GSCI Crude Oil Spot (GSCLSPT)	Datastream
Brent Crude Oil	S&P GSCI Brent Crude Spot (GSBRSPT)	Datastream
Heating Oil	S&P GSCI Heating Oil Spot (GSHOSPT)	Datastream
Natural Gas	S&P GSCI Natural Gas Spot (GSNGSPT)	Datastream
Metals		
Aluminum	S&P GSCI Aluminum Spot (GSIASPT)	Datastream
Copper	S&P GSCI Copper Spot (GSICSPT)	Datastream
Nickel	S&P GSCI Nickel Spot (GSIKSPT)	Datastream
Zinc	S&P GSCI Zinc Spot (GSIZSPT)	Datastream
Gold	S&P GSCI Gold Spot (GSGCSPT)	Datastream
Silver	S&P GSCI Silver Spot (GSSISPT)	Datastream
Agriculture		
Corn	S&P GSCI Corn Spot (GSCNSPT)	Datastream
Soybeans	S&P GSCI Soybeans Spot (GSSOSPT)	Datastream
Wheat (CBOT)	S&P GSCI Wheat (CBOT) Spot (GSWHSPT)	Datastream
Cocoa	S&P GSCI Cocoa Spot (GSCCSPT)	Datastream
Coffee	S&P GSCI Coffee Spot (GSKCSPT)	Datastream
Sugar	S&P GSCI Sugar Spot (GSSBSPT)	Datastream
Cotton	S&P GSCI Cotton Spot (GSCTSPT)	Datastream
Livestock		
Cattle	S&P GSCI Live Cattle Spot (GSLCSPT)	Datastream
Lean Hogs	S&P GSCI Lean Hogs Spot (GSLHSPT)	Datastream
Control variables		
USD Index (broad)	Nominal Broad U.S. Dollar Index (Goods Only) (DTWEXB)	FRED
USD Index (broad)	Nominal Broad U.S. Dollar Index (DTWEXBGS)	FRED
Fed funds rate	Federal Funds Effective Rate (DFF)	FRED
VIX Index	CBOE Volatility Index: VIX (VIXCLS)	FRED

Variable	Description	Source
Macro variables		
World oil production	World oil production (EIA1955)	Datastream
World industrial production	Industrial production of OECD+6 (Brazil, China, India, Indonesia, Russia, South Africa), Baumeister and Hamilton (2019) (OECD+6IP)	Baumeister's webpage
OECD crude oil inventories	OECD crude oil inventories from petroleum stock data (EIA1976, EIA1533, EIA1541), as in Kilian and Murphy (2014)	Datastream
US industrial production	US industrial production index (INDPRO)	FRED
US CPI	US CPI for all urban consumers: all items (CPIAUCSL)	FRED
US PPI	Producer Price Index: all commodities (PPIACO)	FRED
US unemployment rate	Civilian unemployment rate (UNRATE)	FRED
US real GDP	Real Gross Domestic Product (GDPC1)	FRED
US real Investment	Real Gross Private Domestic Investment (GPDIC1)	FRED

Appendix C. Article Handling

C.1. **Sourcing.** We obtain news articles from Reuters via the Factiva Snapshots API over the period May 2000 to May 2023. We apply the following filters and restrictions to construct our news sample.

We restrict attention to Reuters news outlets by limiting the sample to articles with Factiva `restrictor_codes` set to `lba` or `eline`. We further restrict to English-language content by imposing `language_code = 'en'`. We focus on commodity-specific news. We identify such articles using Factiva `subject_codes` that correspond to individual commodities, and retain only those articles whose subject codes include at least one of the following:

`mcroi, mhtgol, mnatgs, mcrntg, malum, mcopp, mnickl, mlead, mzinc, m1421, msilv, mwheat, mcorn, mcoff, msugar, mcocoa, mcott, mhogs, mgrfds`

We exclude articles whose primary Factiva `subject_codes` correspond to the following generic or non-article content types:

- `nnam`: republished news;
- `nrgn`: obituaries, sports, and calendar-type content;
- `ncal`: calendar of events;
- `nlist`: headline listings.

These exclusions remove material that is not original news reporting or that does not contain substantive textual content.

C.2. **Cleaning.** We apply a sequence of standard text-cleaning steps. Each article is first split into sentences and then into individual tokens. Tokens are lowercased, stripped of non-alphanumeric characters (with digits preserved), and standard stopwords are removed. We exclude articles that correspond to "Take a Look" headline-summary pieces. Within the cleaned token lists, we additionally remove placeholder codes such as `[NUC]`, `[ENV]`, `[RNW]`, and `[CO2]`, which would otherwise distort dictionary-based word counts.

To address near-duplicate reporting, we group articles into rolling five-day windows and compare their sentence-level content. Representing each article as a multiset of sentences, we compute the proportion of identical sentences for every pair of articles within windows. Articles sharing more than 70% identical sentences are flagged as near-duplicates and removed from the final sample. This procedure yields a final dataset of 1,059,669 articles after removing 128,973 near-duplicate observations.

Appendix D. 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 A3 to Table A6 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 A7 and Table A8 present the list of roots of increase and decrease words.

Table A3. Supply and demand words: Global Commodity Index

Supply		
suppl*	produc*	output

Demand			
demand*	consum*	buy*	purchas*

Table A4. Supply and demand words: Crude Oil

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

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

TABLE A5. Supply and demand words: Natural Gas

Supply				
suppl*	produc*	output	rig*	drill*
Demand				
demand*	consum*	buy*	purchas*	

TABLE A6. Supply and demand words: Wheat

Supply			
suppl*	produc*	output	crop*
planting*	farm*	harvest*	
Demand			
demand*	consum*	buy*	purchas*

TABLE A7. 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 A8. 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 E. 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 A1 to Figure A4 plot the quarterly comparison for each of the supply and demand components along with the net index performance of the two methods.

FIGURE A1. Human- and computer-based increase indices

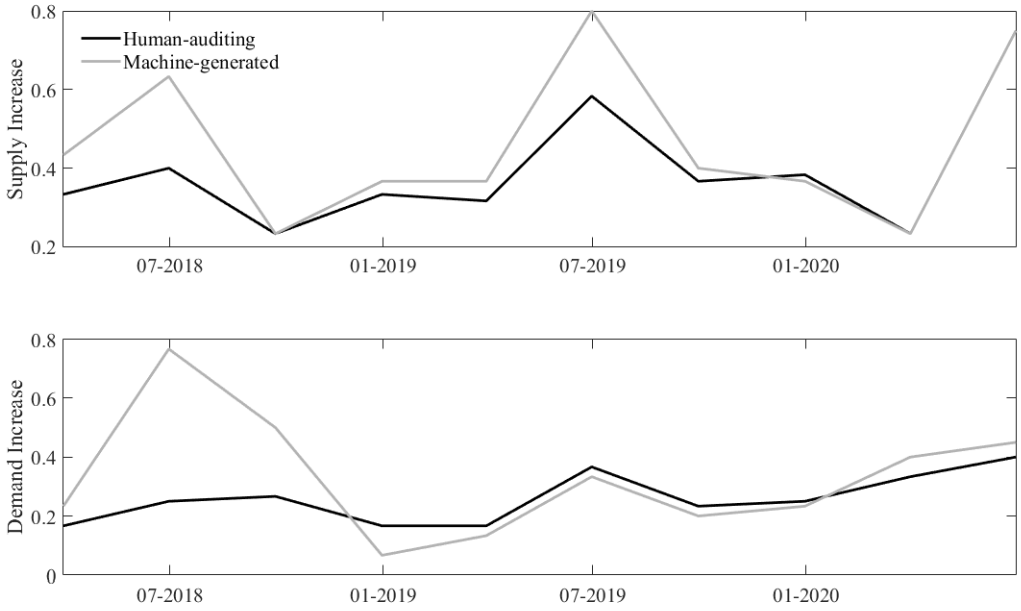


FIGURE A2. Human- and computer=based decrease indices

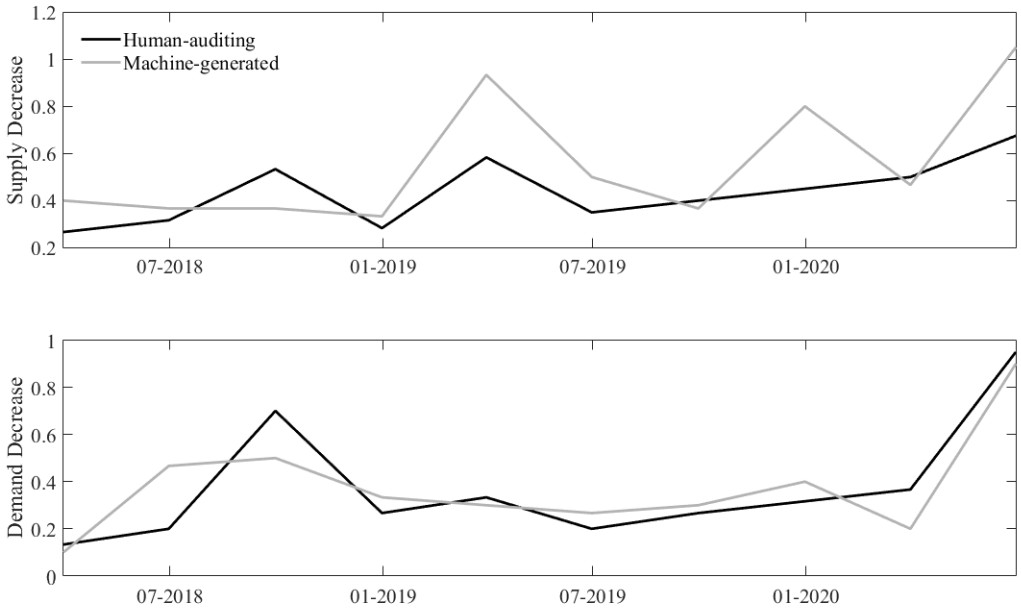


FIGURE A3. Human- and computer-based net indices

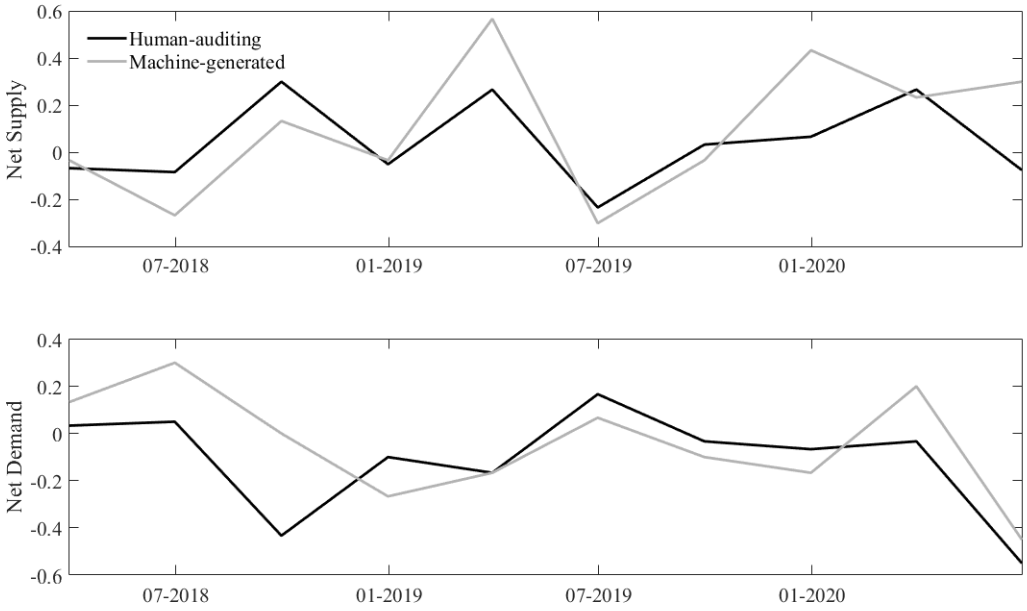


FIGURE A4. Human- and computer-based standardized net indices

