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Dimitris Malliaropoulos
Evgenia Passari
Filippos Petroulakis

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BANK OF GREECE
Economic Analysis and Research Department – Special Studies Division
21, E. Venizelos Avenue
GR-102 50 Athens
Tel: +30210-320 3610
Fax: +30210-320 2432

www.bankofgreece.gr

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UNPACKING COMMODITY PRICE FLUCTUATIONS: READING THE NEWS TO UNDERSTAND INFLATION

Dimitris Malliaropulos
University of Piraeus and Bank of Greece

Evgenia Passari
Université Paris-Dauphine

Filippos Petroulakis
Bank of Greece

ABSTRACT

We show that text-based indicators of supply and demand disturbances in commodity markets provide distinct information about future inflation movements relative to existing predictors, inflation expectations and survey forecasts. Specifically, we document that demand-side disturbances play a significantly larger role in prediction because they typically lead to uniform increases in quantities and prices of goods across the consumer basket, resulting in a clear and positive relationship between commodity prices and overall inflation. Supply-side disturbances matter in particular circumstances, for instance during the recent period of the pandemic and geopolitical shocks. In terms of magnitudes, the commodity-specific indicators reduce out-of-sample inflation forecast errors by up to 30 percent. We finally apply our indexes to the inflation decomposition framework of Blanchard and Bernanke (2023) and corroborate their finding that the bulk of pandemic-era inflation can be attributed to commodity supply disruptions, resulting in price increases in goods markets.

Keywords: inflation, commodities, news, textual analysis, demand, supply

JEL classification*:* C19, E31, E37, Q02

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Correspondence:

Filippos Petroulakis
Economic Analysis and Research Department
Bank of Greece
El.Venizelos 21, 10250 Athens, Greece
Tel.: +30-2103202416
email: fpetroulakis@bankofgreece.gr

1. INTRODUCTION

Monetary authorities recognize that fluctuations in commodity prices are significant determinants of inflation dynamics (Bernanke, 2008). These prices serve as leading indicators of inflation since they are sensitive to changing economic conditions and can influence aggregate prices through distribution channels and second-round effects. Understanding the intricate relationship between commodity price changes and inflation is vital for effective monetary policy, especially in the face of evolving global challenges that can have large effects on commodity markets. How exactly commodity prices affect inflation, however, likely depends on the drivers of commodity price fluctuations. Such fluctuations can arise from demand shifts associated with economic booms and recessions, hedging operations and speculative trading behaviors, supply constraints precipitating precautionary demand pressures, or geopolitical events, including trade agreements and wars. Each of these factors exerts differential influences on aggregate price indices and macroeconomic outcomes, both in terms of magnitudes and persistence. Several studies have documented that specific commodities (for instance, oil) are informative about inflation, but this relation is not stable across different countries and time periods.[1]

We show that commodity prices provide distinct information about future inflation movements relative to existing predictors, inflation expectations and survey forecasts, but that predictive power is obscured by the fact that commodity prices are driven by both supply and demand shocks, and these shocks have different passthrough to inflation. Our starting point is that under the presence of aggregate demand shocks, which typically affect most sectors of the economy in a homogeneous manner, the relationship between commodity prices and inflation tends to be direct and unambiguous, reflecting substantial pass-through effects. Specifically, positive aggregate demand shocks are generally associated with widespread increases in both prices and quantities across the consumer basket, thus establishing a stronger link to overall inflation dynamics.[2] Conversely, supply shocks that are idiosyncratic to specific commodities can generate varying effects on the general price level, depending on the interplay between substitute and complementary goods. For instance, a negative supply shock in the cocoa market may elevate cocoa prices while exerting downward pressure on the price of sugar, given their complementary nature in consumption. Meanwhile, commodities such as coffee, which are imperfect substitutes for cocoa, may see limited demand effects, thereby remaining relatively insulated from price changes. Consequently, although a commodity-specific supply shock might elevate

[1] Commodity prices were effective predictors of inflation until the early 1980s, but their predictive power has diminished since the mid-1980s (Stock and Watson, 2003). The predictive power of commodity prices for aggregate price indices is weak, despite the widespread view that commodity futures capture substantial information regarding underlying supply and demand conditions aggregated by futures markets (Bernanke, 2008). An additional complication, recently emphasized by Shapiro (2020), arises from the aggregation of categorical inflation measures at a broad-index level which can obscure inflation dynamics due to the varying sensitivities of different sectors to distinct underlying factors.

[2] More broadly, shocks to aggregate demand tend to predict future inflation more accurately compared to idiosyncratic supply shocks, particularly when the latter are not accommodated by monetary authorities (Boughton and Branson, 1991).

the price of the affected good, its broader impact on inflation may be attenuated due to weak pass-through to the overall consumption basket.

Identifying supply and demand shocks across different commodity markets entails significant challenges. Although the literature has historically provided us with reliable measures of shocks for the oil market, the price drivers of other commodities remain understudied. To mitigate this challenge, we employ the narrative-based indicators of Mouabbi, Passari, and Rousset Planat (2024), that combine textual analysis with human auditing to construct disaggregated supply- and demand-side disturbances for a wide array of commodities from business news. In addition to these indicators, we also use text-based measures of key risk factors that affect commodity markets, such as severe recessionary regimes and extreme natural disaster events. Employing the narrative-based, commodity supply and demand indicators allows us to cut through the sources of confusion that arise when one looks at the informational content of commodity price developments alone. We then proceed to explore whether these measures that separately identify supply- and demand-side disturbances across commodity markets are able to provide additional information regarding the future trajectory of inflation.

We report three key findings. First, narrative-sourced supply and demand disturbances help predict future inflation, over and beyond common predictors such as past inflation, interest rates, economic growth, stock and bond market indexes, volatility measures and tradable commodity returns. For example, the textual indicators help reduce the out-of-sample forecast error in inflation by 20% to 30%, depending on the horizon and the exact specification. The fact that the textual indicators provide incremental information on top of commodity returns is particularly encouraging and illustrates the benefit of separately examining the supply and demand drivers of commodity prices, given that their importance and persistence may vary. For instance, we find that, on average, demand-side disturbances generally contribute more to the out-of-sample predictability of different inflation baskets. However, supply-side disturbances matter in particular circumstances, such as during the recent period of the pandemic. We further assess the validity of the textual commodity supply and demand indicators by looking at their performance across different regimes and turning points. We follow the approach of Joseph et al. (2021) and split the sample in periods when inflation is increasing, falling or remains stable. Our framework provides clear improvements over the baseline model for headline inflation at the one-year horizon, especially for episodes of falling and stable headline inflation. For episodes of increasing inflation, the narrative measures also provide substantial and consistent improvements across several specifications. For shorter horizons, e.g. six months, the addition of text-based commodity measures again improves the performance of specifications that incorporate additional predictors such as tradable commodity returns.

Second, we use our indicators to separately forecast two key components of inflation: food and energy. In both of these cases, the supply- and demand-side indicators significantly improve the out-of-sample forecast error. Importantly, we document a significant asymmetry: our supply-side indicators are the key drivers of food inflation, whereas energy inflation is primarily forecasted by our demand-side indicators. Additionally, the magnitudes are not small - the improvement in out of sample forecast errors ranges from 10% (food) to 20% (energy). The improvement in forecasting energy inflation is particularly notable, given that (1) energy is one of the most volatile and least predictable components of inflation, and (2) commodity returns have essentially no ability to forecast energy inflation.

Third, after establishing that our measures for oil compare favorably with the structurally identified oil shocks of Baumeister and Hamilton (2019) and Känzig (2021), we examine the effects of our proxies for different inflation baskets in a local projections setup. The bigger role of demand disturbances is once again confirmed by the impulse responses of headline, goods and services inflation. Supply disturbances matter only for the recent period that includes the COVID-19 pandemic. We further show that our indices contain information which is not reflected in various measures of inflation expectations, such as measures derived from financial market prices and survey-based measures of professional forecasters and consumers. Hence, our indices are not merely picking up already-available information but insights that are not apparent to either market participants, forecasters, or households.

Given that various drivers of supply and demand dynamics may have disparate effects on macroeconomic variables, we also study the persistence of these developments on inflation within recessionary regimes and under the impact of severe natural disasters. This part of the analysis is motivated by the recent pandemic experience and the significant economic fluctuations observed over the past decades. This is highly relevant for policy-making because different inflation developments call for different monetary policy responses; central banks can look through transitory shocks, but may have to respond to persistent shocks. We show that accounting for the drivers of demand and supply-side disturbances matters both for the magnitude and the persistence of the pass-through to inflation. We find that a decrease in demand for commodities is deflationary, but in a recession its effect on inflation is more muted and transitory. In contrast, the deflationary effect of a demand decrease is not counteracted under the presence of severe natural disasters, at least in horizons up to one year. On the other hand, the effect of a decrease in demand for commodities on inflation is more persistent than the effect of an increase in demand. Demand decreases appear to be less deflationary in the short run and more deflationary in the long run. Increases in supply of commodities are generally deflationary, regardless of the regime. At the same time, increases in supply do not appear to be generally deflationary unless they coincide with a natural disaster, over and above the effect of the COVID-19 pandemic.

In a final exercise, we illustrate the usefulness of our indexes for decomposing post-pandemic inflation given the recent importance of supply shocks (Banbura, Bobeica, and Martínez Hernández (2023)). We employ the framework of Blanchard and Bernanke (2023), who use a simple structural model to account for the sources of inflation during the pandemic era, between energy and food shocks, labor market tightness, and supply shortages. We use one of our measures (supply decrease) instead of the reduced form measure of Blanchard and Bernanke (2023), derived from Google Trends. Our results are very similar to those of Blanchard and Bernanke (2023), showing that the bulk of inflation during the recent episode can be attributed to commodity shocks and shortages; we, hence, provide strong support to their framework by using a narratively-identified measure of supply developments.

Overall, our work illustrates that the proposed text-based, narrative measures of demand and supply of commodities can inform monetary policy decisions because they have the ability to (i) identify common and idiosyncratic drivers of demand and supply across commodities; (ii) isolate variations in commodity prices that have inflationary implications; and (iii) distinguish between different types of price developments, across a wide range of commodities. For instance, commodity price fluctuations might reflect supply-related events, changes in global demand that are common across commodities, or commodity-specific demand developments; each of these has differential effects on inflation.

To our knowledge, this is the first attempt to employ real-time measures of commodity supply and demand drivers for the understanding and prediction of inflation dynamics. Our analysis further suggests that the supply and demand of commodities have differential impact across different inflation measures.

Our contribution to the literature is threefold. Our primary contribution is the application of measures of commodity-price decomposition that span the broad commodity market for inflation prediction on the backdrop of the disconnect between commodity prices and inflation documented by the literature.[3] The advantages of the employed text-based measures are threefold. First, they leverage the universality of business news as a comprehensive and widely available source of information, ensuring broad applicability across different economic contexts. Moreover, they offer extensive coverage of the highly heterogeneous commodity market, encompassing a diverse range of understudied commodity categories and spanning multiple geographic regions. This breadth allows for a more granular understanding of the drivers of commodity-specific price movements across global markets. Finally, the high frequency of these measures provides timely insights, allowing for more responsive and up-to-date forecasting of inflation dynamics, which is particularly valuable in rapidly evolving macroeconomic

[3]See the works of Hooker (2002), Stock and Watson (2003). A notable exception is the work of Gospodinov and Ng (2013), which demonstrates that the principal components of convenience yields retain predictive power for aggregate price indices and commodity prices.

environments. These characteristics position the employed measures as a robust tool for analyzing the transmission of global shocks and their implications for inflation, particularly in the wake of the recent policy challenges following the COVID-19 pandemic and the global geopolitical tensions.

Second, our work contributes to the growing literature that uses textual analysis for the study of various economic and financial outcomes. Recent contributions include the works of Tetlock (2007), Gentzkow and Shapiro (2010), Hoberg and Phillips (2010), Boudoukh et al. (2013), Alexopoulos and Cohen (2015), Baker, Bloom, and Davis (2016), Allcott and Gentzkow (2017), Hassan et al. (2019), Angelico et al. (2022), Hassan et al. (2023a), and Hassan et al. (2023b). The closest related work is the study of Angelico et al. (2022) that employs Italian tweets to build a real-time measure of consumers' inflation expectations. The authors show that Twitter-based indicators are highly correlated with monthly survey-based and daily market-based inflation expectations. Their measure is found to both lead and provide a good real-time proxy for consumers' expectations. Different from this work, our focus is on inflation prediction. For this reason, we employ a narrative measure that exploits information from business news in a supervized and semi-supervized textual framework which, differently to Latent Dirichlet Allocation (LDA) methods, allows the definition of the source of commodity-price developments ex-ante.

Third, our work complements the extensive literature that tries to identify supply and demand shocks in energy markets (Kilian, 2008; Kilian, Rebucci, and Spatafora, 2009; Kilian, 2009; Kilian and Vigfusson, 2017; Känzig, 2021). Recent papers that construct narrative measures of shock identification in the spirit of Romer and Romer (2010), include the works of Wu and Cavallo (2012), Caldara, Cavallo, and Iacoviello (2019), Loughran, McDonald, and Pragidis (2019) and the study of Datta and Dias (2019). Our approach differs in that we exploit the news analysis coverage of the universe of tradable commodities following the work of Mouabbi, Passari, and Rousset Planat (2024), instead of focusing on the oil market. A more fundamental distinction from the aforementioned literature is that our indexes represent a real-time appraisal of how market participants perceive the current and future state of commodity markets through the news rather than representing commodity-price shocks.

The remainder of the paper is organized as follows. Section 2 introduces our methodology and the text-based commodity indices. Section 3 highlights the distinct properties of supply and demand indices and sets the ground for the empirical analysis. Section 4 presents a forecasting exercise in which we study the differential impact of the proposed text-based commodity indices on a number of broad and disaggregated inflation measures, across different sample periods. Section 5 compares the automated, narrative supply and demand measures to shocks affecting oil prices identified by the literature using structural vector autoregressions (SVAR). Section 6, studies the responses of prices to commodity-market events picked by the textual-based measures. Section 7 builds on the richness of the news informational content to couple supply and demand dynamics with specific regimes which relate to recessionary phases of the business cycle or are characterized by severe natural disasters and provides more intuition about the nature of inflation dynamics as well as their persistence. Section 8 applies our indices to the inflation decomposition framework of Blanchard and Bernanke (2023) and corroborates some of their findings. Section 9 concludes.

2. Textual Analysis and Narrative Identification of Commodity Price Developments

A Text-based Framework for Disentangling Commodity Supply and Demand. We first present the general framework of Mouabbi, Passari, and Rousset Planat (2024) that uses a narrative approach for the construction of supply and demand developments in commodity markets. Indices of supply and demand are constructed first at the market-wide level which summarizes the dynamics across the universe of commodities, and subsequently the analysis is tailored to span a large number of commodity categories, including energy, industrial and precious metals, agricultural commodities, and livestock. Ultimately, individual commodities such as oil, natural gas, copper, iron, gold, wheat, corn, sugar, and hogs are also individually analyzed and mapped.

For the construction of the indices, news reading is simulated in three steps. The first step is content analysis. Words and word combinations are identified within sentences that can be attributed to supply and demand factors. During the second step of refinement, the process is overlayed with additional algorithms that cater to negations, as well as to a number of exceptions that vary across commodity categories. The third step involves an extensive human auditing exercise. Commodity-related information is collected from more than four million articles from Reuters and Dow Jones between January 2000 and June 2023.

A crucial step in content analysis is the use of supervised and semi-supervised methods for learning; the algorithm identifies words and word combinations that can be attributed to supply and demand factors. The starting point is the search for the most popular words over the universe of business news articles. The words that appear more frequently are identified and classified into supply and demand lists. The process is complemented with a large number of human checks. This forms the basis of the creation of the supply and demand dictionaries. Additionally, standard dictionaries of "increase" and "decrease" words that are typically employed in the literature that uses textual analysis for the measurement of economic outcomes are employed. The "supply" and "demand" words are then combined with the "increase" or "decrease" words to form pairs that we count as signals. The following equations detail the construction of suppply increase, supply decrease, demand increase and demand decrease indicators.

$$SI_t = \frac{1}{N_t} \sum_{w}^{W_t} \{1[w = Supply] \times 1[|w - pos_{Increase}| \leq i]\} \tag{1}$$

$$SD_t = \frac{1}{N_t} \sum_{w}^{W_t} \{1[w = Supply] \times 1[|w - pos_{Decrease}| \leq i]\} \tag{2}$$

$$DI_t = \frac{1}{N_t} \sum_{w}^{W_t} \{1[w = Demand] \times 1[|w - pos_{Increase}| \leq i]\} \tag{3}$$

$$DD_t = \frac{1}{N_t} \sum_{w}^{W_t} \{1[w = Demand] \times 1[|w - pos_{Decrease}| \leq i]\} \tag{4}$$

where $w = 0, 1, ..., W_t$ are the words contained in articles, with N_t the number of articles published at date t, and $pos_{Decrease}$ ($pos_{Increase}$) the position of the nearest synonym of decrease (increase). To measure changes in demand or supply, we thus count only mentions of supply or demand that occur within a i-word window of a synonym of increase or decrease. We set $i = 4$ but the validity of the indices is robust to the choice of different word-window sizes.

Net supply is defined as the difference between supply decrease and supply increase and net demand is defined as the difference between demand increase and demand decrease. Consequently, an increase in net supply and an increase in net demand should both have a positive effect on inflation. To quantify the net effects, we thus generate:

$$NetDemand_t = DI_t - DD_t \tag{5}$$

$$NetSupply_t = SD_t - SI_t \tag{6}$$

A standardized version of the indices divides the net supply and demand indicators with the total number of articles published per day, ensuring that they are not artificially inflated by changes in the publication policy of news articles.

Decomposing the Drivers of Supply and Demand Developments. The origins of supply and demand developments can have different implications for inflation. For instance, natural disasters are thought to have an impact mostly on short- to medium-term inflation while environmental regulation could have a lasting effect on inflation by permanently affecting relative prices through expectations. This is highly relevant for policy because it implies that central banks can look through transitory shocks, but may have to respond to persistent shocks. Hence, the decomposition of commodity price fluctuations into a number of key drivers potentially allows the distinction between short and long-term impacts of commodity price developments. Four main drivers of commodity prices are retrieved according to information collected from IMF commodity market reports; namely, a business cycle /recessionary factor, a geopolitical risk factor, a natural disasters factor, and a climate change factor. These four factors potentially explain an important share of inflation variations; coupling the factors with supply and demand dynamics provides more color to the underlying dynamics of commodity prices and can better inform us about their time-varying significance. The commodity drivers' dictionaries are derived using a semi-supervised approach, employing a rich list of authoritative texts for each driver category, according to the approach of Engle et al. (2020).

The proposed framework complements concurrent structural measures for the identification of supply and demand developments that focus on the oil market because it spans most individual tradable commodities. This allows us to study the differential impact of supply and demand developments for different inflation measures and assess their suitability. Additionally, we are able to distinguish across different regimes of supply and demand developments.

Measures of Supply and Demand Developments for a Broad Commodity Index. For the construction of supply and demand indicators for the global commodity index Mouabbi, Passari, and Rousset Planat (2024) retain all articles that provide information about commodity markets that reference any commodity that forms a constituent of the Composite Spot Commodity Index from the Standard & Poors, Goldman Sachs Commodity Index (GSCI) spot price series.[4]

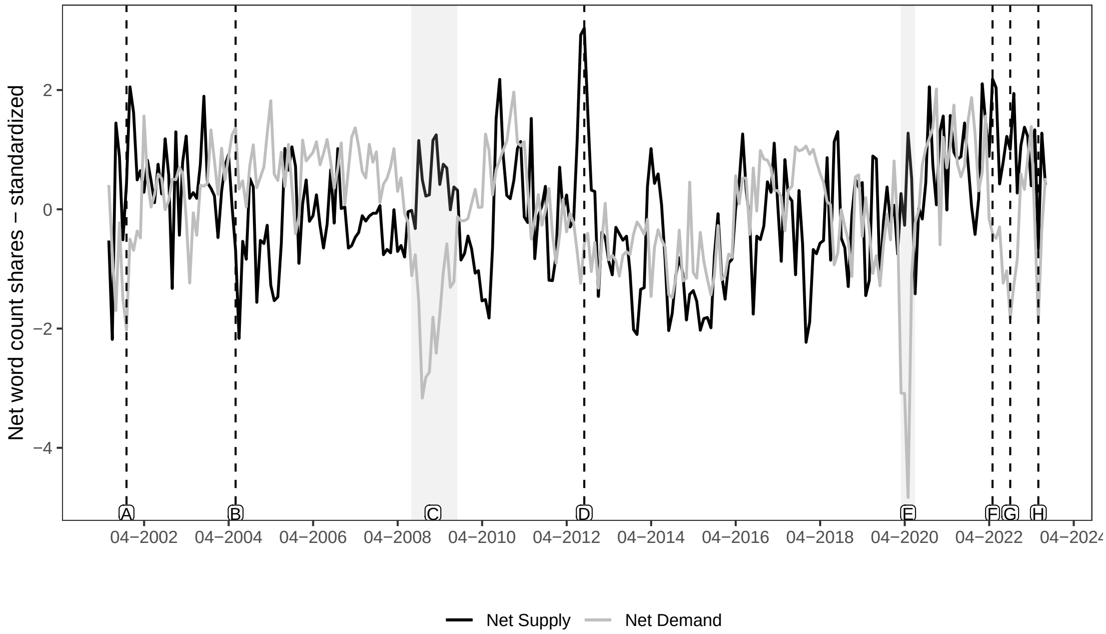
Figure 1 from Mouabbi, Passari, and Rousset Planat (2024) plots the monthly standardized net supply and demand indicators for the full sample period, after adjusting the net supply and demand indicators with the total number of articles per day. The peaks and troughs of the standardized net supply and net demand indices map to well-known commodity-wide developments. Large spikes correspond to major events such the global financial crisis, the trade war, the COVID-19 epidemic, the Russo-Ukrainian War and the U.S. debt-ceiling crisis. Sizable net supply peaks correspond to important oil production cuts by OPEC and to natural disasters.

Measures of Supply and Demand Developments for Individual Commodities. The narrative approach is subsequently tailored to cover commodity categories (energy, industrial metals, precious metals, agricultural commodities and livestock) and individual commodities; oil, natural gas, heating oil, copper, aluminium, zinc, nickel, wheat, corn, soybean, sugar, cocoa, coffee, cotton, cattle and hogs. Methodologically, this is achieved by augmenting the dictionaries of the broad commodity indicators with words that capture commodity-specific supply and demand elements.

Figures A1 and A2 in the appendix plot the standardized net supply and demand indicators for crude oil and wheat for the 2001-2023 period. Interestingly, while the crude-oil narrative indices map to well-known oil developments, such as OPEC meetings and other notable business cycle-related events, including the weakening global demand following the U.S. recessions of 2001 and 2008, and the dramatic increase in US production between 2014 and 2016, wheat is marked by events of a different nature. The wheat index captures a number a supply disruptions that coincide with extreme weather events and natural disasters that affect production. The peaks in

[4] This index tracks the prices of major physical commodities for which there are active, liquid futures markets.

FIGURE 1. Standardized Net supply and Standardized Net Demand across All Commodity-Related News Articles



Note: This figure plots the standardized net supply and demand indicators for the period between 2001 and 2020. The bars map a number of well-known commodity-wide developments. These events are: [A] US recession and events of 9/11 weighed on commodity markets (118th Extraordinary Meeting of the OPEC Conference – production cut), [B] OPEC agreed to raise output quotas (131st Extraordinary Meeting), [C] Global Financial Crisis, [D] Worst drought in more than 50 years in the U.S. severely cut corn and soybeans productions, sparking all-time high prices, [E] COVID-19 dented demand and disrupted supply chains, [F] The Russo-Ukrainian War raised concerns about supply shortages in grains, oil, and metals, [G] Demand concerns from rising global interest rates, China's COVID-19 lockdown extensions, [H] 2023 United States debt-ceiling crisis.
Source: Mouabbi, Passari, and Rousset Planat (2024)

demand, which appears to be rather inelastic, coincide with trade deals between U.S. and China and stockpiling around the pandemic, which is indicative of precautionary demand.

Measures of Commodity Supply and Demand Drivers. As previously discussed, an additional refinement of the employed narrative toolkit is the construction of thematic indices that further characterize the supply and demand of commodities. The latter should coincide with the key determinants that have shaped commodity markets since the beginning of the 21st century. To the extent that these thematic indices could be combined with commodity supply and demand they should contain valuable information about the different properties and persistence of inflation dynamics.

The focus of the present study will be on the interaction of a business cycle (recessionary) and a natural disasters indicator with the supply and demand indices. For this purpose, we agrregagate the business cycle and natural disaster drivers of Mouabbi, Passari, and Rousset Planat (2024) into monthly signals and we subsequently convert them to dummy variables defined by the median value of the original driver series. This allows us to define four distinct regimes; a highly recessionary regime, a low-recession regime, a regime characterized by the presence of severe natural disasters and a regime characterized by the absence of severe natural disasters.

The commodity drivers dictionaries in Mouabbi, Passari, and Rousset Planat (2024) are drawn from a rich list of authoritative texts for each category, following the approach of Engle et al. (2020), as no well-defined dictionaries exist. In particular, the authoritative text for the business cycle is composed of the full history of the Business Cycle Dating Committee Announcements of the NBER (1979-2020). Similarly, for natural disasters we exploit the full database of EM-DAT (the International Disaster Database of the Centre for Research on the Epidemiology of Disasters.

3. Properties of Supply and Demand Measures

In an effort to better understand the behavior of the supply and demand indicators detailed in the previous section, we carry out a number of tests. This process allows us to validate the informational content of the series extracted from business news that talk about commodities and to additionally obtain new insights by studying their properties. Our starting point is the premise that supply and demand shocks manifest in distinct ways in commodity markets and have varied implications for macroeconomic performance and inflation dynamics.

When aggregate demand shocks occur, such as during an economic expansion or increased consumer confidence, they exert upward pressure on prices across a broad spectrum of commodities. This phenomenon is particularly evident in procyclical goods, such as oil or industrial metals. For example, an increase in consumer spending often correlates with rising oil prices, which, in turn, influences transportation and production costs across most sectors. As these costs rise, the higher prices tend to get passed through to consumers, leading to sustained inflationary pressures. This relationship between aggregate demand and commodity prices highlights a significant and homogeneous component that links the behavior individual commodities to their contribution to the overall price level.

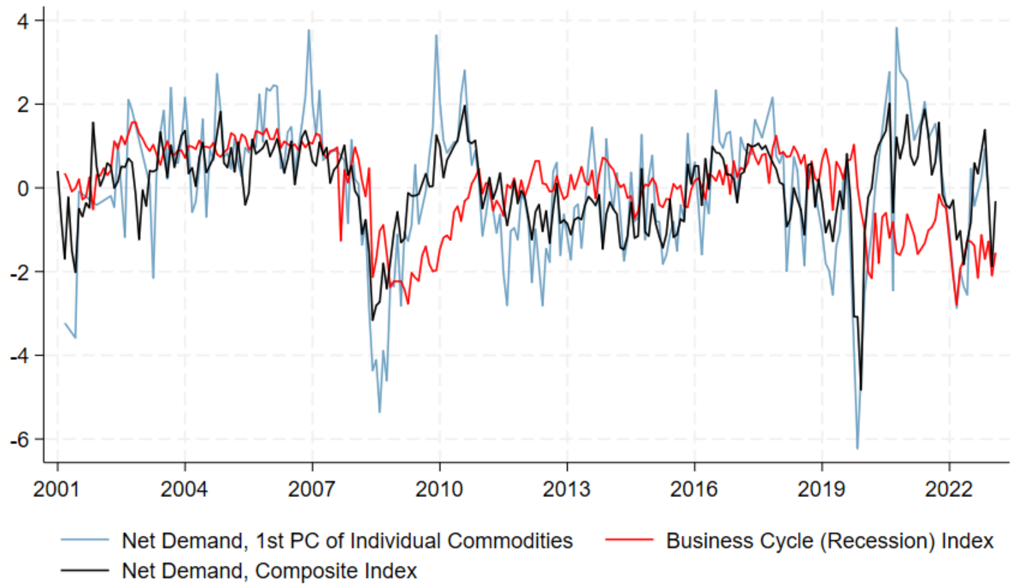
Empirically, the textual composite demand measure captures an aggregate component that reflects a broad-based change in overall economic activity. By encompassing various demand signals across different commodities, this measure allows us to discern shifts (e.g. in consumer behavior or investment patterns) that signal fluctuations in economic performance. Its significance lies in its ability to provide a comprehensive view of demand trends rather than focusing solely on isolated sectors. Descriptive evidence highlights this property, as the composite demand measure displays a high correlation with a textual measure of the business cycle from Mouabbi, Passari, and Rousset Planat (2024). This correlation suggests that as demand across commodities shifts, it coincides with changes in important business cycle components. For instance, a rise in consumer confidence leads to increased spending, which, in turn, bolsters demand for goods and services across multiple sectors, including manufacturing and retail. This interconnectedness reinforces the composite measure's role as a valuable predictor of economic trends. Figure 2 plots the 1st principal component of individual commodities' net demand indexes, the net demand composite index, and a measure of the business cycle, illustrating the high correlation across these measures.

In contrast, supply shocks tend to exhibit idiosyncratic characteristics that can lead to diverse outcomes depending on market conditions and the interrelationships between different goods. Taking the cocoa market as an example, a negative supply shock - perhaps a disease that affects cocoa crops - can result in a sharp increase in cocoa prices. However, since cocoa and sugar are typically used for the production of chocolate, the reduced supply of cocoa can depress the demand for sugar. In such cases, the complementarity between these two commodities results in divergent pricing movements, where sugar prices may decrease even as cocoa prices rise. Thus, while cocoa experiences significant inflationary tension, the overall impact on the consumer price index could be mitigated, showcasing the nuanced effects of supply shocks. The behavior of commodities such as coffee, which act as imperfect substitutes for cocoa further complicates the aggregate effects on prices baskets. A supply disruption affecting cocoa may not lead to a proportional increase in demand for coffee and subsequently coffee prices, but instead may see consumers shifting preferences to tea or other substitutes. This limited demand response within the context of substitute goods demonstrates that supply shocks have unique properties, but also interact with consumer behavior in ways that can dampen their broader inflationary impact. Hence, the interconnectedness of commodities through substitutability and complementarity could lead to varying inflation outcomes even when specific commodities face supply constraints.

Figure 3 plots the eigenvalues of the principal components of textually-extracted individual commodity net demand and supply developments and provides some first evidence that illustrates this point. The scree plot of the principal component analysis of individual commodity net supply indicators does not suggest a natural break between high and low eigenvalues - however, the first eigenvalue from the principal component analysis of the individual commodity net demand indicators is notably larger, showcasing the importance of an aggregate demand component.

Furthermore, Figure 4 presents the pairwise correlations of the supply and demand indices of individual commodities with those of oil. We focus on this relationship due to the unique importance of oil in the production stages across economic sectors, but also due to its prominence in a literature that has historically focused solely on oil behavior to proxy for global supply chain disruptions. With the exception of wheat and sugar–both essential food products with relatively inelastic consumer demand–pairwise supply correlations between energy, industrial, agricultural, and animal commodities and oil are notably lower than the corresponding demand correlations, consistent with our conjecture.

FIGURE 2. Net Demand, Commodities and Composite



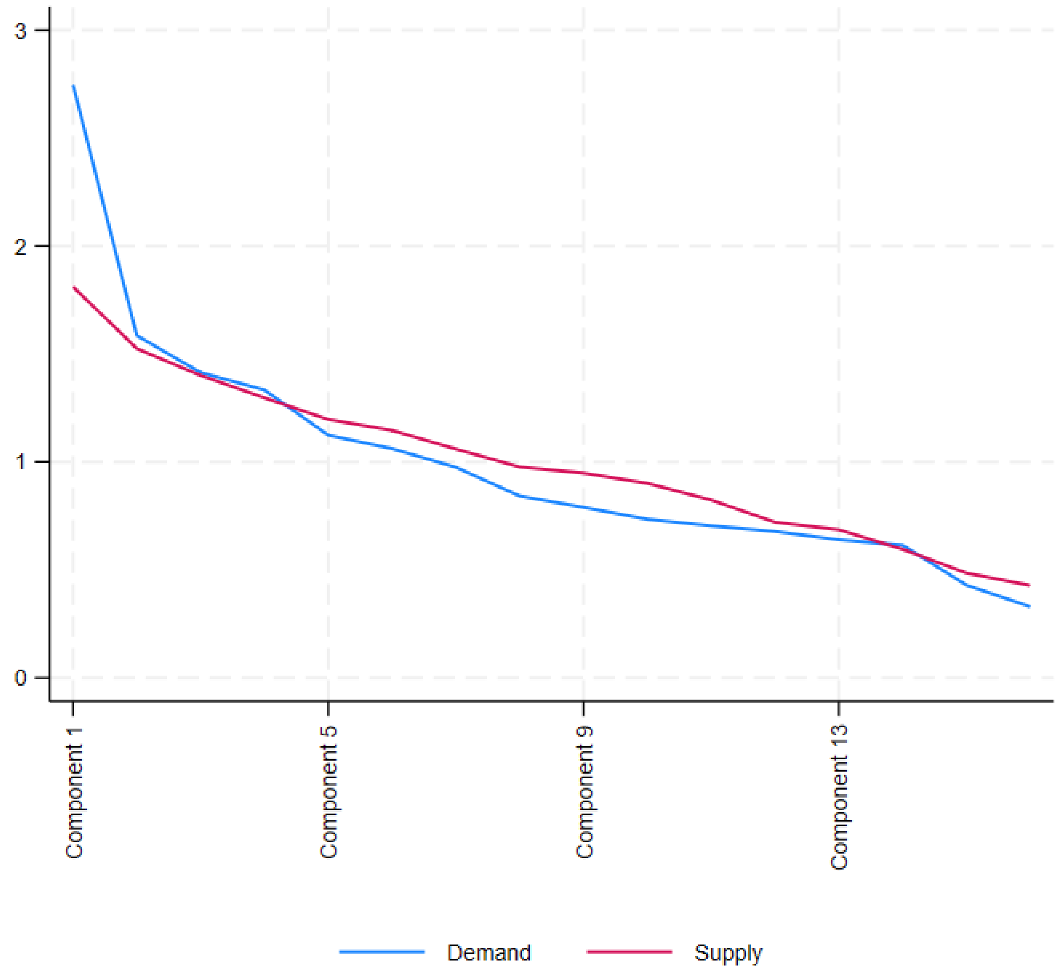
Notes: The figure plots the 1st Principal Component of net demand indexes of individual commodities, the net demand composite index, and the (negative) of the business cycle index. Commodities included are aluminium, cattle, cocoa, coffee, copper, corn, cotton, gasoline, hogs, natural gas, oil, soybean, sugar, wheat and zinc, spanning the period May 2001-July 2023.

Finally, it is crucial to recognize that the different underlying structures of supply dynamics across commodity sectors complicate the overall inflationary landscape. While demand dynamics tend to exhibit significant commonality across diverse commodities, supply dynamics are more fragmented. For example, agricultural commodities like grains may respond strongly to extreme weather events, while energy and metals markets often display less correlation in their supply shocks. Therefore, the idiosyncratic nature of supply – shaped by seasonal conditions, regional disruptions, and specific industry characteristics – becomes essential in understanding inflation transmission. In this context, the presence of both complement and substitute goods becomes pivotal as they influence how supply shocks propagate through the economy, reinforcing the notion that while commodity-specific disruptions can elevate prices, their ultimate effect on inflation may be significantly muted due to a weak pass-through effect on the overall consumption basket.

4. DO THE NARRATIVE COMMODITY INDICES IMPROVE INFLATION FORECASTS?

The analysis presented in the previous sections suggests that textual measures of commodity supply and demand, derived from business news, may contain valuable informational embedded in equilibrium aggregate commodity prices. This finding prompts further investigation into whether differentiating between supply- and demand-side dynamics may provide distinct information about future inflation relative to existing predictors, potentially leading to more accurate inflation forecasts.

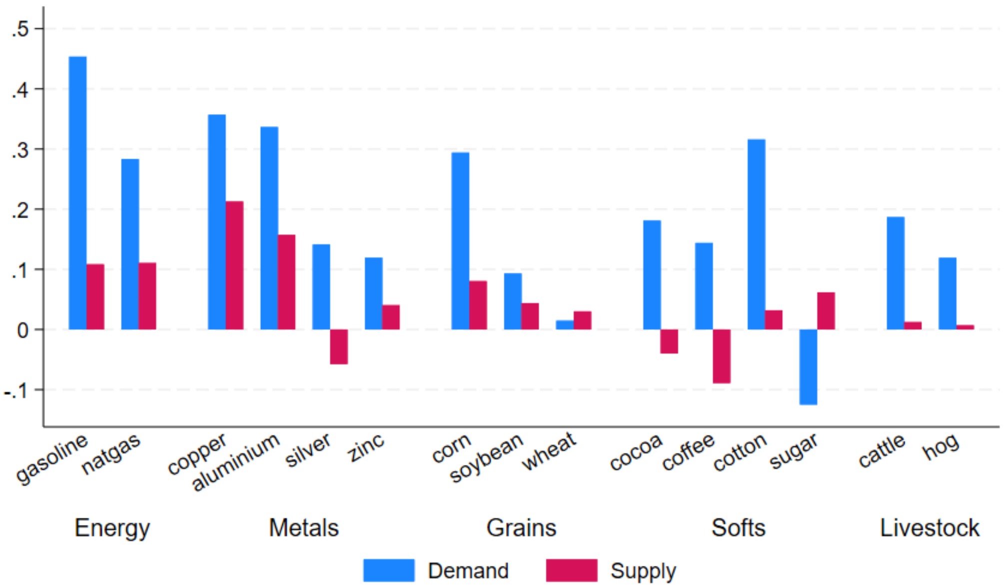
FIGURE 3. Scree Plots from Principal Component Analysis



Note: Scree plots of eigenvalues after principal component analysis conducted on net supply and net demand indices of individual commodities including aluminium, cattle, cocoa, coffee, copper, corn, cotton, gasoline, hogs, natural gas, oil, soybean, sugar, wheat and zinc, spanning the period May 2001-July 2023.

In this section, we evaluate the proposition outlined above. The existing literature remains divided on the utility of commodity prices for inflation forecasting, particularly during the Great Moderation and the post-Great Financial Crisis period. Rather than taking a definitive position on the general forecasting value of commodity prices, we focus on whether our textual measures of supply and demand dynamics can enhance inflation predictions relative to baseline models, both with and without the inclusion of commodity prices. The analysis is conducted for both headline inflation and core inflation, the latter excluding volatile components such as food and energy prices. By doing so, we aim to assess the incremental value that text-based indicators provide over traditional forecasting models in capturing inflation dynamics, especially in the context of heterogeneous drivers across different inflation measures.

FIGURE 4. Correlations of commodity indices with oil index



Notes: The figure shows correlations of net demand and net supply for each individual commodity against oil, spanning the period May 2001-July 2023.

We conduct two broad sets of empirical exercises. In the first, we incorporate our textual indices into a baseline model, without the inclusion of tradable commodity prices or other control variables. This allows us to assess the standalone predictive value of our measures. In the second set of exercises, we introduce commodity prices along with additional macroeconomic and financial controls, evaluating whether our indices offer incremental informational content beyond the effects captured by commodity price movements and other macroeconomic and financial variables. The analysis employs a simple linear model, adhering to parsimonious specifications commonly used in the literature, particularly following the frameworks of Gospodinov and Ng (2013) and Stock and Watson (2003). Specifically, we estimate linear regressions of the following form:

$$\Delta^h(\pi_{t+h}) = \alpha_0 + \beta_0(L)\pi_t + \beta_1(L)index_t + \beta_2 x_t + \epsilon_{t+h}. \tag{7}$$

In the above expression, $\Delta^h(\pi_{t+h})$ represents inflation over a horizon of h months from time t, where $\Delta^h(\pi_{t+h}) = (1200/h) \times ln(p_{t+h}/p_t)$, with p_t denoting the price level at time t. Therefore, π_t is the one-month annualized inflation rate at time t. The coefficients $\beta_k(L)$ are lag polynomials for inflation and the textual indices, where $\beta_0(L)$ is a first-order lag polynomial, $\beta_1(L)$ represents lag polynomials of orders 0 to 2, depending on the specification, and $index_t$ denotes our textual measure of commodity demand or supply. The control variables, x_t, include the one-month log growth in aggregate commodity prices and the policy rate (effective federal funds rate), both entering contemporaneously. In certain specifications, we also incorporate the unemployment gap to capture Phillips Curve effects. For robustness, additional controls such as oil prices, oil production, oil inventories, inflation forecasts (SPF), and oil futures (WTI) are tested. However, these controls do not improve the forecasting performance of models with textual indices and, in fact, increase the RMSE of baseline models. As a result, they are not systematically included in the tables and figures.

The richness of our indices allows for a variety of specifications, which can tease out different patterns in the data. For simplicity, we focus on our composite indices in this section. In line with the parsimony requirement, we examine several combinations of these indices. Specifically, we consider models incorporating: i) net supply and net demand together; ii) only net supply; iii) only net demand; iv) demand increase and decrease; v) supply increase and decrease; vi) supply and demand increase and decrease. Initially, we limit our analysis to the pre-COVID period to establish baseline results. Subsequently, we address the econometric challenges unique to the COVID-19 period, to enhance the robustness of our results in the face of the unprecedented disruptions associated with the pandemic. These distinct specifications allow us to capture the nuanced effects of supply and demand shocks across different time-frames and economic conditions, thereby enhancing the reliability of our inflation forecasting models.

We employ rolling window forecasts, using 120-month windows as is standard in the literature. A potential concern with such long windows is that crises are frequently present in the sample. In addition to the simple AR models[5], as specified in (7), we also consider models incorporating moving average terms, which have been shown to improve inflation forecasts. The $\beta_0(L)$ term is of order 1 for the AR models and IMA(0,2) specifications further include MA terms of order 2 in the residuals.[6,7]

We analyze both Consumer Price Index (CPI) and Personal Consumption Expenditures (PCE) inflation, acknowledging the significant differences between these measures and their potential impact on our findings. CPI is a Laspeyres index derived from consumer survey data, while PCE represents a Fisher-ideal index based on business surveys. Notably, CPI captures only out-of-pocket expenditures, whereas PCE encompasses indirect expenditures, such as those covered by employer-provided health insurance. The PCE is the Federal Reserve's preferred inflation metric; in contrast, the European Central Bank (ECB) focuses on the Harmonized Index of Consumer Prices (HICP), which is also a Laspeyres index sourced from consumer surveys. Although our analysis centers on the U.S. context, the universal applicability of our measures

[5]These models are not strictly autoregressive, as the dependent variable is inflation h periods ahead, while the regressor is a polynomial of one-period inflation. Thus, these models are only truly autoregressive when $h = 1$. For convenience, we maintain this notation.

[6]While the literature typically employs IMA(1,p) models, we found that predictions deteriorate significantly with integrated specifications, likely due to the absence of the high and persistent inflation of the 1970s and 1980s in our dataset, which starts in 2000.

[7]We also test AR models with two lags and IMA(0,1) models, yielding similar results. Lag selection criteria were not employed, as they produce different optimal structures depending on the covariates, and we aimed to avoid confounding our results with varying lag structures.

ensures that our examination of CPI remains relevant and valuable in broader economic discussions.

4.1. **Accounting for the COVID shock.** The unprecedented shock induced by the pandemic has complicated standard time series estimation methods, primarily due to the presence of extreme outliers in the data. This phenomenon has prompted the literature to explore various strategies for addressing these challenges. Researchers have investigated a range of potential solutions, seeking to mitigate the distortions caused by these outliers and enhance the robustness of econometric estimates in the context of such peculiar economic conditions.

In our analysis, we encounter two principal challenges. The first is the non-stationarity introduced by the COVID-19 pandemic, which has significant implications for parameter estimation and the reliability of our models. Second, even if we achieve accurate parameter estimates, our demand indices experience a dramatic collapse in magnitude during the initial three months of the shock. This pronounced decline complicates the forecasting process for the relevant time horizons, as the stability and predictive power of our indices are undermined by these extraordinary conditions.

To address this challenge, we adopt the approach proposed by Lenza and Primiceri (2022), who contend that while excluding extreme outliers from the COVID episode may be suitable for parameter estimation, it is not advisable for forecasting, as this practice risks underestimating uncertainty. They recommend incorporating stochastic volatility within a Bayesian VAR framework, which effectively scales down the variables of interest during the months impacted by the shock. To preserve the parsimony of our model, we implement a simplified version of their approach by replacing the values of the demand indices for the initial three months of the shock with their mean from 2019. Additionally, we include a dummy variable equal to one for the COVID era in our parameter estimation, as suggested by Ng (2021).[8]

4.2. **Forecasts.**

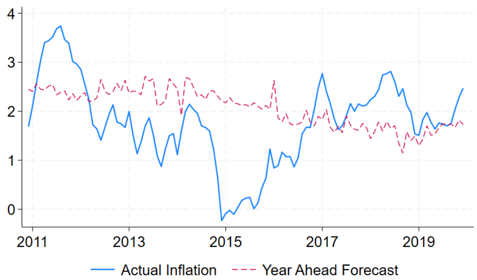
We present our results separately for the pre-COVID period and the entire sample, to evaluate the performance of our framework across different economic regimes. This distinction is particularly relevant as baseline models exhibit significant variations in performance across these regimes, especially for Integrated Moving Average (IMA) specifications. We begin with the forecasting results for Consumer Price Index (CPI) inflation during the pre-COVID period, as detailed in Figure 5 and Table 1.

Figure 5 plots 12-month ahead inflation forecasts together with actual inflation for the period between December 2010 and December 2019. The top panels display the behavior of forecasts

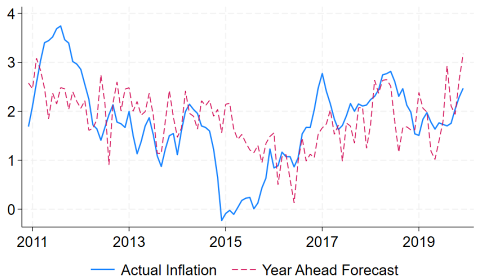
[8] Ng (2021) also advocates for incorporating the log growth of hospitalizations or infections to account for the shock. While this method does enhance prediction accuracy, it offers a smaller improvement compared to the scaling-down approach.

derived from models that only contain autoregressive components (Panel A), or a full set of controls including log monthly changes in commodity prices (Panel B). The bottom panels further introduce the textual indicators of net supply and net demand to the aforementioned models. The improvement in the forecasting performance is evident, even following a comparison with the richer specification of Panel B. The textual indicators appear to offer information not embedded in standard macroeconomic and financial variables traditionally used in the forecasting of inflation.

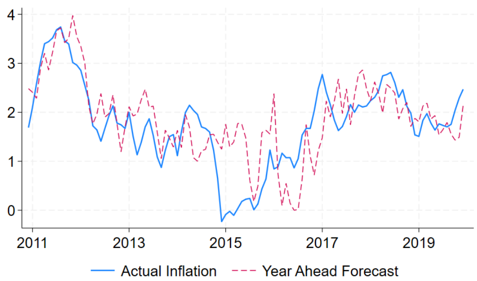
FIGURE 5. Inflation Forecasts versus Actual Inflation, Pre-COVID



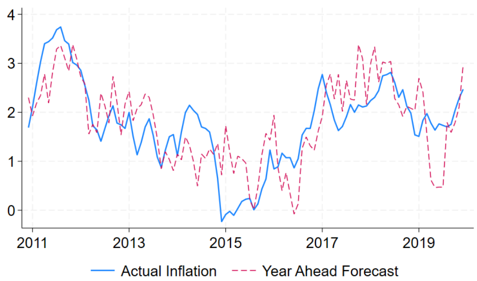
(a) Baseline, no controls



(b) Baseline, controls



(c) No controls, net supply/demand indices

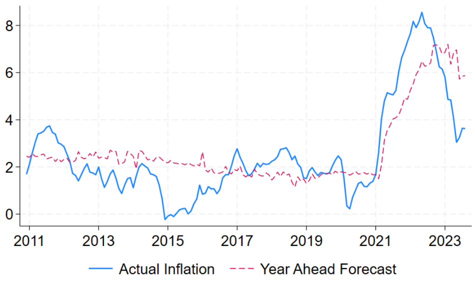


(d) Controls & net supply/demand indices

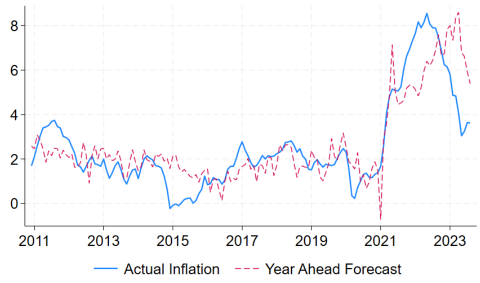
Note: Inflation forecasts plotted together with actual inflation spanning the period December 2010-December 2019. Where noted, controls are: industrial production log monthly change, S&P 500 log monthly returns, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar monthly log returns, and log monthly changes in commodity prices.

Panel A of Table 1 presents the results for models that do not incorporate any control variables (i.e., the set x is null). The Root Mean Square Error (RMSE) for the baseline model across all specifications is reported in the second column for each forecast horizon. We assess the statistical significance of the forecasts relative to the benchmark using the Diebold-Mariano test. Focusing on headline inflation at the h=12 horizon, most Autoregressive (AR) models demonstrate a clear improvement over the baseline, particularly those in columns 1 and 3, which feature a combination of net demand and net supply and net demand alone respectively. Secondary enhancements are observed in columns 4 and 6, which consider demand increase/decrease and supply/demand increase/decrease. This indicates that demand serves as a considerably stronger predictor of future price growth. The Integrated Moving Average (IMA) model yields similar

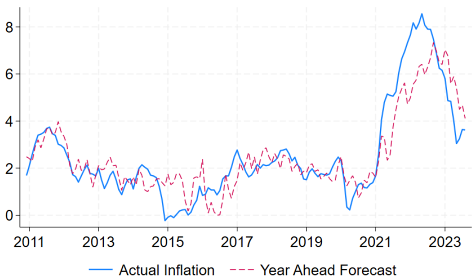
FIGURE 6. Inflation Forecasts versus Actual Inflation



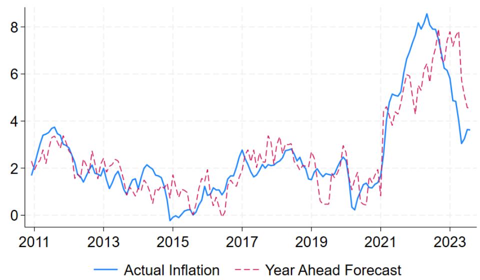
(a) Baseline, no controls



(b) Baseline, controls



(c) No controls, net supply/demand indices



(d) Controls, & net supply/demand indices

Note: Inflation forecasts plotted together with actual inflation spanning the period December 2010-August 2023. Where noted, controls are: industrial production log monthly change, S&P 500 log monthly change, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar monthly log change, and log monthly changes in commodity prices.

findings, with its predictive power being most pronounced at the h=12 and h=6 horizons, where the gains in prediction are statistically significant across models that include textual indices of commodity demand (models 1,3,4,6). We also evaluate a set of specifications that includes a comprehensive array of control variables: the log monthly change in industrial production, S&P 500 log monthly returns, the effective federal funds rate, the spread between 10-year and 2-year U.S. Treasury yields, the VIX, and trade-weighted U.S. dollar monthly log returns. Even when compared to this more competitive benchmark, our framework consistently yields significant improvements for the h=12 horizon.

Panel B presents the results for a baseline model that incorporates commodity price returns as a control variable. Compared to Panel A, the Root Mean Square Error for the autoregressive model is lower across all forecast horizons (however, these differences are not statistically significant). Notably, for the h=12 and h=6 horizons, the models identified as successful in Panel A continue to provide substantial improvements in predictive accuracy in Panel B. This finding indicates that, despite the inclusion of commodity price information in the baseline model, our indices enhance forecasting performance. The same is observed with the Integrated Moving Average (IMA) specification in the absence of controls. When a comprehensive set of controls is included, the predictive gains for the autoregressive model persist for models which include

TABLE 1. Forecast performance (RMSE), Headline CPI inflation, Pre-COVID

	horizon	baseline	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: without commodities								
Autoregressive								
	h=12	0.978	0.682**	0.991	0.687**	0.769**	0.928	0.731**
	h=6	1.373	0.836*	1.022	0.838*	0.863	1.012	0.929
	h=3	1.791	1.015	1.085	0.971	1.011	1.127	1.112
Controls, Autoregressive								
	h=12	0.824	0.819*	1.035	0.803**	0.924*	1.053	0.947
	h=6	1.446	0.963	1.014	0.964	0.983	1.000	1.010
	h=3	1.998	1.016	1.021	0.999	1.024	1.039	1.086
IMA								
	h=12	0.977	0.658**	0.987	0.675**	0.731**	0.900	0.680**
	h=6	1.375	0.777**	0.997	0.798**	0.805*	0.970	0.838
	h=3	1.895	0.917	1.046	0.919	0.965	1.065	1.005
Controls, IMA								
	h=12	0.822	0.786**	1.028	0.756**	0.864**	1.010	0.864**
	h=6	1.261	0.919	0.999	0.930	0.939	0.990	0.954
	h=3	1.859	0.980	0.997	0.976	0.987	1.000	0.996
Panel B: with commodities								
Autoregressive								
	h=12	0.940	0.710**	0.999	0.708**	0.802**	0.950	0.771**
	h=6	1.338	0.858*	1.029	0.852**	0.872*	1.014	0.942
	h=3	1.699	1.017	1.088	0.962	0.993	1.117	1.108
Controls, Autoregressive								
	h=12	0.786	0.871	1.051	0.852	1.001	1.071	1.031
	h=6	1.436	0.978	1.023	0.980	1.004	1.002	1.025
	h=3	1.896	1.040	1.035	1.020	1.049	1.050	1.112
IMA								
	h=12	0.959	0.667**	0.980	0.682**	0.748**	0.894	0.693**
	h=6	1.355	0.782**	0.989	0.804**	0.812**	0.971	0.850
	h=3	1.728	0.988	1.071	0.978	1.044	1.096	1.092
Controls, IMA								
	h=12	0.790	0.818*	1.033	0.782**	0.919*	1.017	0.918
	h=6	1.224	0.941	0.999	0.951	0.963	0.989	0.985
	h=3	1.716	1.043	1.043	1.011	1.028	1.046	1.071
Composite Indices								
Net Supply			X	X				
Net Demand			X		X			
Supply Increase/Decrease							X	X
Demand Increase/Decrease						X		X

Note: The table shows results from forecasts of headline CPI inflation across different monthly horizons, using the composite commodity indices. Columns (1)-(6) show the root mean squared error (RMSE) of each forecast relative to the baseline. Model 1 includes as predictors net supply and net demand; model 2 includes net supply; model 3 includes net demand; model 4 includes demand increase and demand decrease; model 5 includes supply increase and supply decrease; and model 6 includes supply increase, supply decrease, demand increase and demand decrease. The autoregressive specification is given by (7), and IMA specifications further include MA terms of order 2. Each specification includes some of our indexes, as indicated. Where noted, controls are: industrial production log monthly change, S&P 500 log monthly change, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar log monthly change. Panel B also includes log monthly change in commodity prices. Sample: March 2001-July 2023. Newey-West standard errors; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

net demand of commodities (models 1 and 3), although they no longer achieve statistical significance. In contrast, the IMA specification demonstrates considerable predictive improvements for the h=12 horizon.

It is important to note that the baseline model presented here, which incorporates commodity inflation, exhibits a lower Root Mean Square Error (RMSE) than that observed in Panel A. Consequently, our predictive gains are understated when compared to a simple autoregressive model. Nevertheless, given that our primary objective is to demonstrate that our indices offer

TABLE 2. Forecast performance (RMSE), Headline CPI inflation

	horizon	baseline	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: without commodities								
Autoregressive								
	h=12	1.229	0.770**	0.999	0.768**	0.804**	0.988	0.793**
	h=6	1.657	0.882**	1.012	0.882**	0.899*	1.002	0.937
	h=3	2.279	1.005	1.039	0.986	1.014	1.057	1.065
Controls, Autoregressive								
	h=12	1.220	0.831**	1.010	0.820**	0.864	1.018	0.878
	h=6	1.738	0.964	1.004	0.956	0.968	0.987	1.004
	h=3	2.551	1.048	1.006	1.036	1.069	1.033	1.114
IMA								
	h=12	1.889	0.806*	0.957	0.850*	0.826	0.886	0.729
	h=6	2.086	0.838*	0.966	0.879*	0.873	0.942	0.839
	h=3	2.648	0.910	0.982	0.948	0.966	0.981	0.936
Controls, IMA								
	h=12	1.460	0.851*	0.996	0.860**	0.879*	0.991	0.844
	h=6	1.814	0.905	0.989	0.922*	0.923	0.997	0.916
	h=3	2.448	0.955	0.982	0.972	0.976	0.986	0.965
Panel B: with commodities								
Autoregressive								
	h=12	1.172	0.798**	1.005	0.789**	0.831**	0.999	0.828**
	h=6	1.596	0.902**	1.017	0.896**	0.910*	1.000	0.951
	h=3	2.101	1.014	1.046	0.986	1.004	1.052	1.067
Controls, Autoregressive								
	h=12	1.195	0.861*	1.018	0.848*	0.901	1.026	0.918
	h=6	1.724	0.980	1.014	0.969	0.983	0.991	1.017
	h=3	2.343	1.078	1.019	1.059	1.080	1.040	1.137
IMA								
	h=12	1.877	0.809*	0.954	0.853*	0.831	0.880	0.731
	h=6	2.070	0.840*	0.962	0.883*	0.876	0.939	0.842
	h=3	2.548	0.940	0.992	0.976	0.999	0.991	0.969
Controls, IMA								
	h=12	1.448	0.856*	0.996	0.867**	0.892	0.991	0.852
	h=6	1.798	0.913	0.989	0.930	0.933	0.996	0.927
	h=3	2.277	0.994	1.009	0.989	0.998	1.016	1.011
Composite Indices								
Net Supply			X	X				
Net Demand			X		X			
Supply Increase/Decrease							X	X
Demand Increase/Decrease						X		X

Note: The table shows results from forecasts of headline CPI inflation across different monthly horizons, using the composite commodity indices. Columns (1)-(6) show the root mean squared error (RMSE) of each forecast relative to the baseline. Model 1 includes as predictors net supply and net demand; model 2 includes net supply; model 3 includes net demand; model 4 includes demand increase and demand decrease; model 5 includes supply increase and supply decrease; and model 6 includes supply increase, supply decrease, demand increase and demand decrease. The autoregressive specification is given by (7), and IMA specifications further include MA terms of order 2. Each specification includes some of our indexes, as indicated. Where noted, controls are: industrial production log monthly change, S&P 500 log monthly change, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar log monthly change. Panel B also includes log monthly change in commodity prices. Sample: March 2001-July 2023. Newey-West standard errors; $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

additional informational value irrespective of the inclusion of commodity price inflation, we concentrate our analysis on within-class comparisons.

Figure 6 plots inflation forecasts together with actual inflation for the period between December 2010 and August 2023. As before, the top panels display the behavior of forecasts derived from models that only contain autoregressive components (Panel A), or a full set of controls including log monthly changes in commodity prices (Panel B). The bottom panels further introduce the textual indicators of net supply and net demand to the aforementioned models. The inability of all models to timely forecast the inflation surge following the outbreak of the pandemic is obvious and expected. However, there is still some improvement in the forecasting performance of the latter period of the sample when one employs the textual indicators, over the benchmark case or the specification including controls and log monthly changes in commodity prices.

Table 2 shows results for the full sample, which includes the COVID period. As expected, the baseline performance is substantially worse than before, due to the large inflation shock. Perhaps unexpectedly, this worsening is especially pronounced for the IMA models, with RMSE sometimes twice as large relative to the pre-COVID sample. The autoregressive baseline instead has an increase in RMSE of around 25% for the h=12 horizon. Despite these shifts in baseline performance, the relative effectiveness of our models compared to the baseline remains consistent, even compared to models which include commodity prices. Thus, within each class of models examined, our indices yield substantial predictive gains, highlighting their relevance and utility across varying inflationary regimes.

For completeness, we report, in tables C1-C2 in the appendix, results for core CPI inflation. Core CPI presents a more challenging forecasting benchmark, as it includes far fewer commodity-driven components relative to headline CPI. Despite this, we observe notable improvements relative to the baseline, particularly in the IMA models. Interestingly, the most effective models are found in columns 5 and 6, offering a key insight: while headline CPI inflation is better predicted by demand indices, core CPI inflation is more accurately forecasted by supply indices. Model 5, which includes supply indices split into negative and positive movements, performs reasonably well across most specifications. It should be noted though, that few specifications give statistically significant improvements.

Overall, our commodity demand and supply indices appear to contain highly informative content for forecasting aggregate price indices. Demand-driven indices yield significant improvements in predicting headline inflation, particularly over longer horizons, when no additional controls are included. Even when controlling for commodity price inflation and macro and financial variables, these indices continue to provide notable forecasting gains, particularly for longer horizons. In addition, supply indices provide sizable prediction gains for core CPI inflation though they are not always statistically significant.

Tables 3 and 4 present the results for headline PCE inflation, while tables C3 and C4 in the appendix focus on core PCE inflation. Given the key differences between CPI and PCE measures, the results are not necessarily expected to align. For headline PCE, the baseline RMSE is generally lower than for CPI, though it is similar for the core measure in the pre-COVID sample. Despite these differences, the performance of our indices in improving forecasts relative to the baseline remains consistent. Notably, the forecast improvements are more pronounced for Core

PCE compared to Core CPI, with a number of models providing improved forecasts over shorter horizons of three to six months.[9]

TABLE 3. Forecast performance (RMSE), Headline PCE inflation, Pre-COVID

	horizon	baseline	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: without commodities								
Autoregressive								
	h=12	0.779	0.705*	0.979	0.713**	0.781**	0.885	0.717*
	h=6	1.009	0.802	1.008	0.810*	0.821	0.985	0.879
	h=3	1.279	0.982	1.049	0.965	0.995	1.095	1.080
Controls, Autoregressive								
	h=12	0.652	0.810**	1.027	0.789**	0.897*	1.038	0.922
	h=6	1.040	0.939	1.008	0.938	0.951	0.995	0.980
	h=3	1.391	0.990	1.007	0.983	1.003	1.022	1.054
IMA								
	h=12	0.778	0.664**	0.975	0.691**	0.736**	0.864	0.652**
	h=6	1.007	0.729*	0.995	0.757**	0.755**	0.962	0.790
	h=3	1.342	0.879	1.030	0.896	0.931	1.036	0.964
Controls, IMA								
	h=12	0.655	0.789**	1.022	0.761**	0.861**	0.991	0.842*
	h=6	0.894	0.884	0.998	0.900	0.909	0.994	0.941
	h=3	1.314	0.941	0.992	0.943	0.942	0.976	0.944
Panel B: with commodities								
Autoregressive								
	h=12	0.750	0.731*	0.990	0.732**	0.808**	0.906	0.749**
	h=6	0.976	0.822	1.021	0.822*	0.827*	0.990	0.889
	h=3	1.187	0.976	1.063	0.946	0.969	1.092	1.069
Controls, Autoregressive								
	h=12	0.620	0.858	1.040	0.836*	0.963	1.052	0.991
	h=6	1.002	0.969	1.020	0.968	0.986	1.001	1.012
	h=3	1.279	1.019	1.023	1.010	1.034	1.036	1.087
IMA								
	h=12	0.766	0.673**	0.968	0.698**	0.753**	0.856	0.664**
	h=6	0.992	0.734*	0.985	0.763**	0.761**	0.960	0.801
	h=3	1.195	0.964	1.056	0.953	1.010	1.082	1.069
Controls, IMA								
	h=12	0.631	0.827*	1.033	0.789**	0.911	1.004	0.889
	h=6	0.860	0.915	0.999	0.927	0.938	0.994	0.976
	h=3	1.171	1.003	1.027	0.988	0.990	1.016	1.026
Composite Indices								
Net Supply			X	X				
Net Demand			X		X			
Supply Increase/Decrease							X	X
Demand Increase/Decrease						X		X

Note: The table shows results from forecasts of headline CPI inflation across different monthly horizons, using the composite commodity indices. Columns (1)-(6) show the root mean squared error (RMSE) of each forecast relative to the baseline. Model 1 includes as predictors net supply and net demand; model 2 includes net supply; model 3 includes net demand; model 4 includes demand increase and demand decrease; model 5 includes supply increase and supply decrease; and model 6 includes supply increase, supply decrease, demand increase and demand decrease. The autoregressive specification is given by (7), and IMA specifications further include MA terms of order 2. Each specification includes some of our indexes, as indicated. Where noted, controls are: industrial production log monthly change, S&P 500 log monthly change, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar log monthly change. Panel B also includes log monthly change in commodity prices. Sample: March 2001-July 2023. Newey-West standard errors; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

4.3. **Forecasting the turning points of inflation.**

[9]In further extensions, we augment the baseline model with controls to also include oil prices, oil inventories, inflation expectations from SPF, and oil futures. We do not report these results for brevity, because not only do our indicators consistently beat these other baselines, but also because specifications including a combination of these variables peform worse than the simple autoregressive baseline.

TABLE 4. Forecast performance (RMSE), Headline PCE inflation

	horizon	baseline	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: without commodities								
Autoregressive								
	h=12	0.916	0.761**	0.990	0.761**	0.793**	0.956	0.763**
	h=6	1.198	0.871*	1.005	0.875**	0.890*	0.993	0.927
	h=3	1.556	0.987	1.021	0.982	1.014	1.043	1.059
Controls, Autoregressive								
	h=12	0.907	0.811**	1.006	0.800**	0.842**	1.015	0.856*
	h=6	1.242	0.926*	0.996	0.927**	0.942**	0.984	0.966
	h=3	1.644	1.023	0.994	1.022	1.057	1.019	1.098
IMA								
	h=12	1.468	0.828*	0.960	0.867*	0.835	0.875	0.734
	h=6	1.556	0.838*	0.965	0.880*	0.862	0.934	0.827
	h=3	1.881	0.904	0.979	0.951	0.962	0.970	0.922
Controls, IMA								
	h=12	1.104	0.858**	0.997	0.863**	0.878*	0.987	0.842*
	h=6	1.310	0.889*	0.984	0.911*	0.907*	0.992	0.898
	h=3	1.733	0.939	0.979	0.960	0.959	0.979	0.943
Panel B: with commodities								
Autoregressive								
	h=12	0.875	0.785**	0.997	0.780**	0.817**	0.968	0.793**
	h=6	1.155	0.887*	1.012	0.884**	0.897*	0.992	0.936
	h=3	1.436	0.987	1.030	0.974	0.997	1.039	1.054
Controls, Autoregressive								
	h=12	0.890	0.835**	1.012	0.825**	0.872	1.020	0.887
	h=6	1.219	0.942	1.005	0.940**	0.958	0.988	0.982
	h=3	1.509	1.041	1.006	1.036	1.061	1.024	1.107
IMA								
	h=12	1.461	0.832*	0.958	0.872*	0.843	0.869	0.737
	h=6	1.544	0.841*	0.962	0.886	0.868	0.931	0.831
	h=3	1.778	0.950	0.993	0.983	0.997	0.991	0.972
Controls, IMA								
	h=12	1.096	0.865*	0.998	0.869**	0.890*	0.990	0.848
	h=6	1.298	0.898	0.983	0.921*	0.917	0.990	0.906
	h=3	1.619	0.972	0.996	0.981	0.980	1.002	0.981
Composite Indices								
Net Supply			X	X				
Net Demand			X		X			
Supply Increase/Decrease							X	X
Demand Increase/Decrease						X		X

Note: The table shows results from forecasts of headline PCE inflation across different monthly horizons, using the composite commodity indices. Columns (1)-(6) show the root mean squared error (RMSE) of each forecast relative to the baseline. Model 1 includes as predictors net supply and net demand; model 2 includes net supply; model 3 includes net demand; model 4 includes demand increase and demand decrease; model 5 includes supply increase and supply decrease; and model 6 includes supply increase, supply decrease, demand increase and demand decrease. The autoregressive specification is given by (7), and IMA specifications further include MA terms of order 2. Each specification includes some of our indexes, as indicated. Where noted, controls are: industrial production log monthly change, S&P 500 log monthly returns, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar log monthly change. Panel B also includes log monthly change in commodity prices. Sample: March 2001-July 2023. Newey-West standard errors; ${}^{*}p < 0.1, {}^{**}p < 0.05, {}^{***}p < 0.01$.

Another way to assess the performance of our measures is to see how well they perform across different regimes and turning points. Good average performance may mask bad performance at time of falling or rising inflation, rendering the framework problematic when good forecasts are most important.

We follow Joseph et al. (2021) and split the sample in periods when inflation is increasing, falling or is stable. We define an episode as increasing when the 3-month moving average % change in inflation is positive for at least 5 consecutive months; falling when the same measure registers a negative change for at least 5 consecutive months; and stable when it is neither falling nor rising.

Results are shown in Appendix Tables D1 for CPI and D2 for PCE, for h=12 and h=6 horizons. Overall our framework provides clear improvements over the baseline for headline inflation for h=12, especially for episodes of falling and stable headline inflation. For episodes of increasing inflation, some models also provide substantial and consistent improvements, especially models 0, 2 and 4, with the rest providing improvements in some specifications, but not others. For h=6, similar patterns hold, though improvements for increasing episodes are strong only for models with commodities.[10]

4.4. **Forecasting CPI items.**

As a final forecasting exercise, we test whether we can also use our indicators to improve the forecasts of CPI items most related to commodity prices, namely food and energy. We do so using the respective food and energy commodity indices. The results are shown in Tables C5 and C6.

Starting with energy inflation, we first note that energy is extremely volatile, as shown by the baseline RMSE, which is an order of magnitude higher than headline CPI. As such, it is very difficult to forecast. Nevertheless, we do observe model improvements across most models, and in fact quite large improvement with the specification with demand increase and decrease in the model with IMA and controls (column 4). Including tradable commodity returns does not improve the forecasting performance of the model, but the gains from including the narrative based measures improve the forecasting performance by 20%. The improvement is exclusively driven by demand.

As for food, there are some modest improvements from using textual supply indicators across most models, though few are statistically significant. Again, further including tradable commodity returns provides minimal improvement.

5. Oil Price News Shocks and Oil Price Shocks

In order to assess the forecasting power of the textual indicators we don't need to make a statement about the exoneity of commodity-supply and demand signals that are sourced from the news. This is important because the endogenous nature of commodity prices, which are influenced by macroeconomic conditions, complicates the estimation of their causal effects. To address this challenge, the literature has traditionally employed structural vector autoregressions (SVAR) to identify distinct shocks affecting oil prices. These have been identified using (i) zero restrictions (Kilian, 2009), (ii) sign restrictions (Kilian and Murphy, 2012; Lippi and Nobili,

[10] Note that because the sample can be quite small for some cases, we do not perform Diebold-Mariano tests.

2012; Baumeister and Peersman, 2013; Baumeister and Hamilton, 2019), (iii) narrative information (Antolin-Diaz and Rubio-Ramirez, 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 extensive development of methodologies for modeling oil price movements, there is a notable scarcity of analyses on other tradable commodities, such as natural gas and wheat, which have gained significance during the recent period of turbulence.

The purpose of this section is to show that the Oil Net Supply and Net Demand Indices contain valuable information for the understanding and future trajectory of macroeconomic fundamentals, similar to structurally-estimated shocks. To do so, we repeat an exercise from Mouabbi, Passari, and Rousset Planat (2024), who take the "surprise" in the Oil Net Supply series, given by the residuals of an AR(1) regression, and compare the impulses responses of a number of relevant variables to this surprise, relative to two well-known frameworks. The first is the oil supply shock of Baumeister and Hamilton (2019), identified using sign restrictions with informative priors drawn from the literature. The second is the news shock about future oil supply of Känzig (2021), who uses a high-frequency identification scheme exploiting reactions of futures prices to OPEC announcements, and uses them as an external instrument in a standard oil VAR.[11] These two shock series are estimated using two different structural methods and represent the frontier for oil-price modeling. Establishing this benchmark is extremely important against the backdrop of a lack of proxies for the drivers of other commodities (besides oil), which is exactly the gap that this paper aims to fill.

We use the six variables used in the exercise of Känzig (2021): the real WTI spot price, global oil production, inventories (proxied by OECD inventories), global industrial production, US industrial production and US CPI. Following Känzig (2021), the shocks are normalized to a shock that raises the real oil price by 10% on impact. Throughout this set of exercises (as well as in the following section), we plot, as is standard, the coefficients of the Local Projections across horizons, together with 90% and 95% confidence intervals. However, as is well known, the coefficients in Local Projections are highly serially correlated, which can result in separately insignificant coefficients that are jointly significant. We employ the fix of Jordà (2023), and plot the inverted statistic of the test of joint significance at each step h of total horizon H, which is given by $\pm\sigma_h\sqrt{d(H,\alpha)/H}$, where $d(H,\alpha)$ is the critical value of the joint null for significance level α (with an asymptotic χ^2 distribution), and σ_h is the standard deviation of the estimated coefficient at horizon h. These significance bands are useful because while each coefficient may not be statistically significant, they can still be jointly significant, which is the economic effect of interest (i.e. whether a treatment had an effect on the outcome.

Figure 7 and Table 5 present compelling evidence that the textual indices correlate and offer comparable predictions to those of structural methods popular in the literature. In particular,

[11]The authors of these papers provide updated versions of their shocks on their respective websites. We use shocks up to March 2023 from both papers (and not the vintages provided in the replication packages).

Table 5 presents the correlations of the Net Supply and Net Demand Oil Indices of Mouabbi, Passari, and Rousset Planat (2024) with those of Baumeister and Hamilton (2019) and Känzig (2021). The results indicate that a surprise of the simplest Net Supply indicator for oil (computed as the residual of an autoregressive process of order one) has a correlation of 31% with the oil shock series of Baumeister and Hamilton (2019) and 35% with Känzig (2021). Their correlation is 37% for same sample. The surprise of the Net Demand Oil Index has a correlation of 41% with the sum of the three demand components of Baumeister and Hamilton (2019). All correlations are highly significant (over 99.9% confidence level).

The study of the impulse responses of the local projections (Figure 7) further reveals that a negative surprise of the Net Supply Index of Mouabbi, Passari, and Rousset Planat (2024) predicts a substantial and immediate increase in oil prices. Global oil production decreases over the subsequent 24 months. There is also a small but statistically significant short-term inventory depletion. In addition, a negative supply surprise leads to a marked and sustained decline in US and global industrial production, highlighting global vulnerabilities to higher oil prices. U.S. consumer prices rise significantly, on impact, and continue to increase for approximately one year.

TABLE 5. Correlations

	Supply			Demand	
	MPRP 2024	Kanzig 2021	BH 2019	MPRP 2024	BH 2019
MPRP 2024	1.0000			1.0000	
Kanzig 2021	0.3534	1.0000			
BH 2019	0.3138	0.3735	1.0000	0.4109	1.0000

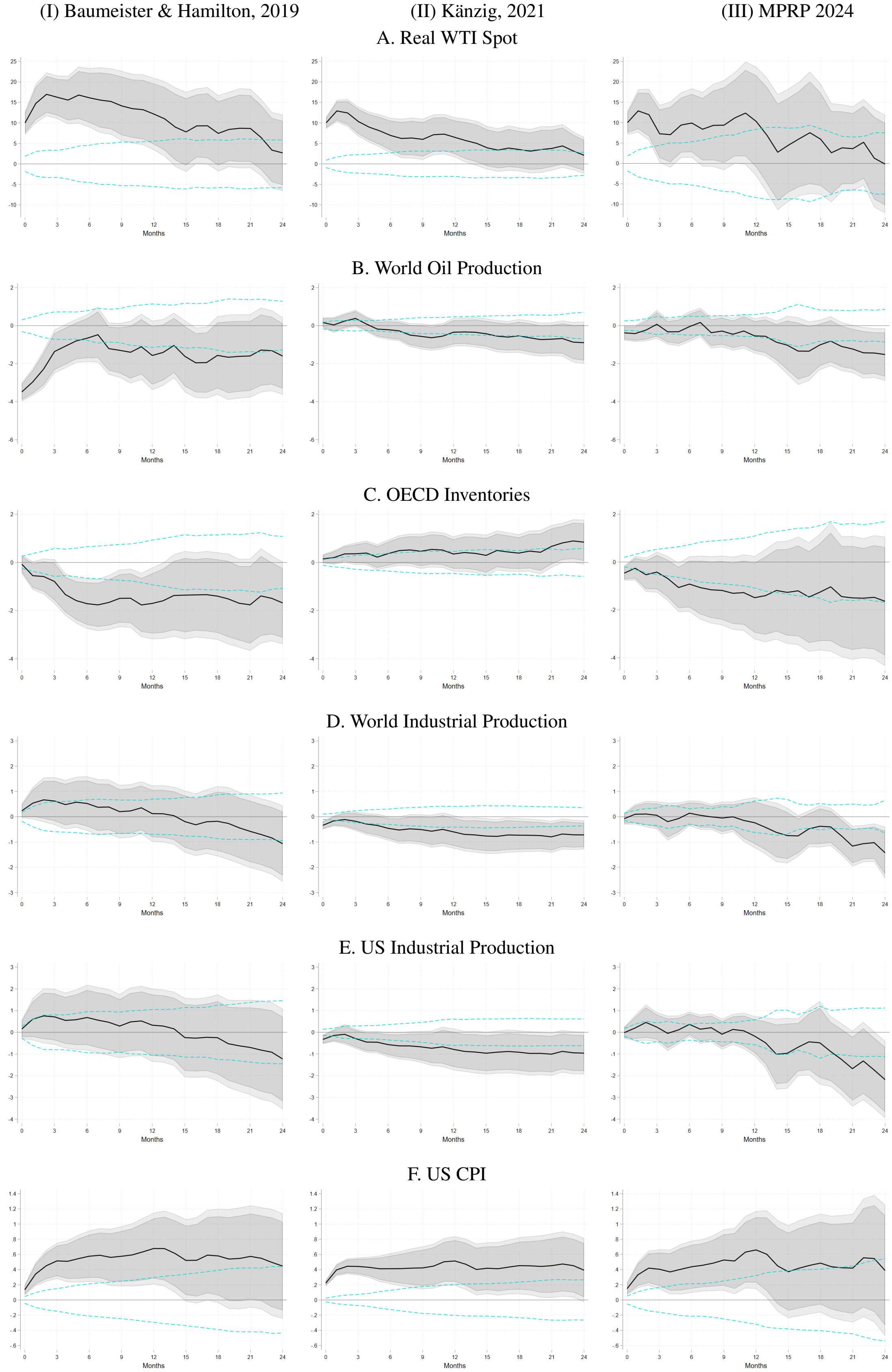
Note: The table shows correlations of the structural shocks of Baumeister and Hamilton (2019) and Känzig (2021) with a surprise series in the indices of Mouabbi, Passari, and Rousset Planat (2024), given by the residuals of a regression of the index on its own lag. We use the Net Oil Supply and Demand indices, respectively.

Interestingly, despite the fact that the textual methodology does not include any data on prices or quantities, the indices are still able to capture similar dynamics to methods that do incorporate this information. The results across the three methods are broadly consistent, both qualitatively and in terms of statistical significance.

Notably, all three exercises match quite closely the effects on the two price series. Our Net Supply surprise yields overall less precise and more erratic impulse responses in further horizons, but this is a well-known feature of local projections relative to Vector Autoregressions (VAR) used to identify the shocks in the other two papers.[12] Overall, the impulse responses of the Net Supply Oil Index compare well with other state-of-the-art measures of the literature that use structural methods.

[12]Intuitively, as detailed by Känzig (2021) and Nakamura and Steinsson (2018), countless shocks hit the economy in longer horizons. Without the additional structure imposed by Structural VARs, estimation is bound to be less precise, also because the sample for high-frequency series is much shorter than with standard macro series.

FIGURE 7. Local Projections Impulse Responses



Note: This figure from Mouabbi, Passari, and Rousset Planat (2024) shows the impulse responses to an oil supply shock (mean and 90% and 95% CI) for the Real Spot Price of Oil, World Oil Production, OECD Oil Inventories, World Industrial Production, US Industrial Production, and US CPI. The teal dashed lines show significance bands for the test that all coefficients of interest are jointly zero, as in Jordà (2023). The shocks are the oil supply shocks of Baumeister and Hamilton (2019) and Känzig (2021) and a "surprise" series, calculated from our Net Supply Crude Oil Index as the residual of an AR(1). The shock is normalized to a shock producing an impact increase of 10% in the real price of oil.

6. The Differential Impact of Commodity Supply and Demand Measures on Inflation

In this section, we study the responses of prices to commodity-market events picked by the textual-based measures. Although the commodity news indicators are not shocks–but rather proxies of shocks–and one cannot readily separate the commodity supply channel from demand or from other inflation drivers, the leveling exercise of the previous section gives us some comfort that the constructed "commodity-news shocks" series behaves in a highly similar way to other, well-established commodity shocks series.

Armed with this observation and the hypothesis that our news-derived proxies are close trackers of real shock behavior, we employ the Local Projections framework of Jordà (2005), which involves regressing successive forward values of the dependent variable on its lags, our indices, and relevant controls. The controls are the log change of industrial production, S&P 500 log returns, the federal funds rates, the 10-year minus 2-year US treasury yield, VIX, and trade-weighted US dollar log returns. We are mainly interested in disentangling the different effects of net supply and demand developments, and we hence include the net supply and demand indices for each category of indices together. We include up to an 18-month horizon, and use Newey-West standard errors.

The impulse responses have been normalized to have the same scale. The indices we use are scale free, and hence the unit standard deviation normalisation commonly used cannot say how large the shocks are, which is not very useful for studying passthrough. The normalisation is akin to the unit effect normalisation of Stock and Watson (2018). We normalize by shocks that raise the annual GSCI growth by its median absolute value (14.3%). Ideally we would normalize by the effect on inflation, but on occasion the impact effect is negative. We could have chosen a different horizon, but in this case we would assume the same effect for both supply and demand. The dependent variable is the natural logarithm of the respective price level (headline CPI or one of its components), and so the coefficients give 100*log points change from the baseline.

A serious issue one needs to address is the non-stationarity induced by the COVID-19 shock, which is particularly severe in our framework. Lenza and Primiceri (2022) argue that, for the calculation of impulse responses, dropping the pandemic is typically sufficient. However, we also want to examine how well our indices perform during this volatile episode, especially because the pandemic coincided with a generational spike in inflation. As such, we take a simple version of the Lenza and Primiceri (2022), whereby we replace our indices with their 2019 mean for the January-April 2020 period, and include a COVID-19 dummy in the regressions, as suggested by Ng (2021). We provide further details on these methods in Section 4.

The Impact of the COVID-19 Pandemic on Inflation. We have already underlined the importance of pinning down the origins of commodity price movements for the modeling of inflation dynamics. The COVID-19 pandemic has posed additional challenges for the understanding of the commodity price-inflation link by creating large and persistent supply shocks with grave and long-lasting inflationary consequences. The inflation discussion this time moved away from crude oil considerations and rather focused on a broader commodity basket that was affected by global supply-chain disruptions.

Figure 8 shows the impact of including the data of the first year of the COVID-19 pandemic in our sample. Panel A plots the Local Projection of CPI to a standardized unit increase in our composite net supply index between 2001 and 2023. This sample includes the Ukraine war, but results are very similar even before the large increase in global energy prices starting in early 2022. The panel to the right (panel B), plots the same response, but calculated only for the pre-COVID sample (until December 2019). The effect of supply developments is much smaller in the pre-COVID sample, and is hardly statistically significant at the 18-month horizon.

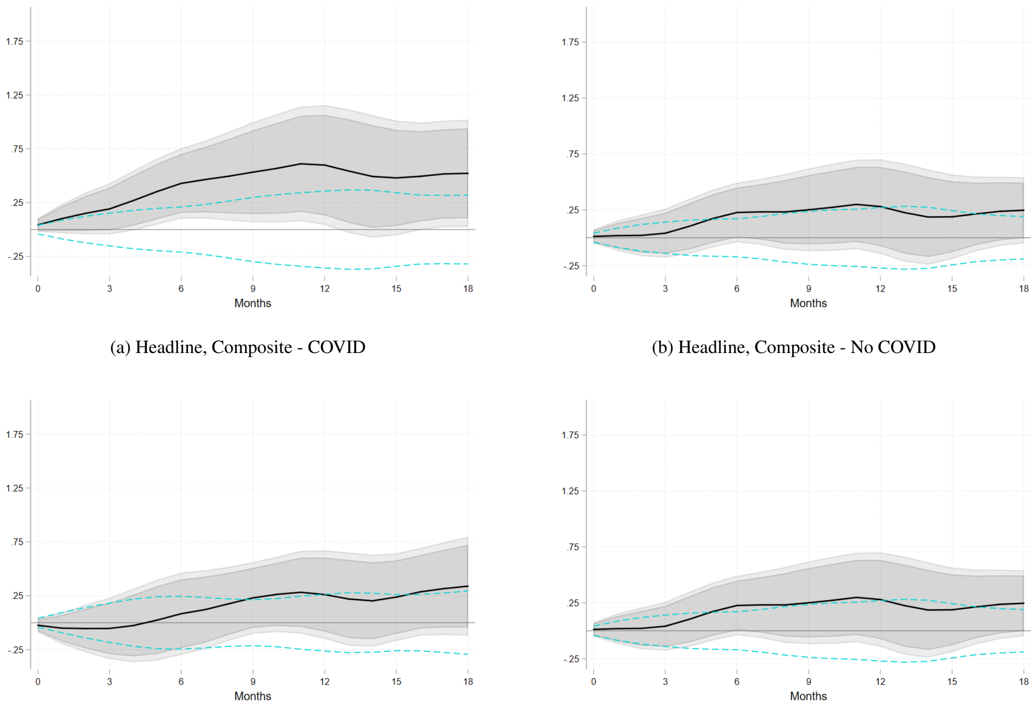
Instead, the result reflects the various supply-related problems created due to the COVID pandemic, such as lockdowns, supply chain disruptions, the rising cost of global shipping, and any other hindrance to the supply of commodities. In particular, 2021 was a year marked by persistent low inventories for a number of key metals, with copper, aluminum, nickel and zinc markets registering a deficit due to both inventory and distribution problems. This is consistent with the inspection of the same set of impulse responses coming only from the oil market (panels C and D). Indeed, the responses of CPI to a standardized unit increase in our net supply of oil index are similar in terms of statistical significance with or without the COVID sample.

Commodity Indices and Inflation. We now turn to the effects of commodity developments (both supply and demand) on aggregate price growth. While some of the US literature tends to focus on PCE inflation, because this is the measure targeted by the Fed, in this section, we focus only on CPI inflation. We do so because most other countries rely on CPI inflation, which is computed from consumer surveys, while PCE is measured from business surveys. Since our framework is designed to be used in any jurisdiction, CPI is the more natural choice. However, we report results for both CPI and PCE in the next section on forecasting.

The first row (panels A and B) of Figure 9 shows the response of annual CPI inflation to supply and demand developments, using the composite indices. The response to demand is almost twice as high, and equally persistent. We argue that this is due to the fact that our composite demand measure captures essentially an aggregate demand component, and so signals a broad-based change in demand. This is evidenced by the fact that the demand measure is highly correlated with the business cycle driver.

The second row (panels C and D) shows the response of core CPI inflation to the same disturbance. As expected, the response is much smaller, because most commodities have been removed from the price index. In this case, the response to supply developments is somewhat larger, and significant for a few months (according to both the standard confidence intervals and

FIGURE 8. CPI Inflation Response to Supply Developments - COVID



(a) Headline, Composite - COVID

(b) Headline, Composite - No COVID

(c) Headline, Oil - COVID

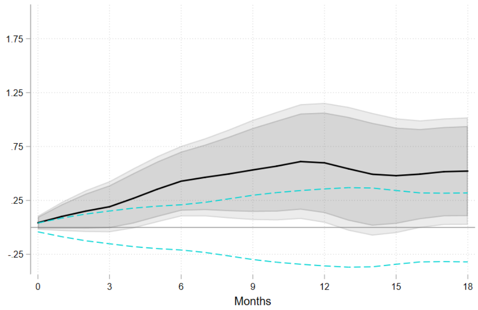
(d) Headline, Oil - No COVID

Note: Log CPI response following a one unit increase in contemporaneous composite net supply up to an 18-month horizon (90% and 95% CI). The response is normalized to a shock that raises the GSCI by 10% in 12 months. The teal dashed lines show significance bands for the test that all coefficients of interest are jointly zero, as in Jordà (2023). Controls: industrial production log change, S&P 500 log returns, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar log returns. Each specification also includes a constant and 13 lags of log CPI. COVID corrections using a COVID dummy and rescaling of the indices for January-April 2020. Sample: March 2001-July 2023.

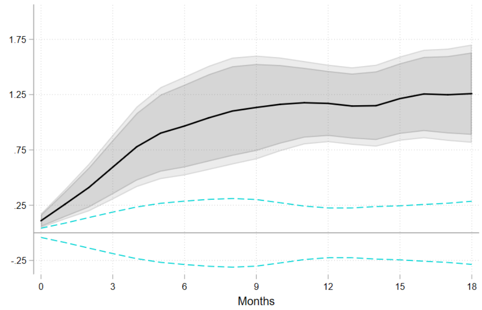
the joint test). In addition to direct effects from other commodities which are still present in the core price index and are captured in our composite indices (e.g. metals), the response also likely captures second-round effects.

Panels E and H further show the responses of goods and services inflation. Services inflation is structurally higher than goods inflation, as it benefits less by productivity growth, but is much less volatile. The response of both is significant and persistent for demand developments, but naturally more pronounced for goods. Goods inflation also responds to supply developments, about half as strongly as to demand developments, while services inflation has a very weak response to supply developments. It should be noted that energy is classified under services in CPI, and so services inflation differs from core inflation. At the same time, a larger chunk of goods CPI is composed of commodities than services CPI, which can also account for the different responses.

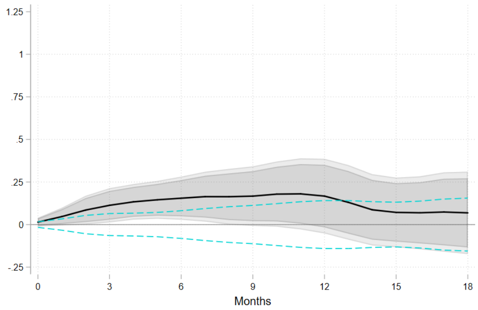
FIGURE 9. CPI Inflation Response to Composite Developments



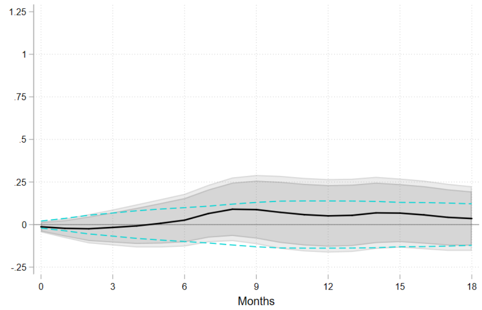
(a) Headline - Supply



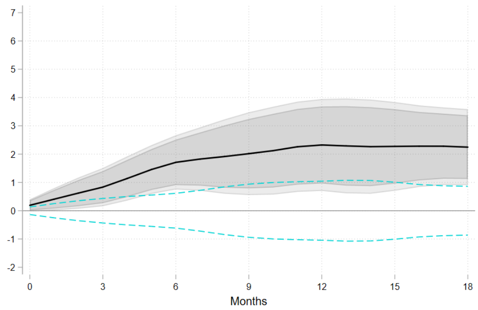
(b) Headline - Demand



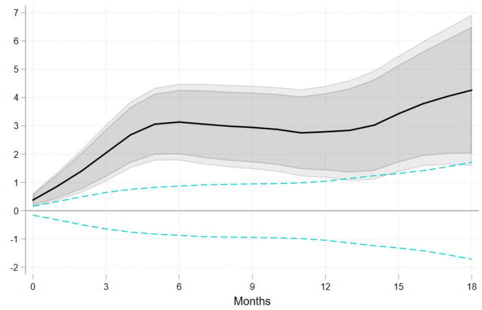
(c) Core - Supply



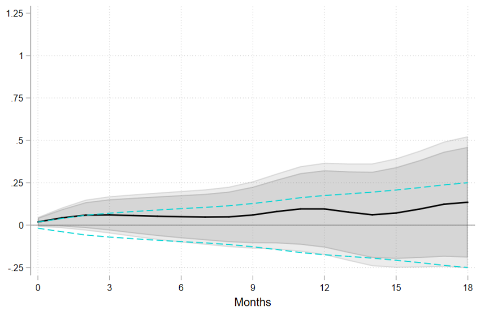
(d) Core - Demand



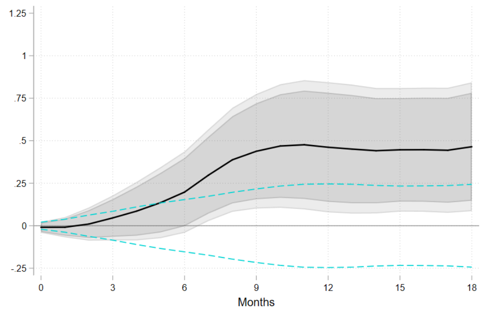
(e) Goods - Supply



(f) Goods - Demand



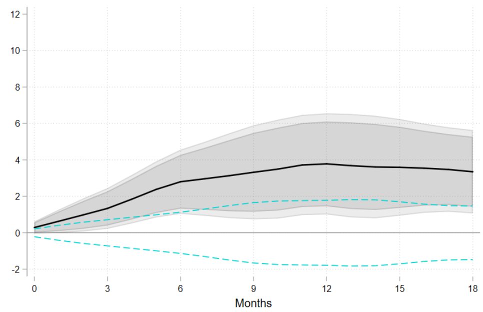
(g) Services - Supply



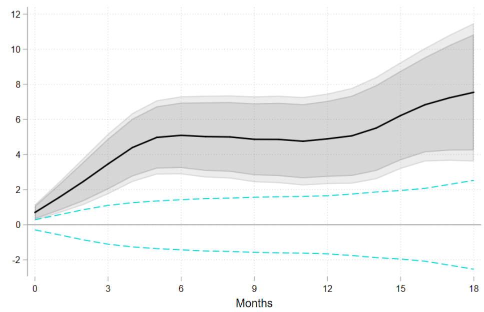
(h) Services - Demand

Note: Log CPI response following a one unit increase in contemporaneous composite net supply and net demand, up to an 18-month horizon (90% and 95% CI). The response is normalized to a shock that raises the GSCI by 10% in 12 months. The teal dashed lines show significance bands for the test that all coefficients of interest are jointly zero, as in Jordà (2023). Controls: industrial production log change, S&P 500 log returns, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar log returns. Each specification also includes a constant and 13 lags of log CPI. COVID corrections using a COVID dummy and rescaling of the indices for January-April 2020. Sample: March 2001-July 2023.

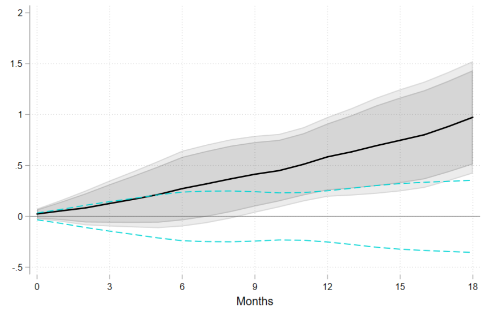
FIGURE 10. CPI Goods Inflation Response to Commodity Developments



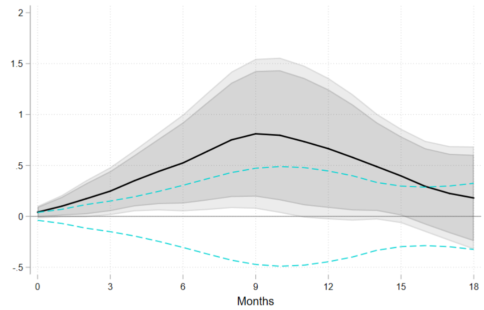
(a) Goods x food - Supply



(b) Goods x food - Demand



(c) Food - Supply



(d) Food - Demand

Note: Log CPI response following a one unit increase in contemporaneous composite net supply and net demand, up to an 18-month horizon (90% and 95% CI). The response is normalized to a shock that raises the GSCI by 10% in 12 months. The teal dashed lines show significance bands for the test that all coefficients of interest are jointly zero, as in Jordà (2023). Controls: industrial production log change, S&P 500 log returns, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar log returns. Each specification also includes a constant and 13 lags of log CPI. COVID corrections using a COVID dummy and rescaling of the indices for January-April 2020. Sample: March 2001-July 2023.

We then turn to considering the response of goods CPI, broken down into food and goods less food (GLF). The latter accounts for around two thirds of the total goods CPI basket, and is composed of roughly equal parts of durables and non-durables less food. GLF inflation is more volatile than food inflation, and so the magnitude of the response to demand developments is substantially larger and highly persistent (Figure 10). The response of food inflation is more gradual, peaking at 9 months, and eventually disappears. This disparate behavior can account for the response of headline CPI inflation to demand developments, which rises fast, plateaus at 8 months, but does not revert even at 18 months (Figure 9b). For both categories, there are positive effects from supply as well; for food CPI, in particular, the response to supply developments is slower than for demand but is persistent, and the overall effect deeper.

Overall our indices provide intuitively reasonable results, showing that our news-reading method manages to extract information not otherwise available in standard macro controls. However, it is possible that we are just picking up information already available to economic agents, which is, however, not embodied yet in time t controls. One way to test this proposition is to see whether our indices can also "predict" agents' expectations; if they do, then we are simply picking up knowledge incorporated into people's forecasts. As such, we repeat the local projection exercise, but instead of regressing future prices on the textual indices, we instead regress various measures of inflation expectations on the textual indices.

We use three different measures of expectations. The first is a market-based measure from inflation swaps, as computed by Haubrich, Pennacchi, and Ritchken (2012), and published by the Cleveland Fed (CLEV). It incorporates expectations for CPI implicit in the bond market. The second comes from the Survey of Professional Forecasters (SPF), a long survey conducted by the Philadelphia Fed, and reflects the views of experts. SPF data is given at a quarterly basis, and we use interpolated monthly measures of annual growth rates, for both CPI and PCE inflation. The third measure comes from the University of Michigan Survey of Consumers (MICH), and is a household measure of inflation expectations. As such, it is not tied to any specific price basket, and is considered to be a less sophisticated measure of inflation expectations.

The results of this exercise are shown in Table 6. Because expectations data are mostly available on an annual basis, we do not conduct a full impulse response analysis, and instead only consider expected inflation over the next 12 months. As such, the baseline comparison is relative to impulse responses of annual price growth rates, not levels, as in the previous exercise. These are shown in Column 1 of Panel A, for actual CPI inflation 12 months ahead, in log growth form. For this exercise, we do not normalize the coefficients, as we only compare the same variables of interest across models. As before, the response to demand is significant 12 months ahead; for supply, the coefficient has a p-value for 0.133, and, as we saw before, a test of joint-significance will reject the null for $h = 12$. Column 2 shows results for the SPF measure. Both coefficients are at least an order of magnitude smaller, and not significant. Column 3 shows results for the SPF measure 12 months ahead, i.e., t+24 inflation expectations of professional forecasters formed at time t+12. Interestingly, the response is much larger in this case, suggesting a delayed response to the information picked up by our indices. Columns 4 and 5 repeat these exercises for CLEV, and the results are very similar; essentially no effect for t+12 expectations at t, and a much larger effect for t+24 expectations at time t+12, though still much smaller than the baseline effect on CPI growth.

Panel B repeats this exercise for PCE inflation, which is only available in SPF, and also provides results for MICH, which is not specific to any particular price basket. The results are very much the same. For completeness, Panels C and D repeat the previous two exercises removing the high inflation sample which began in the COVID era, and where expectations were highly anchored, hence vastly underpredicting actual inflation. However, the results are very similar with the full sample. Overall, the message from Table 6 is that our indices contain information about future inflation not included in measures of inflation expectations derived from financial prices or inflation expectations of professional forecasters and consumers.

TABLE 6. News Indices and Inflation Expectations

	(1)	(2)	(3)	(4)	(5)
Panel A - CPI					
	Baseline	SPF	F12 SPF	Clev	F12 Clev
NetDemand	0.885***	-0.0334	0.150**	0.0493	0.147
	(4.40)	(-0.68)	(3.18)	(0.65)	(1.96)
NetSupply	0.378	0.0115	0.0340	0.00310	0.0644
	(1.51)	(0.33)	(0.85)	(0.06)	(0.66)
N	257	266	259	266	259
Panel B - PCE and Consumers					
	Baseline	SPF	F12 SPF	Michigan	F12 MICH
NetDemand	0.314***	-0.0539	0.124**	-0.0598	0.0711
	(4.23)	(-0.94)	(3.29)	(-0.50)	(1.03)
NetSupply	0.162*	0.00796	0.0361	-0.00314	0.0563
	(2.04)	(0.19)	(0.96)	(-0.03)	(0.86)
N	257	197	202	266	257
Panel C - CPI, Until 2019					
	Baseline	SPF	F12 SPF	Clev	F12 Clev
NetDemand	0.894***	-0.0339	0.128**	0.0215	0.162
	(3.80)	(-0.65)	(2.97)	(0.30)	(1.74)
NetSupply	0.340	-0.0261	0.0112	-0.0593	0.0450
	(1.39)	(-0.82)	(0.31)	(-1.20)	(0.46)
N	224	224	224	224	224
Panel D - PCE and Consumers, Until 2019					
NetDemand	0.254**	-0.102*	0.118**	-0.0254	0.0571
	(3.19)	(-2.04)	(3.11)	(-0.16)	(0.65)
NetSupply	0.112	-0.0191	0.0123	-0.0865	0.0354
	(1.62)	(-0.46)	(0.43)	(-0.70)	(0.57)
N	224	155	167	224	224

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The table reports coefficients from a one standard-deviation increase in contemporaneous composite supply and demand developments. The dependent variable in the baseline column is the annual log growth rate of CPI or PCE, 12 months ahead, as indicated. In columns 2 and 4, the dependent variable is expected inflation at t+12, as of time t, according to the indicated measure. In columns 3 and 5, the dependent variable is expected inflation at t+24, as of t+12. SPF=Survey of Professional Forecasters; Clev=market-implied expectations from Haubrich, Pennacchi, and Ritchken (2012); MICH=Michigan consumer survey. Controls: industrial production log change, S&P 500 log change, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar log change. Each specification also includes a constant and 13 lags of log CPI. COVID corrections using a COVID dummy and rescaling of the indices for January-April 2020. Sample: March 2001-July 2023.

7. DRIVERS OF COMMODITY PRICE FLUCTUATIONS

The applied methodology allows us to dig deeper in the assessment of the commodity supply and demand implications for inflation. We employ two of the thematic drivers of Mouabbi, Passari, and Rousset Planat (2024), the Business Cycle and the Natural Disaster indices. The drivers have been named after the important determinants that have affected commodity markets since the beginning of the 21st century (the driver selection has been driven by information sampled from the IMF commodity reports published between 2000 and 2021). The original indices have been purposely built according to a semi-supervised approach that uses dictionaries sampled from authoritative texts, similar to Engle, Giglio, Kelly, Lee, and Stroebel (2020).

Building these indices requires more detailed information to be extracted from the business news articles. As such, issues that relate to the sparsity of the text-based indicators might occur. Given that the volume of the sentences that combine a commodity instance with a supply or demand development and an underlying driver is low, we employ the driver indicators at the monthly frequency as single unconditional measures sampled independently from supply and demand dynamics.

We consider how these drivers interact with our main indices. To do so, and keeping in mind the sparsity concerns mentioned earlier, we transform them to define different regimes. Specifically, we convert the commodity driver indicators of Mouabbi, Passari, and Rousset Planat (2024) to dummy variables defined by the median value of the original series. We thus define four distinct regimes; a high-recession regime, a low-recession regime, a regime characterized by the presence of severe natural disasters and a regime characterized by the absence of severe natural disasters. We then interact these regimes with the supply and demand indicators.

We then conduct in-sample estimation of year-on-year inflation growth on the disaggregated supply and demand indicators, the driver dummy, and the interaction of each disaggregated supply and demand component with the regime-dummy (one-at-a-time) across horizons. Our analysis spans the three-month, six-month, one-year and 18-month horizons and reveals heterogeneous patterns.

Table 7 shows that an increase in demand is inflationary, especially in the short run, and a decrease in demand is deflationary. However, during a recession their effect on inflation is generally more muted and transitory; it is more pronounced and persistent in normal times. In contrast, the inflationary effect of demand increases and the deflationary effect of demand decreases are both exacerbated under the presence of severe natural disasters.

Increases in supply are generally deflationary, regardless of the regime, and these effects do not change much across regimes and occasionally get amplified. On the other hand, the effect of supply decreases is substantially affected by the business cycle; it is highly inflationary only in a recessionary environment or in the presence of natural disasters in the short-term; the overall effect appears muted when the different regimes are not taken into account.

It is important to note that the amplification effect of natural disasters in supply is on top of the impact of the COVID-19 pandemic, as the latter is controlled for across specifications. The COVID-19 dummy is significant across horizons and the size of its coefficient grows monotonically through time.

TABLE 7. Commodity Developments and Drivers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Business Cycle				Natural Disaster			
	h=3	h=6	h=12	h=18	h=3	h=6	h=12	h=18
Driver	0.210 (0.70)	0.555 (1.44)	0.531 (1.30)	-0.478 (-0.86)	-0.230 (-0.89)	-0.057 (-0.20)	0.602 (1.36)	0.583 (1.60)
DI	0.536*** (3.43)	0.641*** (3.07)	0.427 (1.58)	0.002 (0.01)	0.700*** (4.27)	0.571*** (3.22)	-0.110 (-0.36)	0.001 (0.01)
DD	-0.218 (-1.18)	-0.828*** (-2.95)	-1.522*** (-3.64)	-0.814 (-1.52)	-0.328*** (-2.63)	-0.497*** (-3.06)	-0.610** (-2.22)	-0.876*** (-3.32)
SI	0.063 (0.72)	-0.054 (-0.46)	-0.307* (-1.71)	-0.616*** (-2.73)	-0.077 (-0.89)	-0.240** (-2.40)	-0.361*** (-2.71)	-0.196 (-1.44)
SD	-0.377*** (-2.73)	-0.346* (-1.85)	-0.221 (-0.90)	0.142 (0.50)	-0.076 (-0.64)	-0.005 (-0.03)	0.067 (0.27)	-0.107 (-0.71)
DI × Driver	-0.440* (-1.76)	-0.239 (-0.77)	0.051 (0.15)	0.410 (0.88)	-0.481 (-1.48)	0.104 (0.26)	0.888** (2.16)	0.009 (0.03)
DD × Driver	-0.501* (-1.79)	-0.068 (-0.20)	1.276** (2.49)	1.053* (1.79)	-0.623* (-1.95)	-0.888** (-2.60)	-0.352 (-1.01)	1.173*** (3.33)
SI × Driver	-0.294* (-1.71)	-0.129 (-0.63)	-0.233 (-0.62)	0.402 (0.90)	-0.002 (-0.01)	0.525 (1.62)	-0.046 (-0.15)	-1.058*** (-3.77)
SD × Driver	1.199*** (4.00)	1.222*** (3.75)	0.883** (2.29)	-0.281 (-0.66)	0.779*** (2.64)	0.598* (1.80)	-0.019 (-0.05)	-0.226 (-0.72)
COVID	0.756* (1.72)	1.611*** (2.72)	3.387*** (4.92)	4.358*** (13.83)	0.973* (1.92)	2.001*** (3.18)	3.522*** (5.08)	3.899*** (19.00)
N	266	263	257	251	266	263	257	251

Note: The table shows results from regressing year-on-year inflation across different monthly horizons, on the drivers and their interaction with the indices. The Drivers are dummies equal to one for above-median values of the respective driver. The indices are denoted as: DI=Demand Increase; DD=Demand Decrease; SI=Supply Increase; SD=Supply Decrease. Controls are: industrial production log monthly change, S&P 500 log monthly returns, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar monthly log returns. Sample: March 2001-July 2023. Newey-West standard errors; $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

The results of the analysis hold true also when one focuses on the sub sample that excludes the COVID-19 period. Table 8 conveys a very similar message in terms of significance, sign and magnitude of the reported coefficients.

8. DECOMPOSING THE 2021-2023 INFLATION SHOCK

In a final exercise, we use our indices to account for the drivers of the 2021-2023 inflation shock. In particular, we use the framework of Blanchard and Bernanke (2023) to decompose the sources of inflationary pressures into their most salient possible sources: energy, food, labor market tightness, and supply shortages. Energy and food prices picked up a steep upward trend after the first few months of the COVID shock, likely due to a combination of rising global demand and continued supply constraints, and rose further following the Russian invasion of Ukraine. At the same time, the labor market became increasingly tight, with the vacancy rate rising to unprecedented levels, on the back of a large fiscal expansion and accommodating monetary policy. In turn, supply shortages are crucial to account for the various shocks to the global distribution system, which affect various types of commodities and processed goods.

TABLE 8. Commodity Developments and Drivers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Business Cycle				Natural Disaster			
	h=3	h=6	h=12	h=18	h=3	h=6	h=12	h=18
Driver	-0.459**	-0.258	0.089	0.141	-0.204	0.205	1.016**	0.598*
	(-1.98)	(-0.85)	(0.22)	(0.24)	(-0.73)	(0.92)	(2.42)	(1.78)
DI	0.431***	0.604***	0.404	-0.076	0.620***	0.571***	-0.039	0.041
	(3.18)	(3.07)	(1.57)	(-0.21)	(3.59)	(3.62)	(-0.14)	(0.24)
DD	-0.089	-0.747***	-1.495***	-0.952*	-0.434***	-0.713***	-0.743***	-0.859**
	(-0.64)	(-3.44)	(-3.90)	(-1.94)	(-3.50)	(-4.11)	(-2.66)	(-2.42)
SI	0.104	-0.028	-0.302	-0.629***	-0.003	-0.161	-0.360***	-0.216
	(1.28)	(-0.24)	(-1.59)	(-3.11)	(-0.04)	(-1.65)	(-2.81)	(-1.42)
SD	-0.362***	-0.273*	-0.173	0.183	-0.047	0.047	0.118	-0.143
	(-2.89)	(-1.66)	(-0.71)	(0.68)	(-0.42)	(0.35)	(0.46)	(-0.97)
DI $\times$ Driver	0.057	0.096	-0.018	0.298	-0.244	-0.021	0.261	-0.162
	(0.27)	(0.36)	(-0.05)	(0.61)	(-0.95)	(-0.07)	(0.71)	(-0.41)
DD $\times$ Driver	-0.566**	0.141	1.520**	0.921*	-0.597**	-0.568	-0.286	1.145
	(-2.31)	(0.50)	(2.46)	(1.82)	(-2.05)	(-1.55)	(-0.90)	(1.51)
SI $\times$ Driver	-0.159	0.033	0.030	0.545	0.047	0.475	0.254	-0.888**
	(-0.91)	(0.14)	(0.07)	(1.23)	(0.22)	(1.57)	(0.91)	(-2.38)
SD $\times$ Driver	0.871***	0.815***	0.734*	-0.382	0.543**	0.103	-0.534*	-0.203
	(2.92)	(2.92)	(1.91)	(-0.85)	(2.03)	(0.51)	(-1.73)	(-0.74)
N	266	263	257	251	266	263	257	251

Note: The table shows results from regressing year-on-year inflation across different monthly horizons, on the drivers and their interaction with the indices. The Drivers are dummies equal to one for above-median values of the respective driver. The indices are denoted as: DI=Demand Increase; DD=Demand Decrease; SI=Supply Increase; SD=Supply Decrease. Controls are: industrial production log monthly change, S&P 500 log monthly returns, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar monthly log returns. Sample: March 2001-December 2019. Newey-West standard errors; $^{*}p < 0.1, ^{**} p < 0.05, ^{***} p < 0.01$.

The added value of our indices is in providing a structured measure of shortages. Blanchard and Bernanke (2023) use measures of shortages from Google Trends, which can be useful in measuring specific types of shortages crucial for the period under study, such as cars and chips. On the other hand, because Google Trends are essentially a measure of salience, they reflect perceived, rather than actual shortages. Moreover, such observational measures confer a market equilibrium view, and cannot disentangle supply from demand. Our measures instead cannot exactly pinpoint specific goods and are restricted to raw materials, but can provide a distinct measure of supply constraint (in particular, supply decrease).

We provide a brief description of the model and the econometric exercise, maintaining the original notation of Blanchard and Bernanke (2023). The model boils down to four equations. The wage equation is given as follows:

$$\Delta w_t = (p_t^e - p_{t-1}) + \alpha(p_{t-1} - p_{t-1}^e) + \beta(x_t - \alpha x_{t-1}) + z_t^w, \tag{8}$$

where t is the time subscript, w is the log nominal wage, p^e is the expected log price level, p the actual log price level, x is a measure of labor market tightness, and z^w a contemporaneous shock. The parameter α ($\in [0, 1]$) captures the desired "catch-up" of workers to previous losses to their purchasing power. With α=0, previous price surprises and previous labor market conditions do not matter in wage demands. Higher values of α imply that nominal wage growth will depend on the level and the change in tightness and price surprises, and so lead to higher wage pressures following a series of price shocks.

The price equation is given by:

$$\Delta p_t = \Delta w_t + \Delta z_t^p, \tag{9}$$

where z^p reflects various price shocks. As prices depend on unit labor costs, not simply wages, the empirical implementation also includes labor productivity.

Finally, the model also includes short-term and long-term measures of inflation expectations, given by

$$p_t^e - p_{t-1} = \delta \pi_t^* + (1-\delta)\Delta p_{t-1}, \tag{10}$$

and

$$\pi_t^* = \gamma \pi_{t-1}^* + (1-\gamma)\Delta p_{t-1}, \tag{11}$$

respectively, where * are long-run expectations. Short-run expectations are a weighted average of long-run expectations and short-run price changes, where the degree of anchoring is given by the δ and γ parameters.

The four equations determine the four endogenous variables, p_t, w_t, p_t^e, and π_t^*. We follow exactly the empirical formulation of Blanchard and Bernanke (2023), using their code and data. The sample is from 2001Q1-2023Q1.

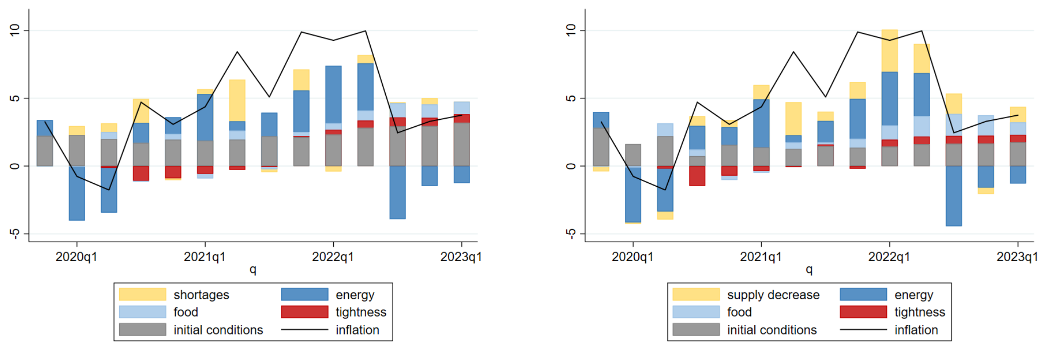
The wage and expectations equations are estimated until 2019Q4, with the exception of the price equation. Blanchard and Bernanke (2023) do this to preserve meaningful variation in their shortage measure. We go one step further and allow for a structural break in the shortage coefficients in the price equation. In particular, we add a full interaction of the shortage measures with a COVID dummy, equal to 1 for the 2020Q1-2023Q1 period. The muted inflation environment of the preceding two decades meant that aggregate prices responded little to shortages, and assuming constant coefficients vastly underestimates the true forces during the present episode. Blanchard and Bernanke (2023) are not affected by this concern because their indicator, which measures perceived shortages, is essentially constant near zero for the pre-pandemic period. The other exception of course lies in the use of different shortage indicators. We use our supply decrease measure, which directly captures the essence of shortages.

Each estimated equation includes four lags of each endogenous and exogenous variable. The implicit restriction used to identify the parameters of interest is that wage growth is affected by all other variables with one lag. Price inflation is affected contemporaneously by wage inflation, not expectations, and both affect expectations contemporaneously. As Blanchard and

Bernanke (2023) note, this setup is akin to a structural vector autoregression framework with exogenous variables: tightness (vacancies to unemployment), labor productivity (eight-quarter moving average of value added over employment), food and energy inflation (quarterly log growth of respective CPI index), and the supply decrease index. The price measure is the log CPI index, the wage measure is the nominal employment cost index, and the short- and long-run inflation expectations are the 1- and 10-year expectation measures of the Cleveland Fed.

We use the estimated coefficients to estimate the historical decomposition of each of the exogenous variables for the 2020Q1-2023Q1 period, taking as a given previous values. The results of this exercise are shown in Figure 11 below. The left panel replicates the original Blanchard and Bernanke (2023) exercise, with the Google Trends shortage indicator, in the 2001Q2-2023Q1 sample, while the original sample starts in 1990, in order to compare our results on an equal footing. The right panel shows the decomposition using our supply decrease measure. Results are by and large quite similar, with our measure showing a somewhat more persistent contribution of supply following a large initial shock in 2021Q2, at the expense of a slightly smaller contribution from energy, but predominantly a lower contribution of initial conditions and productivity. We also find that continued shortages did marginally contribute to abating the fall in inflation in 2022.

FIGURE 11. Decomposition of pandemic inflation



(a) Google shortage measure (b) Supply decrease index

Note: Decomposition of quarterly annualized CPI inflation using the framework of Blanchard and Bernanke (2023). The continuous black lines show actual inflation, and the stacked bars the contribution of each external variable, without including residuals. Initial conditions show the contribution of pre-pandemic data and the productivity variable.

The main message is, however, the same as Blanchard and Bernanke (2023): the primary drivers of inflation during that period were to be found in energy and food prices, and shortages. Our contribution is to confirm their results using a supply based measure of shortages, stripped from demand factors. It should be noted that our supply decrease measure is aggregate, and derived from a wide variety of global commodity markets, including energy- and food-related commodities. As such, one concern may be that we are simply picking up the correlation of food and energy inflation with our supply based measure of shortages, and not a true measure of shortages. However, the correlation of our supply decrease measure with food and energy prices is not high, and is in fact negative (with energy) for part of the sample. By contrast, it is quite high (over 60%) with the Google Trend shortage measure, suggesting that we do successfully manage to catch a distinct part of supply chain disruptions. Indeed, to the extent that we can capture markets less salient to consumers, and hence less likely to be searched, our measure can give a broader measure of aggregate shortages.

9. Concluding Remarks

In this paper, we employ a computer-based, narrative approach that builds on the work of Mouabbi, Passari, and Rousset Planat (2024) for the analysis of inflation as emanating from developments in commodities. By leveraging the rich informational content of business news, we distinguish between demand- and supply-side drivers of commodity price movements and their respective impacts on future inflation, controlling for widely-used predictors. Our findings point to the dominant role of demand-side developments as inflation drivers. Nonetheless, we also document a notable increase in the significance of supply-side shocks under certain conditions, particularly in recent years. The COVID-19 pandemic, in particular, has introduced new complexities in understanding the relationship between commodity prices and inflation.

We find that our indices play a crucial role in enhancing out-of-sample forecasts of inflation by significantly reducing forecast errors. These indicators not only facilitate an understanding of the persistence of shocks generated by various commodity drivers, but they also offer substantial incremental information beyond that provided by commodity returns alone. This underscores the importance of analyzing supply and demand side factors independently, given the varying persistence they may exhibit. The text-based commodity demand and supply measures also demonstrate robust performance across different economic regimes, including periods characterized by declining, stable, and rising headline inflation. The employed framework has the additional benefit of catering to the forecasting of inflation components via the mapping of individual commodities to different inflation baskets, yielding further forecasting improvements. Furthermore, narratively dissecting the drivers of commodity supply and demand provides novel insights regarding the magnitude and persistence of the pass-through effect to inflation. Notably, we illustrate the utility of the narrative indicators in decomposing the inflationary drivers during the pandemic era, thereby providing valuable contributions to the empirical understanding of inflation dynamics in unprecedented economic conditions.

The interplay of global supply chain disruptions and substantial fiscal stimulus, compounded by the geopolitical ramifications of Russia's invasion of Ukraine, has precipitated multi-decade highs in annual inflation indicators, necessitating a rigorous analysis of the underlying inflation dynamics. In this context, the growing literature that utilizes advancements in computational linguistics to analyze economic narratives is emerging as a promising avenue for deepening our understanding of the complexities inherent in inflationary behaviors. While additional research in this domain is essential, the implications for monetary policy could be significant. Our forecasting exercise, while intentionally straightforward and parsimonious, demonstrates that the indices developed herein yield considerable forecasting improvements compared to conventional autoregressive and moving average benchmarks. The real-time applicability of this framework allows for its integration into existing forecasting methodologies employed by central banks, thereby enhancing the precision and responsiveness of inflation predictions.

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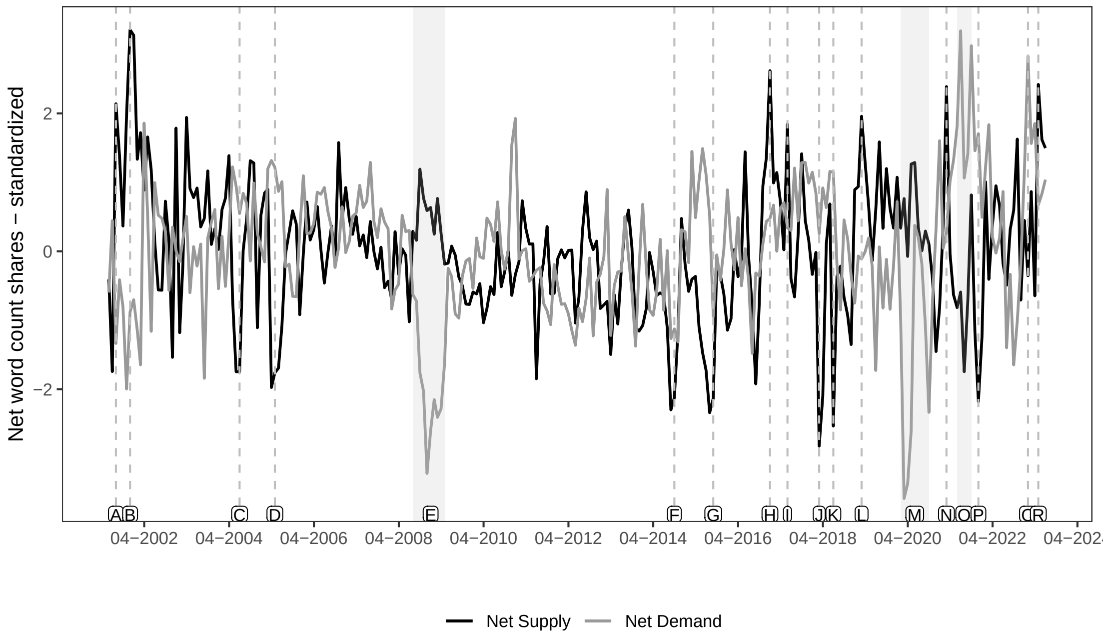
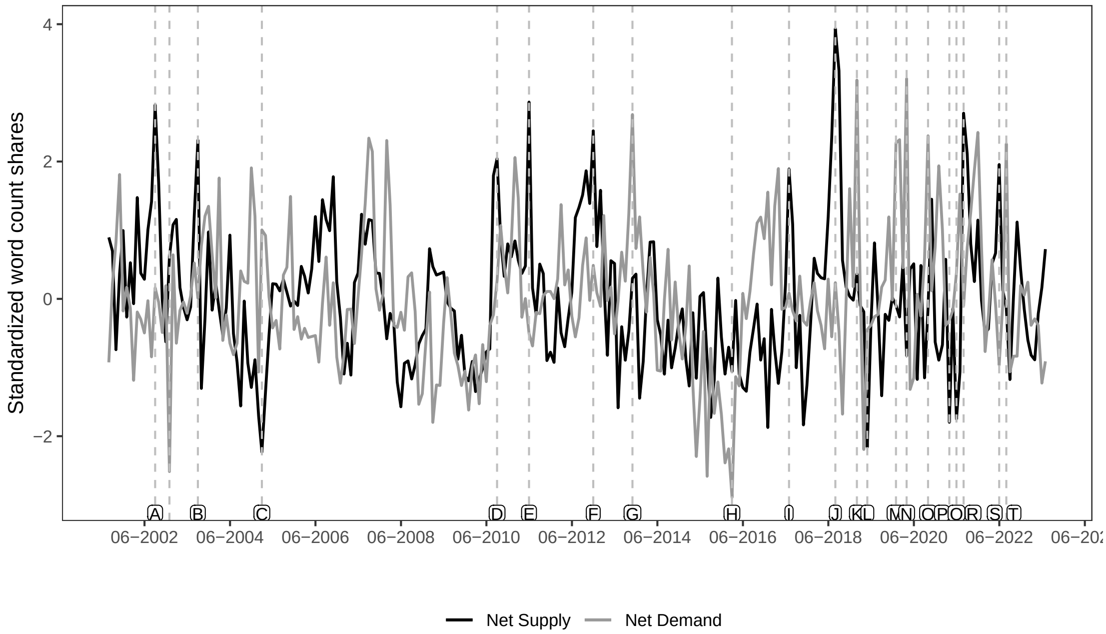
Appendix A. Additional Figures

Figure A1. Crude Oil Index: Standardized Net supply and Standardized Net Demand Share of Total Number of Words per Month



[A] OPEC cuts output to lift oil prices following US 2001 recession. [B] 118th OPEC Meeting, production cut following US economic slowdown & 9/11. [C] OPEC to raise output quotas (131st E.M.). [D] OPEC pumps at 25-year highs to cater for high demand expected from China. [E] 150th & 151st OPEC E.M.: production cut (GFC). [F] Faster than expected recovery of Libyan oil production & unaffected Iraq production: perceived glut. [G] Worries about oversupplied oil market (Chinaâs slowdown); Middle East producers pump crude at record levels. [H] OPEC 171st Meeting: OPEC & non-OPEC to cut output for first time in 8 years. [I] OPEC+ extended cuts in oil output to battle global glut. [J] US record oil production: oversupply worries. [K] OPEC to raise oil production amid calls from top consumers to cool prices & support world economy. [L] OPEC production cuts & US sanctions on Iranian and Venezuelan crude. [M] COVID-19. [N] Winter storm in Texas causes US crude production drop. [O] Global economy and oil demand recover faster than expected following vaccination. [P] The US announces release of millions of barrels from strategic reserves in coordination with China, India, South Korea, Japan & Britain, to cool prices. [Q] Subsiding recession risks in major economies & reopening of China's economy boost demand. [R] Surprise decision by OPEC+ to cut output (48th JMMC). Source: Mouabbi, Passari, and Rousset Planat (2024)

FIGURE A2. Wheat Index: Standardized Net supply and Standardized Net Demand Share of Total Number of Words per Month



[A] Severe drought in Canada cuts wheat production by more than 25%. Worrisome dry weather in Australia & US Northern Plains. [B] Hot & dry weather trims European output & Canada's crop. [C] Ample world wheat supplies amid bumper crops. [D] Due to heatwave Russia bans exports of wheat; Ukraine imposes export quotas. [E] Dry weather stresses crops in Plains; wet weather slows wheat seedings in northern Plains. [F] Weather sparks worries about world supply. [G] Prospects of strong demand from China. [H] Sluggish demand for US supplies due to China's policy shift that favors other grains. [I] Dry weather in US northern Plains threatens crops. [J] Severe drought in Europe cuts harvests. [K] Resuming trade talks between China & the US boosts higher wheat demand. [L] Abundant world supplies due to crop-friendly weather in key areas. [M] China & the US reach phase one trade deal. [N] Covid-19 cause panic shoppers around the world to stock up on wheat-based items. [O] Strong demand from China following trade deal with the US. [P] Improved US wheat condition ratings. [Q] Above-average global yield expectations pressures wheat markets. [R] Adverse weather conditions & reduced expectations for Russia's harvest. [S] Easing fears of global recession & renewed import demand. [T] US winter crop ratings fall amid droughts; hot weather curbs India's production.

Source: Mouabbi, Passari, and Rousset Planat (2024)

APPENDIX B. DICTIONARIES

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

Table B1 to Table B3 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 B4 and Table B5 present the list of roots of increase and decrease words.

TABLE B1. Supply and demand words: Global Commodity Index

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

Source: Mouabbi, Passari, and Rousset Planat (2024)

TABLE B2. Supply and demand words: Crude Oil

Supply				
suppl*	produc*	output	discovery	glut*
reserv*	surplus*	rig*		
Demand				
demand*	consum*	buy*	util*	drain*
deplet*	refin*			

Source: Mouabbi, Passari, and Rousset Planat (2024)

TABLE B3. Supply and demand words: Wheat

Table B4: Supply and demand words
Wheat

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

Source: Mouabbi, Passari, and Rousset Planat (2024)

TABLE B4. 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*	

Source: Mouabbi, Passari, and Rousset Planat (2024)

TABLE B5. 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*	

Source: Mouabbi, Passari, and Rousset Planat (2024)

APPENDIX C. ADDITIONAL TABLES

TABLE C1. Forecast performance (RMSE), Core CPI inflation, Pre-COVID

	horizon	baseline	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: without commodities								
Autoregressive								
	h=12	0.302	1.130	1.054	1.075	1.066	0.961	1.050
	h=6	0.496	1.059	1.023	1.025	1.045	0.976	1.051
	h=3	0.608	1.036	1.015	1.011	1.070	1.032	1.100
Controls, Autoregressive								
	h=12	0.339	1.090	1.027	1.056	1.131	1.045	1.117
	h=6	0.531	1.061	1.022	1.038	1.086	1.029	1.065
	h=3	0.627	1.068	1.035	1.033	1.097	1.098	1.157
IMA								
	h=12	0.304	1.084	1.016	1.059	1.027	0.919	0.984
	h=6	0.505	1.025	0.996	1.009	1.007	0.949	0.987
	h=3	0.652	1.010	0.994	0.999	1.034	1.004	1.053
Controls, IMA								
	h=12	0.336	1.032	1.001	1.019	1.073	0.971	1.026
	h=6	0.512	1.025	1.001	1.018	1.055	0.984	1.004
	h=3	0.629	1.028	1.008	1.014	1.060	1.066	1.093
Panel B: with commodities								
Autoregressive								
	h=12	0.306	1.144	1.053	1.083	1.077	0.956	1.066
	h=6	0.498	1.062	1.023	1.027	1.054	0.977	1.060
	h=3	0.607	1.034	1.014	1.012	1.073	1.032	1.100
Controls, Autoregressive								
	h=12	0.344	1.077	1.027	1.051	1.118	1.044	1.107
	h=6	0.537	1.060	1.023	1.039	1.082	1.027	1.062
	h=3	0.627	1.064	1.037	1.033	1.096	1.098	1.153
IMA								
	h=12	0.303	1.084	1.015	1.062	1.030	0.917	0.986
	h=6	0.504	1.024	0.995	1.011	1.009	0.949	0.989
	h=3	0.651	1.014	0.999	1.002	1.031	1.009	1.049
Controls, IMA								
	h=12	0.335	1.021	1.002	1.006	1.056	0.981	1.023
	h=6	0.513	1.026	1.003	1.018	1.051	0.988	1.009
	h=3	0.630	1.030	1.011	1.016	1.054	1.067	1.092
Composite Indices								
Net Supply			X	X				
Net Demand			X		X			
Supply Increase/Decrease							X	X
Demand Increase/Decrease						X		X

Note: The table shows results from forecasts of Core CPI inflation across different monthly horizons, using the composite commodity indices. Columns (1)-(6) show the root mean squared error (RMSE) of each forecast relative to the baseline. Model 1 includes as predictors net supply and net demand; model 2 includes net supply; model 3 includes net demand; model 4 includes demand increase and demand decrease; model 5 includes supply increase and supply decrease; and model 6 includes supply increase, supply decrease, demand increase and demand decrease. The autoregressive specification is given by (7), and IMA specifications further include MA terms of order 2. Each specification includes some of our indexes, as indicated. Where noted, controls are: industrial production log monthly change, S&P 500 log monthly returns, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar log monthly change. Panel B also includes log monthly change in commodity prices. Newey-West standard errors; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

TABLE C2. Forecast performance (RMSE), Core CPI inflation

	horizon	baseline	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: without commodities								
Autoregressive								
	h=12	0.645	0.998	1.007	0.985	0.976	0.997	0.983
	h=6	0.891	1.011	1.000	1.008	0.989	0.976**	1.000
	h=3	1.407	1.009	0.997	1.009	0.997	1.003	1.017
Controls, Autoregressive								
	h=12	0.633	1.011	1.009	0.999	1.016	1.026	1.016
	h=6	0.887	1.010	0.997	1.011	1.015	1.021	1.033
	h=3	1.476	1.016	1.003	1.012	1.029	1.016	1.044
IMA								
	h=12	1.146	0.901	0.948	0.935	0.923	0.888	0.835
	h=6	1.207	0.935	0.948	0.973	0.974	0.925	0.913
	h=3	1.615	0.949	0.959	0.985	0.990	0.932	0.935
Controls, IMA								
	h=12	0.900	0.938	0.979	0.955	0.961	0.972	0.922
	h=6	1.055	0.962	0.982	0.978	0.985	0.988	0.960
	h=3	1.475	0.980	0.986	0.989	0.991	0.995	0.978
Panel B: with commodities								
Autoregressive								
	h=12	0.619	1.023	1.010	1.009	0.998	0.994	1.005
	h=6	0.877	1.010	1.002	1.006	0.990	0.974**	0.997
	h=3	1.373	1.005	0.997	1.006	0.993	1.001	1.013
Controls, Autoregressive								
	h=12	0.623	1.027	1.010	1.017	1.034	1.027	1.036
	h=6	0.871	1.025	1.005	1.021	1.026	1.029	1.047
	h=3	1.453	1.012	1.004	1.009	1.021	1.016	1.037
IMA								
	h=12	1.146	0.898	0.946	0.934	0.920	0.886	0.832
	h=6	1.208	0.931	0.947	0.972	0.971	0.925	0.914
	h=3	1.606	0.948	0.961	0.983	0.987	0.937	0.924
Controls, IMA								
	h=12	0.892	0.943	0.983	0.959	0.966	0.978	0.929
	h=6	1.049	0.968	0.987	0.982	0.992	0.995	0.971
	h=3	1.425	0.991	0.993	0.997	1.004	0.992	0.984
Composite Indices								
Net Supply			X	X				
Net Demand			X		X			
Supply Increase/Decrease							X	X
Demand Increase/Decrease						X		X

Note: The table shows results from forecasts of Core CPI inflation across different monthly horizons, using the composite commodity indices. Columns (1)-(6) show the root mean squared error (RMSE) of each forecast relative to the baseline. Model 1 includes as predictors net supply and net demand; model 2 includes net supply; model 3 includes net demand; model 4 includes demand increase and demand decrease; model 5 includes supply increase and supply decrease; and model 6 includes supply increase, supply decrease, demand increase and demand decrease. The autoregressive specification is given by (7), and IMA specifications further include MA terms of order 2. Each specification includes some of our indexes, as indicated. Where noted, controls are: industrial production log monthly change, S&P 500 log monthly returns, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar log monthly change. Panel B also includes log monthly change in commodity prices. Newey-West standard errors; ${}^{*}p < 0.1, {}^{**}p < 0.05, {}^{***}p < 0.01$.

TABLE C3. Forecast performance (RMSE), Core PCE inflation, Pre-COVID

	horizon	baseline	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: without commodities								
Autoregressive								
	h=12	0.294	0.948	1.006	0.893	0.918	0.901	0.873
	h=6	0.438	1.000	0.995	0.977	1.010	0.943	1.009
	h=3	0.569	1.050	0.977	1.033	1.059	0.970	1.081
Controls, Autoregressive								
	h=12	0.278	0.979	1.053	0.923	0.982	1.034	1.023
	h=6	0.445	1.025	1.023	1.003	1.028	1.008	1.041
	h=3	0.586	1.088	1.072	1.029	1.054	1.083	1.134
IMA								
	h=12	0.296	0.893	0.996	0.872	0.866	0.887	0.791*
	h=6	0.436	0.957	1.005	0.948	0.962	0.947	0.939
	h=3	0.581	0.987	0.978	0.984	0.984	0.937	0.992
Controls, IMA								
	h=12	0.292	0.920	1.013	0.894**	0.943	0.947	0.910
	h=6	0.422	0.973	0.997	0.969**	0.989	0.961	0.974
	h=3	0.562	1.025	1.034	0.999	0.986*	1.025	1.035
Panel B: with commodities								
Autoregressive								
	h=12	0.289	0.987	1.013	0.933	0.946	0.911	0.900
	h=6	0.430	1.014	1.002	0.995	1.026	0.949	1.020
	h=3	0.543	1.049	0.983	1.039	1.063	0.968	1.074
Controls, Autoregressive								
	h=12	0.277	1.015	1.058	0.954	0.997	1.037	1.035
	h=6	0.440	1.044	1.027	1.017	1.042	1.010	1.058
	h=3	0.563	1.100	1.081	1.032	1.064	1.094	1.145
IMA								
	h=12	0.295	0.897	0.994	0.877	0.870	0.885	0.792*
	h=6	0.436	0.955	1.000	0.947	0.958	0.942	0.936
	h=3	0.562	1.001	0.975	0.995	0.992	0.943	1.001
Controls, IMA								
	h=12	0.289	0.946	1.029	0.906*	0.947	0.972	0.916
	h=6	0.420	0.986	1.001	0.976**	0.991	0.974	0.985
	h=3	0.534	1.047	1.039	1.019	1.009	1.024	1.059
Composite Indices								
Net Supply			X	X				
Net Demand			X		X			
Supply Increase/Decrease							X	X
Demand Increase/Decrease						X		X

Note: The table shows results from forecasts of Core PCE inflation across different monthly horizons, using the composite commodity indices. Columns (1)-(6) show the root mean squared error (RMSE) of each forecast relative to the baseline. Model 1 includes as predictors net supply and net demand; model 2 includes net supply; model 3 includes net demand; model 4 includes demand increase and demand decrease; model 5 includes supply increase and supply decrease; and model 6 includes supply increase, supply decrease, demand increase and demand decrease. The autoregressive specification is given by (7), and IMA specifications further include MA terms of order 2. Each specification includes some of our indexes, as indicated. Where noted, controls are: industrial production log monthly change, S&P 500 log monthly returns, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollarlog monthly change. Panel B also includes log monthly change in commodity prices. Newey-West standard errors; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

TABLE C4. Forecast performance (RMSE), Core PCE inflation

	horizon	baseline	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: without commodities								
Autoregressive								
	h=12	0.467	0.922	0.989	0.910*	0.910*	0.974	0.898*
	h=6	0.678	0.989	0.986	0.992	1.013	0.975**	1.025
	h=3	0.990	1.007	0.975	1.018	1.033	0.973	1.042
Controls, Autoregressive								
	h=12	0.438	0.945	1.010	0.930	0.946	1.022	0.963
	h=6	0.645	0.988	0.990	0.995	1.022	1.005	1.033
	h=3	0.936	1.023	1.002	1.020	1.062	1.019	1.087
IMA								
	h=12	0.969	0.893	0.952	0.927	0.902	0.876	0.808
	h=6	0.977	0.919	0.953	0.960	0.954	0.920	0.897
	h=3	1.234	0.942	0.950	0.983	0.979	0.914	0.910
Controls, IMA								
	h=12	0.689	0.911	0.983	0.923	0.923	0.974	0.896
	h=6	0.783	0.932	0.976	0.952	0.951	0.978	0.933
	h=3	1.091	0.964	0.986	0.976	0.966	0.977	0.946
Panel B: with commodities								
Autoregressive								
	h=12	0.434	0.968	0.996	0.953	0.945	0.978	0.938
	h=6	0.656	1.003	0.991	1.006	1.027	0.978**	1.035
	h=3	0.930	1.012	0.978	1.026	1.036	0.973*	1.046
Controls, Autoregressive								
	h=12	0.429	0.980	1.016	0.964	0.972	1.026	0.991
	h=6	0.636	1.011	1.000	1.013	1.039	1.012	1.054
	h=3	0.896	1.032	1.008	1.027	1.061	1.024	1.090
IMA								
	h=12	0.969	0.894	0.951	0.929	0.902	0.873	0.807
	h=6	0.978	0.919	0.951	0.961	0.952	0.919	0.897
	h=3	1.165	0.955	0.951	0.996	0.995	0.945**	0.944
Controls, IMA								
	h=12	0.683	0.919	0.989	0.928	0.928	0.981	0.900
	h=6	0.778	0.938	0.980	0.957	0.955	0.985	0.939
	h=3	1.049	0.984	0.988	0.987	0.982	0.969	0.952
Composite Indices								
Net Supply			X	X				
Net Demand			X		X			
Supply Increase/Decrease							X	X
Demand Increase/Decrease						X		X

Note: The table shows results from forecasts of Core PCE inflation across different monthly horizons, using the composite commodity indices. Columns (1)-(6) show the root mean squared error (RMSE) of each forecast relative to the baseline. Model 1 includes as predictors net supply and net demand; model 2 includes net supply; model 3 includes net demand; model 4 includes demand increase and demand decrease; model 5 includes supply increase and supply decrease; and model 6 includes supply increase, supply decrease, demand increase and demand decrease. The autoregressive specification is given by (7), and IMA specifications further include MA terms of order 2. Each specification includes some of our indexes, as indicated. Where noted, controls are: industrial production log monthly change, S&P 500 log monthly returns, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar log monthly change. Panel B also includes log monthly change in commodity prices. Newey-West standard errors; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

TABLE C5. Forecast performance (RMSE) of indices, Energy CPI inflation

	horizon	baseline	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: without commodities								
Autoregressive								
	h=12	10.794	0.965	0.979	0.978	0.912	1.077	1.026
	h=6	14.697	1.020	1.017	1.000	0.934	1.068	1.026
	h=3	19.413	1.060	1.067	1.003	0.994	1.088	1.065
IMA								
	h=12	10.884	0.95	0.976	0.954	0.854	0.973	0.915
	h=6	15.033	0.973	0.979	0.975	0.887	0.962	0.928
	h=3	19.843	0.992	0.999	0.977*	0.964*	0.982	0.967
Controls, IMA								
	h=12	10.282	0.946	0.999	0.947	0.808*	1.004	0.873
	h=6	14.156	0.997	0.987	0.992	0.894***	0.992	0.953**
	h=3	19.920	0.984	0.995	0.966*	0.931**	0.999	0.958***
Panel B: with commodities								
Autoregressive								
	h=12	10.057	1.032	1.01	1.031	0.964	1.143	1.072
	h=6	14.113	1.072	1.059	1.019	0.986	1.110	1.054
	h=3	18.189	1.087	1.071	1.033	1.047	1.092	1.093
IMA								
	h=12	10.046	0.999	1.009	1.000	0.897	0.983	0.945
	h=6	14.443	1.005	1.004	0.994	0.910**	1.002	0.972
	h=3	19.466	0.990	1.002	0.984	0.980	1.004	0.978
Controls, IMA								
	h=12	10.283	0.95	1.002	0.959	0.800**	0.994	0.873
	h=6	14.231	1.004	0.994	0.977	0.888***	0.982	0.947**
	h=3	20.392	0.971**	0.989	0.940***	0.923***	0.970	0.933***
Energy Indices								
Net Supply			X	X				
Net Demand			X		X			
Supply Increase/Decrease							X	X
Demand Increase/Decrease						X		X

Note: The table shows results from forecasts of headline CPI inflation across different monthly horizons, using the energy indices. Columns (1)-(6) show the root mean squared error (RMSE) of each forecast relative to the baseline. Model 1 includes as predictors net supply and net demand; model 2 includes net supply; model 3 includes net demand; model 4 includes demand increase and demand decrease; model 5 includes supply increase and supply decrease; and model 6 includes supply increase, supply decrease, demand increase and demand decrease. The autoregressive specification is given by (7), and IMA specifications further include MA terms of order 2. Each specification includes some of our indexes, as indicated. Where noted, controls are: industrial production log monthly change, S&P 500 log monthly returns, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar monthly log returns. Panel B also includes log monthly change in commodity prices. Newey-West standard errors; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

TABLE C6. Forecast performance (RMSE) of indices, Food CPI inflation

	horizon	baseline	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: without commodities								
Autoregressive								
	h=12	1.242	1.015	1.022	0.990	1.048	0.981	1.019
	h=6	1.396	1.037	1.025	1.017	1.027	1.006	1.009
	h=3	1.440	1.073	1.054	1.022	1.029	1.049	1.065
IMA								
	h=12	1.320	0.903*	0.996	0.920	0.943	0.953	0.917
	h=6	1.628	0.893	1.007	0.866	0.899	0.993	0.908
	h=3	1.783	0.973***	1.005	0.977	0.955	0.991	0.955***
Controls								
	h=12	1.021	1.007	1.047	1.011	0.940	0.880	0.854
	h=6	1.468	0.982	1.004	0.930	0.954	0.961	0.926
	h=3	1.580	1.004	1.013	0.969	0.947	1.009	0.921
Panel B: with commodities								
Autoregressive								
	h=12	1.219	1.079	1.035	1.059	1.004	0.974	1.004
	h=6	1.421	1.052	1.015	1.037	1.025	0.998	1.019
	h=3	1.489	1.062	1.035	1.024	1.033	1.039	1.069
IMA								
	h=12	1.215	0.953**	0.999	0.958	0.901	0.955	0.896
	h=6	1.578	0.951	0.994	0.955	0.941	0.997	0.945
	h=3	1.736	0.994	0.997	1.002	0.980	1.015	0.975**
Controls, IMA								
	h=12	1.030	0.989	1.037	1.004	0.936	0.881	0.837
	h=6	1.459	0.972	1.018	0.930	0.957	0.979	0.939
	h=3	1.560	1.001	1.014	0.972	0.944	1.018	0.927
Food Indices								
Net Supply			X	X				
Net Demand			X		X			
Supply Increase/Decrease							X	X
Demand Increase/Decrease						X		X

Note: The table shows results from forecasts of headline CPI inflation across different monthly horizons, using the food indices. Columns (1)-(6) show the root mean squared error (RMSE) of each forecast relative to the baseline. Model 1 includes as predictors net supply and net demand; model 2 includes net supply; model 3 includes net demand; model 4 includes demand increase and demand decrease; model 5 includes supply increase and supply decrease; and model 6 includes supply increase, supply decrease, demand increase and demand decrease. The autoregressive specification is given by (7), and IMA specifications further include MA terms of order 2. Each specification includes some of our indexes, as indicated. Where noted, controls are: industrial production log monthly change, S&P 500 log monthly returns, FFR, 10-year minus 2-year US treasury, VIX, trade-weighted US dollar monthly log returns. Panel B also includes log monthly change in commodity prices. Newey-West standard errors; $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

Appendix D. Turning Points

TABLE D1. Forecast performance (RMSE) in turning points, CPI inflation

	h=12						h=6					
	Headline			Core			Headline			Core		
	Fall	Incr	Stable	Fall	Incr	Stable	Fall	Incr	Stable	Fall	Incr	Stable
Panel A: without commodities												
Autoregressive	1.510	0.987	0.849	0.060	0.109	0.086	4.400	1.59	1.436	0.697	0.261	0.212
model 0	0.858	0.378	0.840	1.953	2.313	1.476	0.621	0.969	1.041	1.017	1.174	1.037
model 1	1.057	1.043	0.991	2.049	2.164	1.515	1.035	1.182	1.034	0.991	1.100	1.019
model 2	0.931	0.503	0.744	2.455	1.464	1.495	0.649	1.116	0.924	1.013	1.146	1.002
model 4	0.466	0.729	0.588	2.333	1.563	1.508	0.620	1.245	0.868	1.022	1.206	1.108
model 5	0.637	1.421	0.600	0.992	1.120	0.946	0.553	1.965	1.005	0.981	1.625	0.957
model 6	0.441	0.690	0.661	2.317	1.472	1.336	0.455	1.337	1.046	1.343	1.634	1.252
IMA												
model 0	0.858	0.532	0.678	0.909	1.359	0.880	0.734	0.815	0.726	0.739	1.551	0.849
model 1	1.032	1.045	0.934	0.876	1.367	0.960	0.992	0.965	0.943	0.627	1.591	0.878
model 2	0.961	0.594	0.654	0.831	1.406	0.917	0.745	1.130	0.690	0.698	1.596	0.867
model 4	0.466	0.826	0.471	0.406	1.415	0.930	0.727	1.025	0.581	0.673	1.586	0.865
model 5	0.550	1.403	0.568	0.773	1.172	0.809	0.568	1.328	0.782	0.658	1.500	0.849
model 6	0.276	1.184	0.471	0.986	1.187	0.794	0.473	1.428	0.645	0.757	1.509	0.809
Panel B: with commodities												
Autoregressive	1.094	1.125	0.613	0.038	0.210	0.131	3.113	1.800	1.391	0.757	0.352	0.236
model 0	0.773	0.322	0.865	2.309	0.938	0.955	0.803	0.552	1.039	1.084	0.957	1.084
model 1	1.074	1.097	0.995	1.112	1.031	1.025	0.982	1.119	1.003	1.033	1.004	1.058
model 2	0.912	0.385	0.722	1.999	0.898	0.913	0.796	0.742	0.911	1.023	0.970	1.009
model 4	0.655	0.999	0.797	1.856	1.014	0.967	0.821	0.784	0.970	0.976	0.959	1.050
model 5	0.999	1.163	1.010	3.925	0.774	0.562	0.958	1.563	1.032	1.180	0.927	0.991
model 6	0.706	0.914	0.995	4.773	0.715	0.751	0.685	0.945	1.182	1.226	0.927	1.066
IMA												
model 0	0.717	0.602	0.700	0.939	0.861	0.920	0.795	0.577	0.758	0.665	0.984	0.938
model 1	1.013	1.076	0.956	1.026	0.891	0.928	0.972	0.986	0.904	0.623	0.994	0.965
model 2	0.870	0.562	0.675	1.225	0.865	0.885	0.894	0.843	0.754	0.693	1.013	0.942
model 4	0.647	0.840	0.695	0.907	0.866	0.939	0.939	1.024	0.745	0.696	1.009	0.954
model 5	0.851	1.135	0.788	2.927	0.665	0.455	0.770	1.233	0.864	0.757	0.928	0.862
model 6	0.426	1.166	0.764	4.261	0.646	0.579	0.598	1.065	0.844	0.773	0.894	0.873

Note: The table shows results from forecasts of headline CPI inflation across different monthly horizons, using the composite commodity indices. Each column shows the root mean squared error (RMSE) of each forecast relative to the baseline. The autoregressive specification is given by (7), and IMA specifications further include MA terms of order 2. Each specification includes some of our indexes: i) model 0: net supply and net demand; ii) model 1: net supply; iii) model 2: net demand; iv) model 4: demand increase and decrease; v) model 5: supply increase and decrease; vi) model 6: supply and demand increase and decrease. Panel B also includes log monthly change in commodity prices and the FFR. Fall: 3-month moving average % change in inflation negative for at least 5 consecutive months; Incr: same measure positive for at least 5 consecutive months; Stable: neither falling nor rising.

TABLE D2. Forecast performance (RMSE) in turning points, PCE inflation

	h=12						h=6					
	Headline			Core			Headline			Core		
	Fall	Incr	Stable	Fall	Incr	Stable	Fall	Incr	Stable	Fall	Incr	Stable
Panel A: without commodities												
Autoregressive	0.906	0.430	0.571	0.119	0.098	0.081	2.437	0.967	0.744	0.142	0.297	0.183
model 0	0.893	0.452	0.876	1.200	0.702	1.326	0.572	1.067	0.991	0.389	1.066	1.118
model 1	0.973	0.819	1.046	1.558	0.691	1.392	1.034	1.112	1.034	0.927	1.076	1.022
model 2	0.871	0.611	0.803	0.463	0.940	1.054	0.594	1.192	0.921	0.553	0.945	1.100
model 4	0.469	0.633	0.629	0.473	0.906	1.022	0.579	1.282	0.831	0.469	0.962	0.991
model 5	0.595	1.388	0.514	1.062	0.971	0.974	0.580	1.748	0.936	0.267	1.563	0.842
model 6	0.485	1.004	0.561	0.443	0.812	1.002	0.386	1.154	1.062	0.132	1.110	1.141
IMA												
model 0	0.865	0.371	0.686	0.855	1.175	0.701	0.777	0.642	0.670	0.692	0.993	0.939
model 1	1.011	0.888	0.980	1.173	0.922	0.976	1.071	1.000	1.003	1.393	1.019	1.012
model 2	0.907	0.478	0.698	0.940	1.103	0.788	0.753	0.873	0.656	1.286	0.831	0.985
model 4	0.406	0.769	0.556	0.507	0.787	0.824	0.687	0.849	0.520	0.954	0.746	0.777
model 5	0.572	1.271	0.477	0.328	0.814	0.753	0.668	1.302	0.824	0.487	1.314	0.751
model 6	0.332	1.271	0.417	0.487	0.667	0.715	0.343	1.053	0.703	0.750	0.951	0.806
Panel B: with commodities												
Autoregressive	0.656	0.459	0.402	0.051	0.087	0.111	1.798	0.966	0.679	0.116	0.316	0.164
model 0	0.919	0.381	0.928	1.036	1.357	0.798	0.790	0.850	0.950	0.448	0.884	1.094
model 1	1.045	0.988	1.028	1.010	0.896	1.053	0.956	1.121	1.014	0.767	1.066	1.009
model 2	0.880	0.486	0.804	0.948	1.345	0.694	0.889	0.892	0.823	0.716	0.853	1.049
model 4	0.677	0.879	0.848	0.994	1.006	0.952	0.939	0.941	0.889	0.841	0.828	1.115
model 5	0.992	1.132	1.006	1.325	0.534	0.699	0.859	1.600	1.107	0.922	1.057	0.939
model 6	0.800	0.954	0.950	1.445	0.670	0.676	0.724	0.947	1.198	0.534	0.843	1.138
IMA												
model 0	0.954	0.379	0.792	1.086	0.878	0.688	0.957	0.427	0.600	0.670	0.757	0.949
model 1	1.156	0.794	1.080	1.325	0.787	0.994	1.090	0.859	0.881	1.007	1.058	0.985
model 2	0.929	0.529	0.811	1.176	0.985	0.669	1.037	0.735	0.586	0.940	0.762	0.993
model 4	0.568	0.871	0.805	1.087	0.824	0.866	1.015	0.814	0.655	1.040	0.761	0.916
model 5	0.970	1.075	0.939	1.446	0.442	0.676	1.001	1.095	0.891	0.822	1.026	0.897
model 6	0.522	1.271	0.761	1.153	0.565	0.568	0.601	0.815	0.981	0.634	0.691	0.945

Note: The table shows results from forecasts of headline CPI inflation across different monthly horizons, using the composite commodity indices. Each column shows the root mean squared error (RMSE) of each forecast relative to the baseline. The autoregressive specification is given by (7), and IMA specifications further include MA terms of order 2. Each specification includes some of our indexes: i) model 0: net supply and net demand; ii) model 1: net supply; iii) model 2: net demand; iv) model 4: demand increase and decrease; v) model 5: supply increase and decrease; vi) model 6: supply and demand increase and decrease. Panel B also includes log monthly change in commodity prices and the FFR. Fall: 3-month moving average % change in inflation negative for at least 5 consecutive months; Incr: same measure positive for at least 5 consecutive months; Stable: neither falling nor rising.

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