Deciphering Financial Market Reactions to OPEC Announcements: A Neural Network Approach

Paul L. Tran*

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Abstract

This paper shows that OPEC communications affect oil supply expectations, oil prices, and the macroeconomy beyond the effects of setting production limits and changing current production. Using neural network methods for text analysis, I create a new oil supply expectations "text shock" from OPEC statements that is derived from variation in oil futures prices purified of noise, demand information, and endogenous responses to global economic activity. The "purified surprises" correlate with 74% of the observed supply surprises. Impulse responses from vector autoregressions using my shock do not exhibit output puzzles and are more consistent with theory than those previously reported.

Keywords: OPEC announcements, oil supply expectations shocks, oil supply, neural networks, machine learning, text analysis

JEL Codes: C45, E31, E32, Q43

*Department of Economics, The University of Texas at Austin. 2225 Speedway, BRB 2.128, C3100, Austin, TX 78712, USA. Email: pltran@utexas.edu. Website: https://paulletran.com/. I am indebted to my committee — Oli Coibion, Chris Boehm, Saroj Bhattarai, and Amy Handlan — for their invaluable guidance and support. For helpful comments and suggestions, I also wish to thank Andi Mueller, Andrew Chang, and David Ly.

1 Introduction

OPEC is at the heart of any analysis of oil prices: it produces about 40% of the world's total crude oil supply and controls almost 80% of proven oil reserves (OPEC (2021)). Therefore, post-meeting announcements from the organisation about their output quota decisions can be useful in identifying and isolating unexpected variation in future oil supply conditions (Lin and Tamvakis (2010)). However, ensuring that measurements of these variations are exogenous is difficult because oil prices are endogenous and respond to global economic conditions. Therefore, accounting for the shock initiating the movements in oil prices is needed for proper analysis (Kilian (2009)). Using machine learning, I show that these announcement text can purify these measures such that they only reflect unexpected variation in future oil supply.

Previous literature, such as Känzig (2021), use changes in the prices of oil futures contracts computed on the final day of released OPEC announcements — when the output quotas are announced — to obtain a measure of exogenous changes in expected oil supply. These oil supply surprises can then be used as a proxy to identify the effects of a shock on supply expectations. Although OPEC decisions about quotas are endogenous responses to global economic conditions, the surprises still represent a sequence of event studies that reflect the market's changing beliefs about future oil supply under certain conditions. Two such conditions are that the event windows are narrow enough such that the effect of other shocks on the market's beliefs do not enter the surprises and that OPEC and the market have equal information sets.[1]

I argue that both these conditions are possibly violated. In contrast to the intraday event windows used in the monetary policy literature, Känzig (2021) uses a daily event window due to data limitations. Given how global internet protocol standards allow for information transfer within milliseconds, a daily window permits the market to update their beliefs with unrelated information. Therefore, it is possible to introduce biases when identifying a

[1]The last assumption is that the risk premia do not change within the event window.

shock to oil supply expectations using these oil supply surprises. Relatedly, papers such as Miranda-Agrippino and Ricco (2021) document the predictability of monetary policy surprises with publicly available macroeconomic information predating FOMC announcements.

Regarding the second condition, OPEC has an information advantage relative to the private sector about future oil supply. As argued in Degasperi (2021), this difference causes OPEC announcements to not only reveal deviations from expected oil supply, but also to clarify markets' expectations about oil demand and possibly contain information about OPEC's endogenous response to global economic activity. Because the surprises contain all this information, using the surprises as is for identification would conflate shocks to expectations of both oil supply *and* demand.

I propose a novel method to purify these oil supply surprises of noise and information effects that revolves around OPEC announcement text specifically pertaining to oil supply. In particular, this paper studies how the information contained in OPEC communication affects expectations of oil supply, the real oil price, and other variables beyond the effect of setting production limits. I adapt neural network methods for text analysis to predict surprises using OPEC announcements about oil supply. Changes in these oil futures prices encompass changes in market expectations about future oil prices. Therefore, the network's predictions can be interpreted as the amount of observed variation in oil futures prices isolated to OPEC announcement text. Using the neural network, OPEC statements, and an edited version of statements with demand information and OPEC's endogenous response removed, I obtain what I call the "purified" oil supply surprises, which I use to create an oil supply expectations shock series called the "text shock". A positive text shock means that the OPEC statement has shifted the path of oil price expectations upwards. Therefore, a positive text shock can be interpreted as a negative oil supply expectations shock.

The text shock represents innovations of oil supply expectations and I use this series to investigate the effects of unanticipated changes in supply expectations on the oil market and macroeconomy. I obtain three main findings:

First, I find that predictions from the neural network using OPEC announcements about future oil supply are correlated with 74% of the observed variation in oil futures prices, *conditioning on the weights and embedding of the neural network.*

Second, if a positive text shock occurs, the real oil price responds with an immediate and large increase, world oil production drops on impact and continues with a gradual but significant decline, and world oil inventories significantly rises on impact. Global economic activity contracts on impact and declines persistently. U.S. industrial and consumer activity fall, unemployment and inflation rise unambiguously.

Third, text shocks derived from using the purified surprises as proxy for supply expectations give impulse responses that are unambiguously consistent with theory in both the short and long horizons, addressing some "output puzzles" obtained when using shocks derived from the observed surprises as proxy for supply expectations.

Whilst the differences between the impulse responses from the text shock and shocks derived using the observed surprises are empirically small, the economic significance of these differences is anything but. Because of the training process behind the neural network method proposed in this paper, the derived text shocks are not only cleaner of noise and information effects, but they are also directly tied and isolated to OPEC's communication about future oil supply conditions by construction. These differences were unobservable from filtering attempts in prior studies.

There currently exists a large literature investigating the effects of OPEC announcements on oil supply expectations and prices, such as Draper (1984) and Demirer and Kutan (2010). My paper joins Känzig (2021) in studying the macroeconomic effects of these announcements by combining event study techniques and standard oil market vector autoregressive (VAR) analysis. In his paper, he cleverly implements a novel identification design by exploiting the institutional features of OPEC and changes in oil futures prices at a daily event window around the OPEC announcements. I branch off of his work by providing a unique approach that identifies a text shock purified of noise and information effects and showcases how OPEC uses its language about future oil supply to impact the economy and oil market.

From a methodological perspective, this paper belongs to the broad literature of text analysis applications in economics. However, few papers have focused on oil-related communication and its effect on the oil market. Brunetti et al. (2024) utilises Structural Topic Modelling to analyse OPEC communication and identify several topics related to supply, demand, and speculative activity in the oil market. Nazer and Pescatori (2022) uses cosine similarity to investigate the repetitiveness of OPEC announcements with regard to content, which is less informative to the market. Datta and Dias (2020) apply word count and proximity techniques on two highly regarded energy-related publications to construct indices that track oil market developments. My paper differs from these prior studies by using state-of-the-art natural language processing methods to specifically measure the effects of OPEC communication on oil supply expectations, beyond the oil market, and on the broader macroeconomy.

When it comes to applications of text analysis in economics, most empirical studies have employed the techniques of clustering words into topics or using word counts to construct sentiment lists. Many such examples exist in the monetary policy literature, such as Acosta (2023) constructing measures of expansionary versus contractionary monetary policy sentiment. These techniques are popular because they allow for researchers to choose the importance of individual words, but often fail to capture more complex features of text, such as context and word interdependencies.[2] In contrast, neural networks for text analysis do not overlook these characteristics. Until recently, applying these neural networks to economics have been impossible because training a network for language processing typically requires millions of text documents. However, the successful adaptation of neural networks on smaller text samples from the computer science literature now make it possible to study the communication of institutions, such as OPEC, with these methods.

The most similar examples to the methodology of my paper are Handlan (2020) and

[2]See Section 4 for examples.

Gong et al. (2022). In particular, the former paper utilises the state-of-the-art neural network, XLNet of Yang et al. (2020), to create monetary policy text shocks that are isolated to the forward guidance component from Federal Open Market Committee (FOMC) official and alternative statements. Impulse responses of variables from her text shock follow the same trends and amplitudes as those predicted by theory. Gong et al. (2022) apply several machine learning methods on online oil news headlines to predict oil futures prices. Specifically, the authors create novel indicators from the text features with these methods and use these indices alongside financial variables to forecast oil futures prices, which outperforms conventional forecasting techniques. My paper is the first to apply XLNet on OPEC statements that have been isolated to oil supply information and more cleanly measure the effects of these statements beyond the oil market and on the broader economy. Overall, my paper showcases how neural networks for text analysis are an alternative for purifying oil supply expectational shock measurements of noise and information effects.[3]

Recall that OPEC's information advantage results in the surprises to conflate information about revisions to expected oil supply and demand. Degasperi (2021) disentangles these shock components by imposing an assumption on the sign of the co-movement between the surprises and stock indices, where the latter proxy for economic activity (e.g., Jarociński and Karadi (2020)). I draw a parallel to the literature intersecting Handlan (2020), Gong et al. (2022), and Degasperi (2021) by constructing my text shock through manually cleaning every OPEC statement such that they only contain words about expected oil supply and the final decision on oil production limits and quotas. I then determine if the edited statement is "readable" to a human. If so, I use the edited text as input for the neural network. Otherwise, I delete the excerpt discussing oil demand or OPEC's endogenous response, even with the risk of losing supply information. Relatedly, my usage of OPEC's language to purify the surprises of information effects is similar to papers such as Romer and Romer (2004), who remove the FOMC's private information using internal forecasting materials.

[3] Gong et al. (2022) do not attempt to explicitly separate oil supply and oil demand information for their purpose of more accurately predicting oil futures prices.

2 Data

2.1 Background on OPEC and the Oil Futures Market

OPEC is an intergovernmental organisation of oil producing nations that possesses the largest market share in the global oil market. Its self-declared mission is to stabilise oil market prices in order to secure a steady income stream to producers; an efficient, economic, and fair supply of petroleum to consumers; and a fair return to those investing into the petroleum industry (OPEC (1961)).

At the heart of the organisation is the OPEC Conference, composed of delegations headed by oil ministers of all member countries. The conference meets in order to decide oil production policies. Since 1982, these policies include setting an overall and individual member oil production ceilings.[4] At minimum, the conference holds two "Ordinary" meetings annually. However, "Extraordinary" meetings can be scheduled if deemed necessary. Although the conference operates under the system of "one member, one vote" and strives for unanimity, Saudi Arabia is arguably the "de facto leader" of OPEC due to being its largest oil producer by far.

Crude oil is a frequently traded commodity at the international scale and coexists with a liquid futures market. This paper exclusively uses West Texas Intermediate (WTI) crude futures for two reasons. First, WTI is the main grade of crude oil and benchmark used to price oil in the U.S., which is the country of interest. Second, WTI crude futures have the longest available history because they were the first traded contracts about crude oil, introduced to the New York Mercantile Exchange in 1983. The WTI oil futures prices modified in this paper were provided by Känzig (2021) through his online replication package hosted and licensed under openICPSR.[5]

[4]Prior to 1982, OPEC focused on targeting oil prices instead.
[5]https://www.openicpsr.org/openicpsr/project/122886/version/V1/view

2.2 OPEC Announcements

The decisions of the OPEC Conference are usually announced to the public via press releases shortly after the meeting ends. These statements typically contain a review of the oil market outlook, discussions about future oil market conditions, and the final decision agreed upon regarding the overall and individual production ceilings.

For my analysis, I collect all 119 announcements from July 1983 through November 2017. The end date was chosen to properly compare impulse responses from vector autoregressions using my text shock to those estimated in Känzig (2021). All announcements dating back through 2002 were sourced from the official website of OPEC.[6] I extend my sample back through July 1990 using the Wayback Machine.[7] Statements dating back through July 1983 are hand-typed from OPEC (1990).

To prepare my sample for analysis done by the neural network, I clean the text in two steps. First, I pre-process all OPEC announcements by converting them into plain text format and removing all URLs, copyright disclaimers, introductions, congratulatory sentences, and declarations of the next scheduled Ordinary meeting.[8]

Second, I duplicate the set of preprocessed OPEC announcements. One set of statements is put aside whilst the other set has the text manually filtered such that only predictions about future oil supply and the decision made about the production ceiling and quotas remain. Therefore, this step deletes text excerpts that contain information about oil demand and OPEC's endogenous response. Importantly, I also remove language that interweave oil demand with future oil supply in order to ensure that information solely about future oil supply remain in the edited announcements.

An interpretation of the two set of OPEC announcements is that the set which only underwent preprocessing contains both oil supply and demand information (i.e., the set of S+D statements). The product of both steps is the set of text that contain only information

[6] https://www.opec.org/opec_web/en/press_room/28.htm
[7] A non-profit digital archive of the World Wide Web created by the Internet Archive.
[8] I keep declarations of the next scheduled Extraordinary meeting since these are less common.

about future oil supply conditions (i.e., the set of S statements).

Figure 1 presents the total number of words and presence of demand information in each announcement in order to observe the evolution of OPEC communication over time. From the top figure, we immediately see announcements made between the mid-1980s and mid-1990s have abnormally high word counts. It is observed from the text that OPEC frequently discussed disagreements amongst members about production quotas and repeatedly stressed that all members should obey meeting agreements. Many consider the time period to be when OPEC struggled to fulfil its statute of oil price stability. The corresponding text support this claim. Additionally, the word density of these statements have increased since 1995, possibly a result from OPEC's growing efforts to clarify its actions and role to the global oil market.

The bottom figure displays presence of demand information in OPEC communication, calculated as the ratio of sentences with demand information to the total number of sentences in each statement. Whilst the presence of demand information was sporadic before 2000, statements afterwards nearly always contained at least one sentence with demand information. This simple metric presents evidence that using the oil supply surprises as is would be problematic for identifying oil supply expectational shocks; these surprises are conflated with demand information.

2.3 Oil Market and Macroeconomic Variables

All variables used for my analysis come from Känzig (2021) and his full replication package. The baseline measurements are the real price of oil, world oil production, world oil inventories, world IP, U.S. IP, and U.S. consumer price index (CPI). For the real oil price, I use the WTI spot price and deflate it by U.S. CPI. For world IP, I use Baumeister and Hamilton (2019)'s index for OECD countries and six other major economies. For world oil inventories, I use the measure from Kilian and Murphy (2014). For U.S. IP, I use the IP Total Index measured by the Federal Reserve Board (FRB)'s G.17 publication. For U.S. CPI, I use the

Bureau of Labor Statistics (BLS)' measurement for all urban consumers and all items. All variables are at monthly frequency and run from January 1974 through December 2017. I perform the Census X13 adjustment to eliminate seasonality.

Augmented monthly variables are the U.S. civilian unemployment rate, personal consumption expenditures (PCE) and its components, CPI components, and the narrow and broad nominal effective exchange rates (NEERs). Quarterly variables used are U.S. real GDP, investment, and consumption. The unemployment rate and CPI components come from the BLS. PCE, real GDP, investment, and consumption come from the Bureau of Economic Analysis (BEA). I deflate PCE using a chain-type price index, also from the BEA. Both NEERs are calculated by the FRB's H.10.

3 Econometric Methodology

3.1 Construction of Observed Oil Supply Surprises

I follow Känzig (2021) to calculate the oil supply surprises. First, I compute the (log) difference of the price of WTI oil futures contracts on the day of the OPEC announcement and the price on the last trading day prior to the announcement. Standard asset pricing theory implies that the contract price is equal to the difference between the expected oil price and the risk premium (refer to Pindyck (2001)). If the risk premium is constant within the daily window,[9] we can interpret the daily surprise as revisions to oil price expectations caused by the OPEC announcement.

Recall that Känzig (2021) uses a daily event window due to practical limitations. First, official announcement times are published only at the daily frequency. Second, intra-daily calculation of WTI crude oil futures contracts only became available much later into the sample period. Shown in Nakamura and Steinsson (2018), using daily windows can be

[9] Piazzesi and Swanson (2008), Hamilton (2009), and Nakamura and Steinsson (2018) have recorded that the risk premia of futures prices in general vary at lower frequencies.

problematic by introducing background noise into the surprises.

The surprises are calculated using oil futures contracts whose maturities range from 1- to 12-months because they have a longer trading history and are more liquid (Alquist and Kilian (2010)), causing them to be less affected by risk premia. At OPEC meeting frequency, I compute the first principal component of the variations in oil futures prices for all maturities to capture the common variation across WTI oil futures contracts in a single dimension, as in Nakamura and Steinsson (2018). The surprises are then aggregated to monthly frequency to match the data used in the VAR analysis. Months with multiple statements are assigned the sum of the daily surprises. Months without statements are set to zero.

3.2 External Instrument VAR Approach

The primary method used to analyse how the text shock affects the oil market and broader economy draws from Känzig (2021) and was first developed by Stock and Watson (2012) and Mertens and Ravn (2013). Specifically, I use XLNet's predictions of the first principal component of the oil supply surprises (i.e., the purified surprises) as an external instrument in an oil market VAR model to identify an text shock.

4 Text Analysis of OPEC Announcements

Popular text analysis methods in economics can be summarised as "fitting predictive models on simple counts of text features" (Gentzkow et al. (2019)). However, these methods often miss how words within and across sentences relate to each other. For example, the phrases "with *prices* expected to be low, the Conference lowers *oil production limits*" and "with *prices* expected to be high, the Conference raises *oil production limits*" would produce the same measures. Alternatively, methods that measure the frequency of neighbouring words, called "n-grams", often miss information that are spread out across a sentence. For the following phrase, "The Conference will raise production limits, but spread out over the rest of the year" a trigram would count "raise production limits", but would miss how the increases are spread out.

In contrast, neural networks can approximate the complex relationships between words such as context and interdependencies. Using these methods, excerpts "spread out" and "over the rest of the year" could both be associated with "raise production limits" for prediction, even though these words are not all adjacent within the sentence. Indeed, with other social sciences observing success in applying natural language processing, economics could witness similar benefits when using these methods to study the communication of organisations such as OPEC (Gentzkow et al. (2019)).

4.1 XLNet, a Neural Network for Text Analysis

The off-the-shelf neural network for text analysis used in this paper is XLNet from Yang et al. (2020). It is considered a state-of-the-art method for text analysis tasks such as regression. In particular, the network structure, embedding, word representations, and generalisability of XLNet allow it to "understand" the direct mapping between OPEC communication about oil supply surprises.

I also choose this network for the following reasons. First, Handlan (2020) finds XLNet to outperform other networks when regressing on small samples of text using a transfer learning approach, which is essential for constructing the purified surprises. Second, XLNet abandons the literature practices of "corrupting" input text through masking the words of prediction-interest and assuming that these masked words are independent of each other. The former can lead to discrepancies when subsequently training the network on a different set of text without masking. The latter is an assumption that is often violated.[10] Instead, XLNet considers all possible information from all permutations of words around the words of interest in its pre-training phase, learning from bi-directional context without the usage and weaknesses of masking.

[10]Consider the example phrase, "The Conference will raise production limits". The words "production" and "limits" are masked. However, these words still share implicit relations to each other.

Appendix A explains how Yang et al. (2020) initially train XLNet and how the version of XLNet used in this paper addresses look-ahead bias.

4.2 XLNet, OPEC Statements, and Supply Expectations

I use the pre-trained parameters of XLNet as initial values for my task: Predicting changes in oil supply expectations that directly come from the OPEC statements that have been cleaned using the two-step process described in Subsection 2.2. I split my sample into training and testing subsamples such that 20% of OPEC statements and corresponding surprises belong in the testing sample. Splitting the announcements are conditioned by the type of decision OPEC made to the production ceiling, who the OPEC general secretary was, and by imposing both subsamples to have equal distribution of statements according to word count. This conditioning yields five distinct training-testing subsample folds such that no testing subsample shares statements with another. Additionally, these folds can be thought as sets of input-output pairs, where the inputs are the OPEC statements and the outputs are the oil supply surprises. I train XLNet to approximate this mapping for all five folds. This overall process, called "stratified sampling k-fold cross validation for $k = 5$" in the machine learning literature, accounts for any variation in the network's predictions coming from the sample folds themselves.[11] Although this technique is usually performed for optimal model selection and this paper only uses one model, the exercise still serves as a robustness check on the generalisability of XLNet on OPEC language. The results presented in this paper are for one of the five folds.

To fully understand how XLNet produces predictions that allow for the derivation of the text shock, its training process must be broken down into two steps:

First, I fine-tune the neural network to predict oil supply surprises from the text in the set of S+D statements. The rationale is that both the surprises and set of S+D statements

[11] Stratified sampling k-fold cross validation minimises the differences between the population distribution of OPEC announcement characteristics and the subsample distributions of these characteristics, which is necessary for training neural networks on small samples through transfer learning.

contain the same information content about oil demand and supply. When combined with its state-of-the-art abilities, this commonality allows XLNet to have an easier time transitioning from understanding general English to "OPEC English". The end result is a fine-tuned XLNet that can predict surprises coming solely from OPEC communication whilst *accounting for noise from unrelated sources.*

The second step has the trained version of XLNet predicting surprises from the text in the set of S statements, resulting in a set of predicted oil supply surprises coming solely from OPEC communication *about oil supply conditions, additionally accounting for information effects.* This final output is what I call the purified surprises and are used as the proxy in the VAR model that yields the text shock.

I restrict XLNet to consider a maximum input-sequence length of 512 word tokens for each OPEC announcements.[12] As shown in Figure 1, statements have an average of 300 words (with a peak of 760 words). Therefore, I assume that XLNet should still have adequate headroom to understand the full meaning of most statements.

Performance of the trained network is measured by the accuracy of its predicted surprises for OPEC statements that were not used to train and update XLNet's parameters. Note that the machine learning literature evaluates neural networks primarily under this metric and places no meaning on the network's parameter estimates because network parameters do not have the same interpretation as those of parametric models (Athey and Imbens (2019)). Therefore, my paper cannot describe the causal effect of one word over another within OPEC communication about oil supply on market expectations. Instead, the training process behind the neural network allows me to approximate this relationship and use its predictions to obtain text shocks directly tied to OPEC and purified of noise and information effects.

[12] For example, {"decreasing", "increasing"} can be broken into: {"de", "in", "creas", "ing"}.

4.3 Evaluation of Purified Surprises

For ease of interpretation, I evaluate XLNet by calculating the Pearson correlation between the testing purified and observed surprises. However, the issue of overfitting must first be addressed. Overfitting is inevitable due to XLNet having hundreds of millions of parameters. This issue shows up as a difference between the training and testing Pearson correlations. I perform the following to minimise this difference:

Specifically, I limit XLNet's training through the number of training iterations used and the learning rate. Too many training iterations causes the neural network and its weights to perfectly match the training data whilst deteriorating its out-of-sample prediction accuracy and generalisability. The learning rate is the rate at which a neural network updates its parameters to the training data. Too high of a learning rate will result in the network to forget information learnt from prior training iterations, causing its out-of-sample predictions to either degrade rapidly over fewer training iterations or stop updating. Conversely, too low of a learning rate results in XLNet to never fully learn the mapping between OPEC communication and oil supply surprises. Because I am applying the transfer learning approach, the initial parameter values of XLNet are already optimised to understanding general English. Therefore, I can ensure that XLNet remains generalisable to new data by limiting how much its parameters can update both within and across training iterations.

Ultimately, training a neural network is a balancing act: I train XLNet to meaningfully approximate the desired mapping without overfitting to the point that the network weights are non-generalisable. With the limitations on the aforementioned hyperparameters in place, I track the network's out-of-sample Pearson correlation during training and stop training XLNet at the iteration where in-sample accuracy increases, but out-of-sample accuracy decreases. Because out-of-sample predictions can be volatile when applying transfer learning onto small samples, I select the version of XLNet from the training iteration that displays this simultaneity only if future iterations result in permanently worse out-of-sample prediction accuracy.[13]

The issue of overfitting is also addressed in the second step of XLNet's training process. By having the version of XLNet trained on the set of S+D statements make predictions *using the text in the set of S statements*, the network is forced to generalise its predictions using OPEC announcements never seen before. As a result, the purified surprises account for noise, information effects, and *overfitting to a degree.*

Additionally, I perform the robustness exercise of artificially augmenting the set of S statements through the process of "back-translation" in order to examine the generalisability of the final version of XLNet. The computer science literature has shown that translating input text into another language and then back to the original language using software introduces noise into the input text without changing the meaning and tone. Therefore, the same oil supply surprises (i.e., the same actual output values) can be assigned to the artificially augmented text. I apply back-translation on both sets of S+D and S statements and create predictions using XLNet already trained on the original set of S+D statements. Results from this robustness check are similar to the original predictions. Therefore, the paper proceeds with the trained network and corresponding predictions without back-translation.

At last, Figure 2 plots $\varDelta\widehat{E[P]}_{Text}$ predicted by XLNet on the horizontal axis against the actual $\varDelta E[P]_{Futures}$. The blue dots and red squares represent values in the training and testing subsamples, respectively. The testing and training Pearson correlations are 14.3% and 78.7%, respectively. Overall correlation between the purified and observed oil supply surprises is 74%, which I interpret as the proportion of the observed surprises that can be attributed to the text of OPEC announcements about future oil supply, *conditional on the embedding and weights of XLNet.*[14]

[13] I also keep track of the training and testing mean squared and absolute errors to ensure that the Pearson correlation for each iteration isn't misleading.

[14] This conditionality is important because the neural network can potentially struggle to approximate a mapping between OPEC communication and changes in oil supply expectations.

4.4 Different Wording Leads to Different Predictions

The following exercise highlights XLNet's ability to "understand" and detect discrepancies in OPEC statements such as small wording and meaning changes. I first choose statements that are temporally adjacent and convey similar meaning and conclusions. I then look at the difference in what XLNet predicts for the announcements' corresponding changes in oil supply expectations. I use the predictions from the text in the S statements to show that the neural network is able to "understand" and approximate the desired mapping between OPEC communication about oil supply and purified surprises. Figure 3 displays three announcement pairs for comparison.

The first row compares the June and September 2004 announcements. Both statements convey OPEC's beliefs that the higher prices were due to market fears about future supply shortages. However, the latter statement emphasises how "OPEC's timely actions had been effective in ensuring that the market remains well supplied". Given this difference, we can expect the latter statement to increase supply expectations more than the former statement. XLNet's predictions support this hypothesis.

The second row compares the September and December 2009 announcements. Both maintain production levels. However, only the former statement states that the "market remains over-supplied". Removal of this information should should shift oil supply expectations more downwards. XLNet can convey this difference.

The final row compares the March and October 2010 announcements. In particular, both maintain production limits and express with concern about the market being over-supplied. However, the latter statement further notes the ease in oil oversupply and "reaffirm[s OPEC's] determination to ensure reliable supply to the market". Therefore, the latter statement is more likely to induce increased future supply expectations, which XLNet captures by predicting a purified surprise.

4.5 Diagnostics of Purified Surprises

I perform a variety of robustness checks to examine the validity of the purified surprises. Because this paper showcases how neural networks can filter out noise and information effects, I visually inspect the differences between the purified and observed surprises. Figure 4 graphs the two instruments scaled by their respective standard deviations over time. We can see that the purified surprises are smaller in many instances. At the same time, several announcement dates — where the observed surprises are at least two standard deviations— see purified surprises of even greater magnitude. These results complement the main finding in Subsection 4.3: 74% of the observed surprises can be attributed to the text of OPEC statements about future oil supply, conditional on the embedding and weights of the network.

Other desirable properties for the purified surprises include being neither autocorrelated nor forecastable (Ramey (2016)). Figure 5 presents no evidence of serial correlation. I finally perform several Granger causality tests to investigate if other macroeconomic variables have forecasting power on the purified surprises. Table 1 displays no evidence that any of the selected variables Granger-cause the purified surprises at the 5% significance level. Overall, the results of these diagnostic tests support the validity of the purified surprises predicted by XLNet.

5 Oil Supply Expectations Text Shocks

5.1 First-stage Verification of Instrument Strength

My deployment of the proxy-VAR approach to extract the text shock assumes that the instrument used, i.e., the purified surprises, is correlated with the former but uncorrelated with other shocks. Even so, standard inference will be invalid if the desired correlation is weak. I follow the suggestions of Montiel Olea et al. (2021) to test the strength of the purified surprises as an instrument. Specifically, I perform an F-test in the first-stage regression of the oil price residual from the VAR model on the purified surprises as the instrument. The authors recommend instruments having F-statistics of at least 10 to safely conclude that a weak instrument problem is not present. The text found in Figure 6 between the second and third row of plots shows that the F-statistic associated with using purified surprises as an instrument is safely above the recommended threshold. Specifically, the purified surprises have an F-statistic of 11.46 and explain about 2.18% of the oil price residual (about 2% when adjusted). When allowing for heteroscedasticity, the F-statistic falls to 6.87.

Note that the observed surprises have F-statistics of 22.67 and 10.55, where the latter statistic allows for heteroscedasticity. The relatively lower F-statistics of the purified surprises is consistent with the evidence of this paper and Degasperi (2021) that the observed surprises are conflating both demand and supply shocks, which can inflate F-statistics. Overall, I assume that no weak instrument problem is present.

5.2 Effects on the Oil Market and the U.S. Economy

Figure 6 presents the impulse responses to the text shock in black and blue, identified using the proxy-VAR approach. To ensure that interpretation of the responses are not due to the text shock's variance, I first scale the purified surprises by its standard deviation. I then normalise the shock to increase the real oil price by 10% on impact. The black lines are the point estimates and the blue areas are 68% confidence bands.[15]

A negative oil supply expectations shock (i.e., positive text shock) results in the immediate and statistically significant rise in the real oil price. World oil production declines shortly after impact, consistent with how OPEC announced quota cuts are implemented with a lag. This decline continues until a trough about 40 months out. World oil inventories increase persistently. One possible reason for this response is how negative supply expectations shocks coming from OPEC statements are viewed as signals for greater uncertainty about the future. Therefore, people prepare and stock up on oil inventories. Some stud-

[15] As all variables are in logs, the responses can be interpreted as elasticities. I follow Känzig (2021) and calculate the confidence bands using a moving block bootstrap with 10,000 simulations.

ies have shown empirical evidence for this behaviour, such as Gao et al. (2022). World IP contracts on impact and descends with time. When combined with the significant real oil price and global output responses, the response in oil inventories aligns with the literature about oil inventory demand shocks (e.g., Kilian and Murphy (2014)). The theory behind this interpretation is that oil inventory demand shocks driven by expectations of higher oil prices will increase inventories on impact, holding all else constant. Overall, the findings provide evidence that text shocks reflect changes to future oil supply expectations.

Text shocks also significantly impact the U.S. economy. Domestic IP declines immediately from a positive text shock and only bottoms out roughly 40 months out. Simultaneously, U.S. CPI stays elevated for most of the time horizon, peaking at 20 months after impact. The unemployment rate rises to a peak of around 0.2 percentage points and aggregate PCE continuously falls to -0.6%.[16] Overall, the FRB finds itself in a precarious position. Increasing the Federal Funds Rate could fight inflation, but would risk further shrinking economic activity and the labour market.

I also investigate the sensitivity of these impulse responses with respect to data frequency and sample periods in Appendix A.3.

5.3 OPEC's Words' Contribution to the Real Oil Price

This subsection follows Känzig (2021) by performing a historical decomposition of the real oil price to the text shock from 1975 through 2017.

Recall that the text shocks are derived from surprises isolated to OPEC's words about future oil supply, conditional on the embedding and weights of XLNet. Therefore, the decomposition only captures information about the portion of changes in oil supply expectations that is correlated with OPEC language. Given this, Figure 7 shows the cumulative historical contribution of text shocks to the real oil price.

[16] As in Känzig (2021), the impulse responses of these two variables are obtained by augmenting the baseline VAR model by one variable at a time. Whenever available, the augmented VAR models are estimated on the same sample period as the baseline model.

When OPEC strife was rampant during the late 1980s, high supply expectations contributed to the decline in the real oil price. Many believed in 1985 that OPEC quotas were unenforceable, especially with Saudi Arabia raising its own production to punish disobeying members (Yergin (2011)). A small reversal in supply expectations is seen when OPEC attempted to reunite in 1986–1987, contributing to the temporary reversal in the real oil price. The text shock also influenced the spike in prices during 1990–1991 since supply disruptions were expected from the Gulf War.

Changes in supply expectations have also had major contributions to the rise in real oil prices, as seen during the Venezuelan crisis. With a general strike causing oil production to drop by almost 3 million barrels per day, lower supply expectations increasingly explained the following climb in prices between late 2002 and 2006.

Changes to supply expectations from OPEC's words also played a role in recent times. For instance, with Saudi Arabia choosing not to cut production after the 2014 oil price collapse, the oil glut was expected to remain (Arezki and Blanchard (2015)).

Note that there are times when the contribution of text shocks is negligible. Two examples are how the increase in the real oil price between 2006 and mid-2008 was driven by higher oil demand (Kilian (2009)), and the elevated price in 2010–2014.

Overall, this decomposition shows how changes in supply expectations from OPEC's words affected the real oil price throughout time with strong and muted contributions. The two findings in tandem validate the text shock of the neural network.

6 Puzzles Disappear Using Purified Surprises

6.1 Differences in Baseline VAR Impulse Responses

Given my hypothesis that the training process of the XLNet purifies the surprises of noise and information effects, impulse responses estimated from my text shock and those estimated from Känzig (2021)'s news shock should be different. Figure 6 shows this comparison, where black and blue depict the former and red depicts the latter.

One immediate difference is that world IP expands for roughly the first 10 months after impact of Känzig (2021)'s news shock. As argued in the informational frictions model of Degasperi (2021), although the shock is representative of negative supply expectations and is normalised to increase the real oil price on impact, the initial expansion in the response is an output puzzle. In contrast, a positive text shock presents no such puzzle by causing world IP to contract on impact and declines more negatively over time. This difference within the first year showcases the improvement from XLNet: An impulse response that is more aligned with theory overall.

Additional evidence supporting the text shock as being cleaner is the differences in response of the real oil price. The point estimate of the response coming from the text shock drops more sharply and quickly compared to that coming from the news shock for much of the first year. One potential explanation behind the response differences is that the text shock is purified of demand information that would otherwise inflate the impulse responses. This rationale is supported by the conclusion of the historical decomposition in Figure 7 and the findings of Kumar and Mallick (2024): oil supply expectations from OPEC's words have both strong and minute contributions to price fluctuations over time due to possible mechanisms such as increased substitutability between crude oil and other forms of energy (e.g., shale oil).

Regarding world oil inventories, the point estimate coming from the text shock are above and outside the confidence bands of the response coming from the news shock. This amplified magnitude corroborates the findings of Moussa and Thomas (2023), who show that forward-looking variables like world oil inventories have a strong and immediate response to negative oil supply expectations shocks. That is, the text shock results in world oil inventories to respond more as expected. Overall, the combined responses of world oil inventories, global output, and the real oil price from the text shock are also consistent with estimations from Baumeister and Hamilton (2019) and Kilian and Murphy (2014) regarding oil inventory demand shocks.

A similar puzzle arises in the U.S. economy when Känzig (2021)'s news shock. In particular, the unemployment rate declines on impact for several months before rising as expected. Conceptually, negative supply expectations shocks should cause an unambiguous increase in unemployment through channels such as precautionary savings (Edelstein and Kilian (2009)). However, the variable responds to the text shock by *unambiguously* increasing with roughly the same magnitude as those estimated in Känzig (2021). Similar to the oil market variables, the observed surprises being conflated with oil demand information could be a culprit behind this puzzle.

Importantly, the impulse response of U.S. CPI from the text shock are quantitatively weaker within the first year compared to that from the news shock. Conventional wisdom suggests that *both* oil supply and demand expectations shocks cause overall inflation to rise due to crude oil costs indirectly affecting consumer prices through the channel of refined products. By using XLNet to filter out demand information from the text shock, the impulse response of domestic inflation is no longer inflated and is instead isolated to changes in supply expectations.

The differences in responses of the baseline variables suggest that noise and information effects found in Känzig (2021) might have heterogeneous effects. Further differences in responses of wider transmission mechanisms can be found in Appendix A.3.3. Importantly, credence is lent towards neural network methods for the literature. By removing noise and information effects, these methods allow for event study techniques applied on OPEC and the oil market to extract supply expectational shocks without violating the identification assumption and produces empirical responses that align with those predicted by theory about the oil market and the economy.

6.2 Differences in Filtering Effects

As part of a sensitivity analysis, Känzig (2021) does investigate if the observed surprises contain information effects by constructing an alternative oil supply surprise series using revisions in OPEC's global oil demand forecasts around conference meetings and strategies from the monetary policy literature (e.g., Romer and Romer (2004); Miranda-Agrippino and Ricco (2021)). Because the impulse responses of the baseline variables from this informationally robust expectations shock were more or less contained within those from the main news shock, Känzig (2021) concludes that the observed surprises don't suffer from any strong confounding factors.

However, there are some possible issues with this refinement attempt. First, the alternative surprises only go back to 2001 due to OPEC making its global oil demand forecast reports available only back to that year. Second, Känzig (2021) notes that several reports have a timing issue where the forecasts and released before the OPEC announcements. Therefore, the already shorter alternative surprise series could have months where the refinement attempt is unable to remove information effects. Third, remember from Figure 1 that the OPEC statements contain varying percentages of demand sentences throughout time. As a result, market participants reacting to these announcements will be reading text that contain information about both oil supply and demand. The market reaction to the latter information component doesn't necessarily equal the reaction to OPEC's separate oil demand forecast reports. Therefore, the alternative surprises potentially still conflate oil demand information from the headline text of the OPEC statements.

Because the two-step training process of XLNet forces it to predict what the surprises should be using only information about expected oil supply from the direct and headline communication of OPEC, the possibility of demand information conflating the purified surprises through the channel of statement text is not a concern. My purification of the surprises is why the differences between the impulse responses from the text shock and those from the news shock are economically significant.

Appendix A.3.4 also presents how differences between the impulse responses of the baseline variables from my text shock and those from the heteroscedasticity-based approach of Rigobon and Sack (2004) for filtering are still economically significant.

7 Conclusion

This paper uses XLNet, a state-of-the-art neural network for text analysis, to approximate the mapping from OPEC statement text to oil supply expectations. Using the trained network and a distinct set of OPEC statements manually edited to only discuss about future oil supply, I produce a new oil supply expectations shock series that is directly tied to OPEC called text shocks. These text shocks are derived from a unique two-step training process that forces XLNet to first understand the relationship between OPEC language and variations in oil futures prices, then to predict variations that come only from statements about expected oil supply. The result is a text shock purified of noise, demand information, and OPEC's endogenous response.

Text shocks have significant and meaningful impacts on the oil market and economy, such as causing strong stagflation on the U.S. macroeconomy and contributing to historical movements in the real oil price. I also find that these text shocks produce impulse responses that are more in-line with theory. In contrast to previous studies, output puzzles, such as world production expanding and the U.S. unemployment rate declining in the near-term, disappear when faced with a positive text shock.

Whilst the differences between the impulse responses from my text shock and the news shock of Känzig (2021) are empirically small, their economic significance is anything but. By using the untapped information contained in the text of OPEC communication about expected oil supply and the state-of-the-art performance of XLNet, I create an oil supply expectations shock that is not only more directly tied to the organisation, but is also free of demand information coming from the text itself. In contrast, this source of conflation has not been addressed in prior studies. Ultimately, the application of this paper showcases neural networks for text analysis as a legitimate and novel tool to extract a text shock that is one step closer towards being a cleaner oil supply expectations shock.

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Figures and Tables

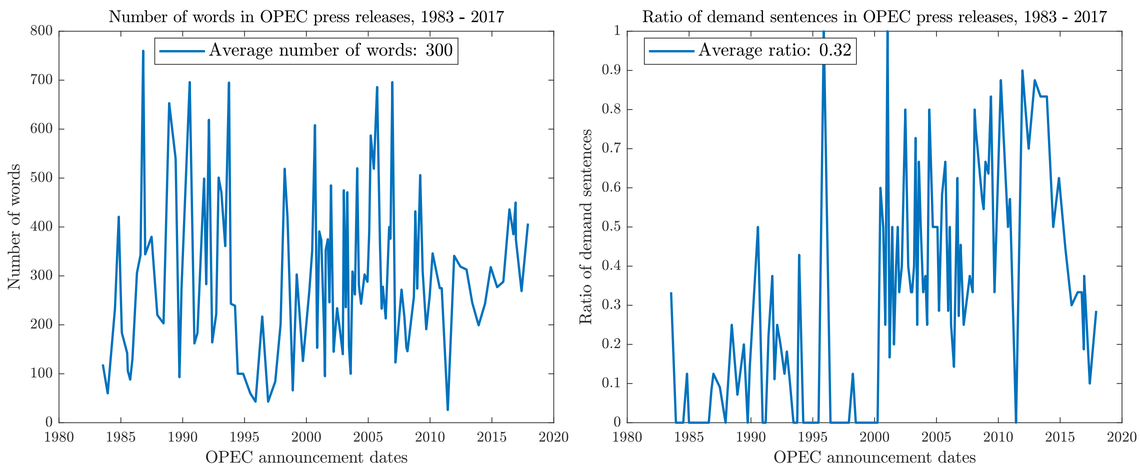


Figure 1: Word count (top) and percentage of demand sentences (bottom) of OPEC announcements, 1983 - 2017

The above counts are for OPEC announcements that have underwent pre-processing. The presence of demand information is shown by calculating the ratio of demand sentences removed in an OPEC announcement to the total number of sentences.

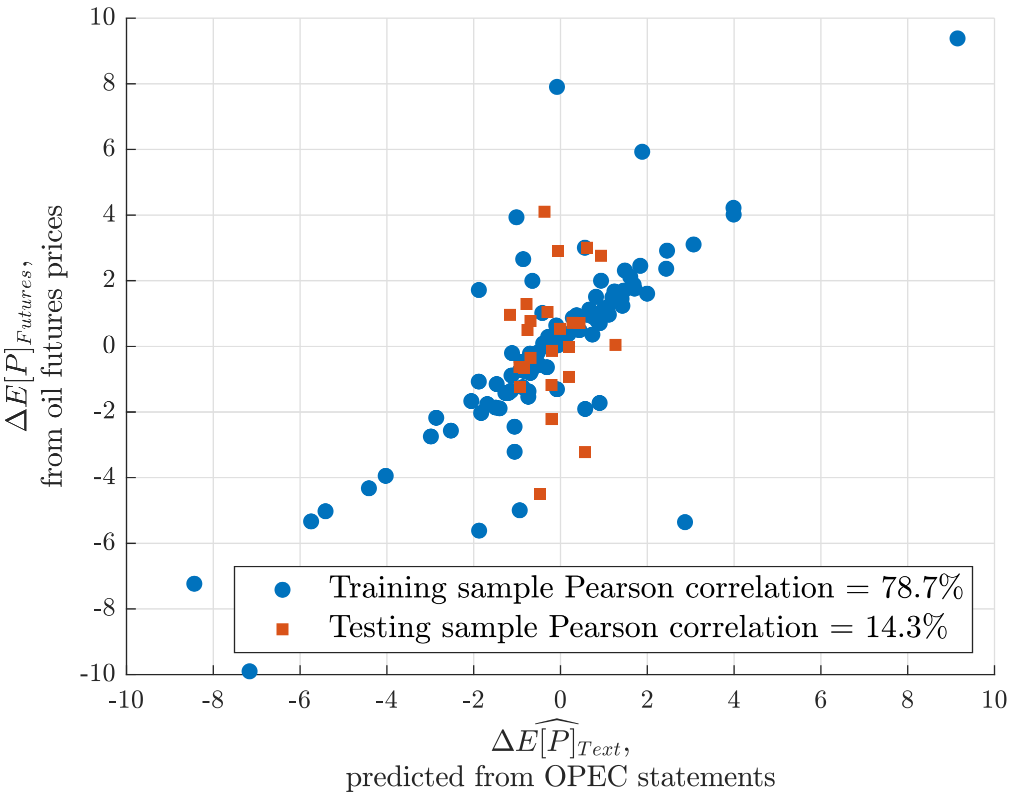


Figure 2: Pearson correlation coefficient between neural network predictions and measured oil supply surprises

The vertical axis, $\Delta E[P]_{Futures}$, is the first principal component of changes in oil futures prices for the day of and day before OPEC announcements. The horizontal axis, $\Delta \widehat{E[P]}_{Text}$, is the neural network's predictions of $\Delta E[P]_{Futures}$ from OPEC announcements.

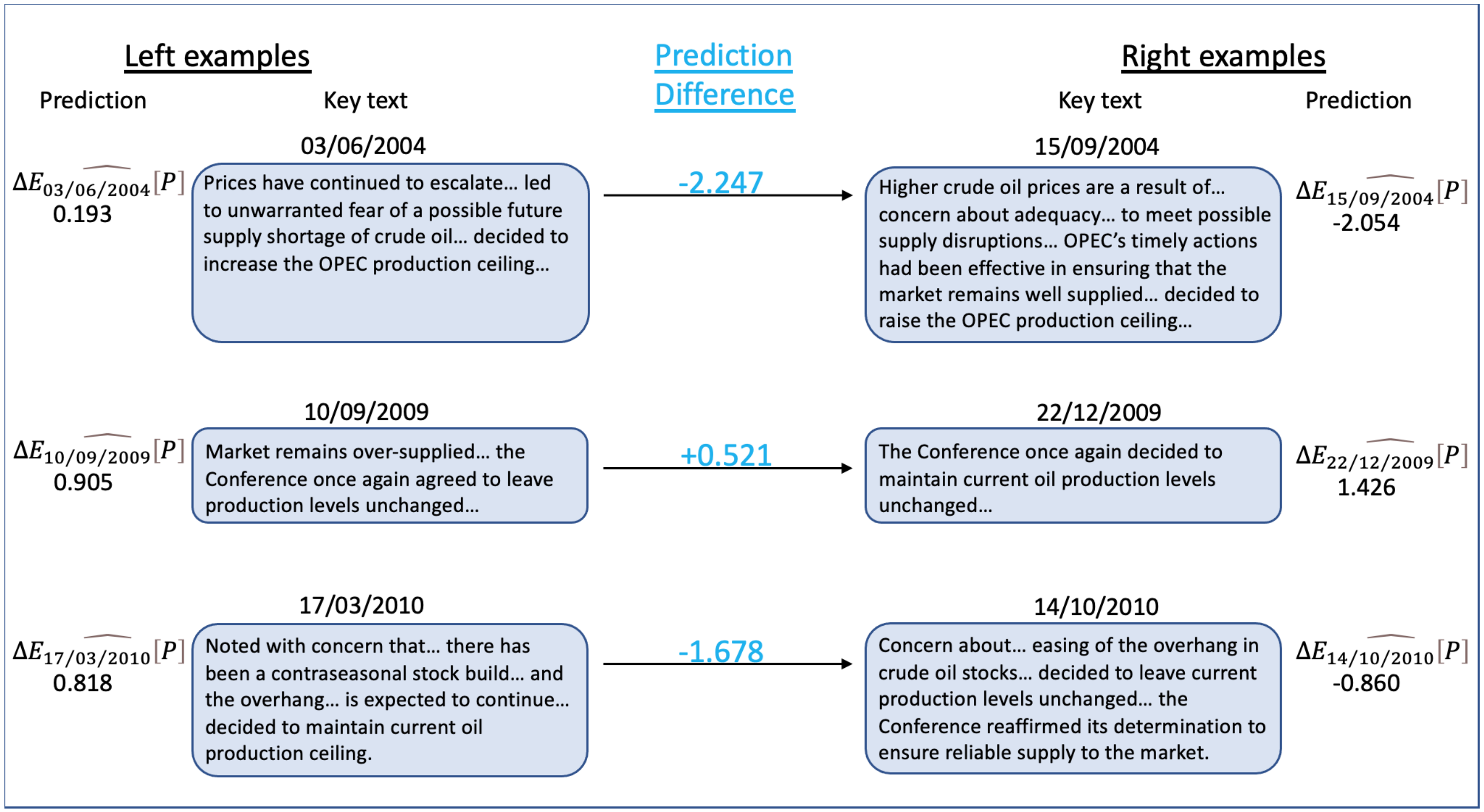


Figure 3: Neural network predictions for different OPEC announcements

Each row compares two OPEC announcements that have similar text regarding wording and meaning. The primary differences are written in the blue boxes. These example announcements have few differences as to be able to identify what is possibly underlying the change in XLNet's predictions.

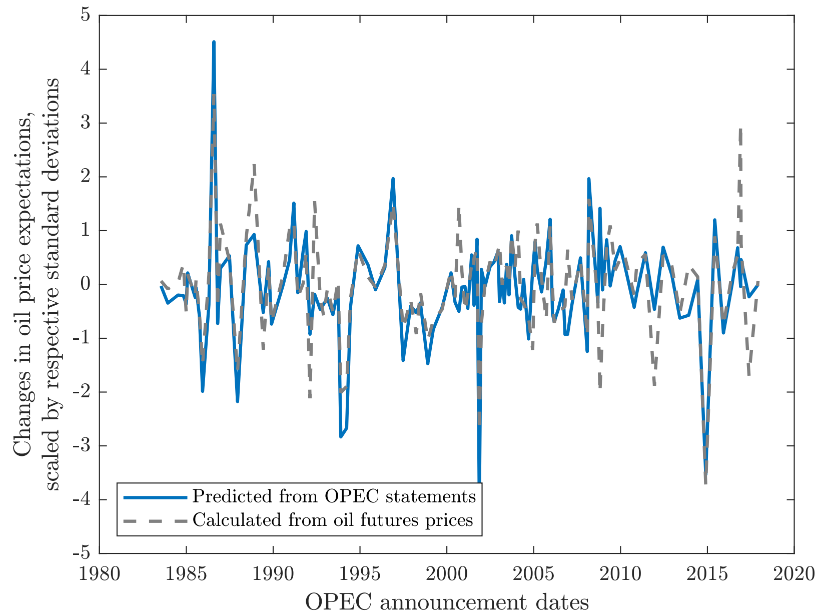


Figure 4: Changes in oil supply surprise series v. in text shocks, scaled by respective standard deviations

The dashed grey line is the oil supply surprise series, calculated from oil futures prices. It is the first principal component of two variables: changes in oil futures prices (using the 1-month to 12-month WTI crude contracts) for the day of and day before OPEC announcements. The solid blue line, $\widehat{\Delta E[P]_{Text}}$, is the neural network's prediction of the previous variable from OPEC statements.

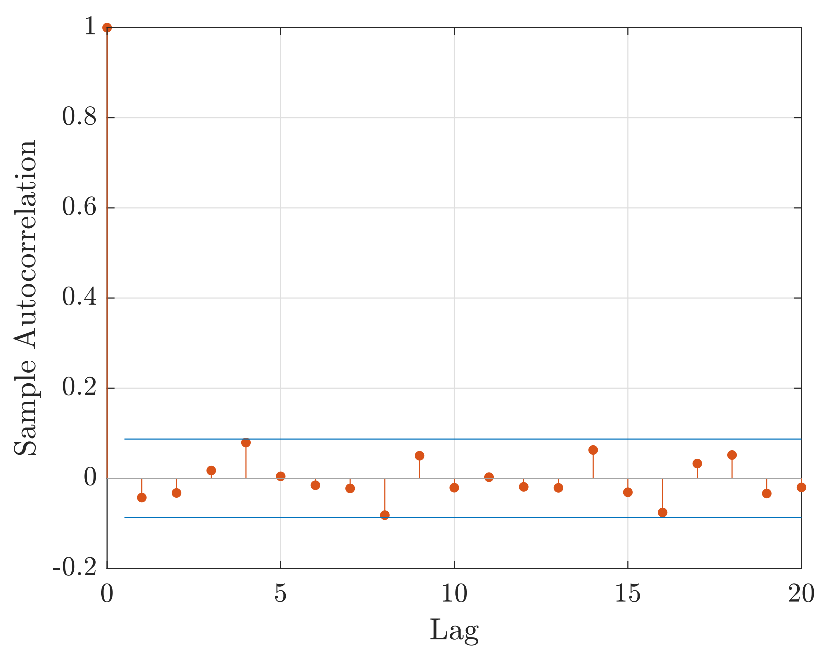
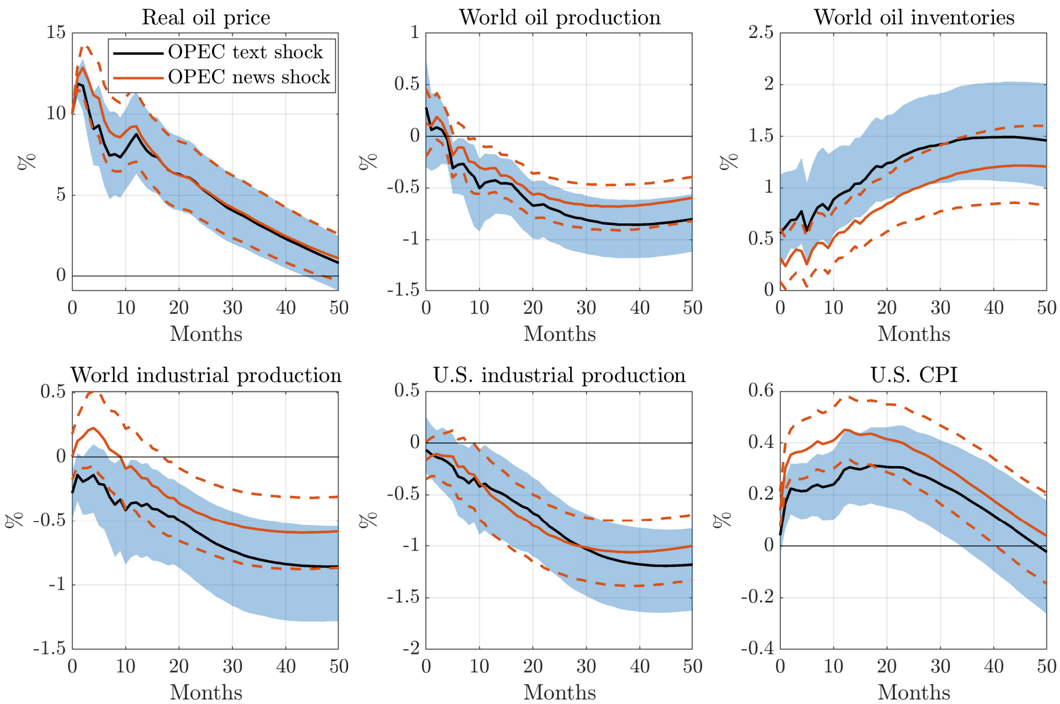


Figure 5: The autocorrelation function of XLNet's predicted oil supply surprises up to 20 lags

Explanatory Variable	p-value
Purified oil supply surprises	0.5154
Oil price	0.7925
World oil production	0.1620
World oil inventories	0.7627
World industrial production	0.9970
U.S. industrial production	0.9182
U.S. CPI	0.9379
Fed funds rate	0.6118
S&P 500	0.9539
Nominal effective exchange rate	0.5697
Geopolitical risk	0.1580
Joint	0.6526

Table 1: Granger causality tests

The table shows the p-values of a series of Granger causality tests of the purified oil supply surprises using a variety of macroeconomic and financial variables. In order to conduct standard statistical inference, all series are made stationary by taking first differences whenever necessary. A lag order of 12 was selected and a constant term was included.



First stage regression: Coeff.: 2.07, F: 11.46, Robust F: 6.87, R^2: 2.18%, Adj. R^2: 1.99%, Obs.: 516

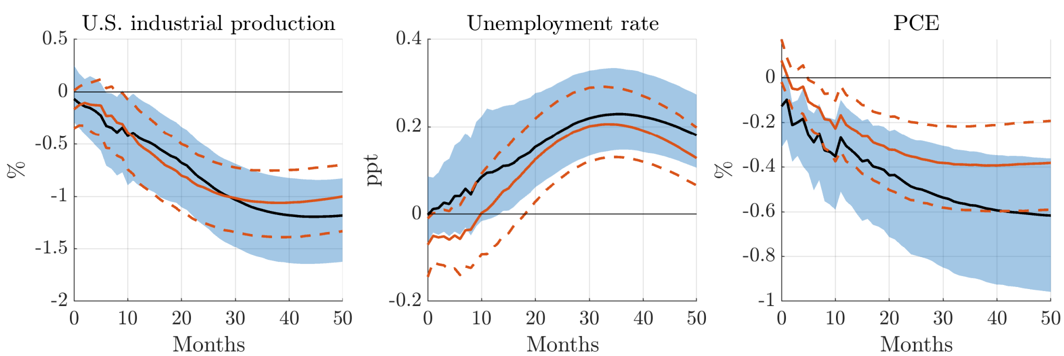


Figure 6: Test on instrument strength of the purified oil supply surprises and impulse responses to text shocks v. to oil supply news shocks

Results of the first-stage regression of the oil price residual on the purified surprises from XLNet as the instrument are presented between the second and third rows. Strong instruments are recommended to have F-statistics greater than 10. The impulse responses are normalised to increase the real oil price by 10% on impact. The black (red) lines are the point estimates made using the text shock (news shock). The shaded areas (dashed lines) are 68% confidence bands.

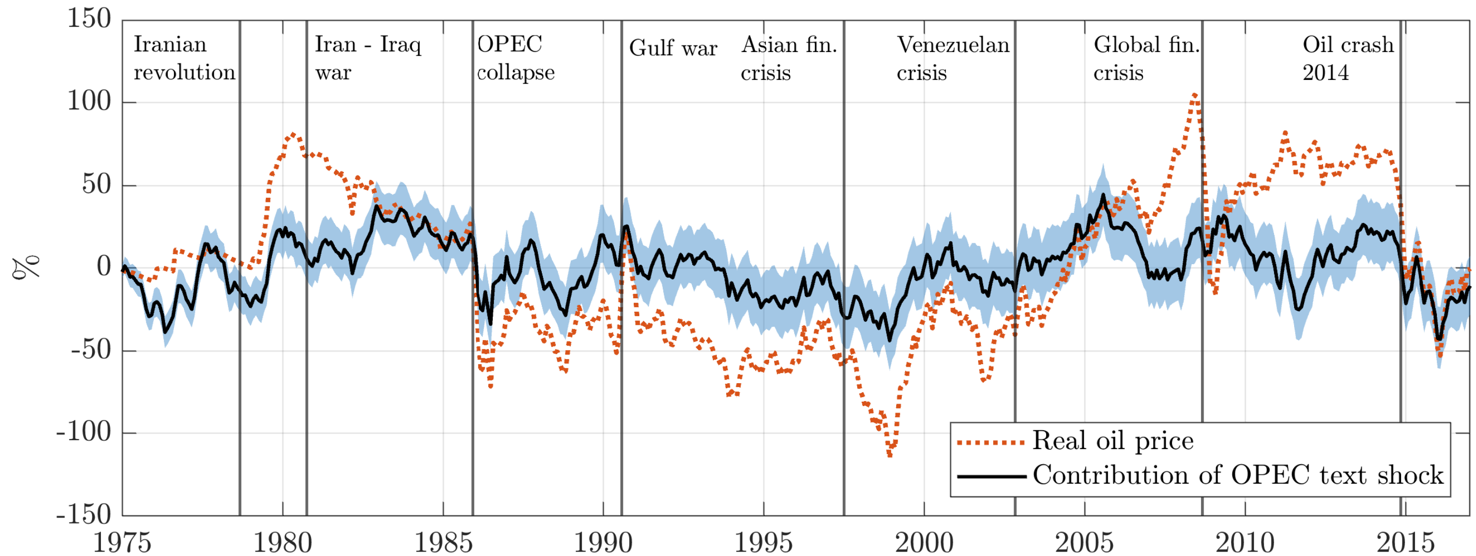


Figure 7: Historical decomposition of text shocks to the real oil price

The black line is the cumulative historical decomposition of text shocks to the real oil price. The shaded area represents 68% confidence bands. The dotted red line is the percentage change from the mean of the oil price. The grey, vertical lines indicate historical events in the oil market. From left to right, highlighted events are the start of the Iranian revolution in Sep. 1978, the beginning of the Iraq-Iran war in Sep. 1980, the collapse of OPEC in Dec. 1985, the start of the Persian Gulf war in Aug. 1990, the Asian financial crisis of Jul. 1997, the Venezuelan crisis in Nov. 2002, start of the global financial crisis in Sep. 2008, and the collapse of the real oil price in Jun. 2014.

A XLNet's Initial Training, Look-ahead Bias, and Robustness Checks

A.1 Initial Training of XLNet

Yang et al. (2020) train their neural network to predict missing words when given input text that is converted to only contain word tokens.[17] The parameters of the neural network then update such that it is able to more accurately and consistently predict the missing words. This task was only achievable through training XLNet with the BookCorpus (11,038 books), the entire English Wikipedia (over 6.5 million articles), Giga5 (9.9 million news articles), ClueWeb12 (733 million websites), and Common Crawl (text from websites totalling over 1,000 terabytes of data). The generality of this dataset allows for XLNet to build a foundation in understanding the general English language with state-of-the-art recognition in the machine learning literature.

Yang et al. (2020) then take XLNet's structure, trained weights, and embedding as a starting point to perform other tasks that are considered benchmark exercises in the literature of machine learning for text analysis. These exercises allow for XLNet's parameters to undergo further adjustment through a process known as fine-tuning. The authors demonstrate that by using the pre-trained weights, they were able to achieve greater accuracy on these new tasks compared to not using the pre-trained weights and to other text analysis methods. This approach of pre-training parameters on a large and general collection of text and then using them as initial parameters before fine-tuning for a new task is called transfer learning. Most relevant for this paper is how Yang et al. (2020) and others show that transfer learning decreases the data requirement whilst achieving similar accuracy on new tasks.

A.2 Addressing Look-ahead Bias

A valid concern when using off-the-shelf neural networks for text analysis is look-ahead bias. As explained in Sarkar and Vafa (2024), look-ahead bias occurs whenever these networks predict values in the past using information in the future. The reason for the existence of this issue comes from how these neural networks are initially trained with large amounts of data sources, which increases the probability that information from the future was used in this initial training of the network weights.

From Appendix A.1, recall that XLNet was initially trained by Yang et al. (2020) using a large variety of data, which includes headline news text from sources such as Bloomberg. Regardless, the specific version of XLNet used in this paper, called xlnet-base-cased, addresses the concern of look-ahead bias because its initial training data was restricted by its authors to only BookCorpus and the entire English Wikipedia. Whilst this restriction was originally implemented in order to properly compare the performance of XLNet against competing state-of-the-art neural networks, it also benefits this paper because little to no information about the intersection of OPEC communication, the oil futures market, and oil supply expectations shocks is used to initially train the neural network.

[17] This conversion reduces the input vocabulary size. For example, {"decreasing", "increasing"} can be broken into the following tokens: {"de", "in", "creas", "ing"}.

A.3 Robustness Checks

A.3.1 Data Frequency

Because the baseline VAR model runs on monthly data, I have to aggregate the model to quarterly frequency in order to investigate the effects of the text shock on important macroeconomic variables, such as real GDP. This aggregation also serves as an opportunity to see if the text shock is sensitive to data frequency. Appendix Figure D.6 display impulse responses (the variables of quarterly investment and consumption) that are qualitatively similar to the monthly baseline and augmented VAR models. Whilst the results show that the purified surprises are a weaker instrument in this exercise, this decline should be expected for two reasons. First, oil demand information and OPEC's endogenous response to global economic activity are no longer conflating the instrument. Second, aggregating to quarterly frequency results in a lower data sample and thus, lower signal-to-noise ratio.

A.3.2 Sample Periods

Given the severity and implications of the text shock on global output and the U.S. economy, it's important to consider how sensitive these results are to the sample period of data considered. I estimate the baseline and augmented VAR models for three smaller subsamples: From July 1982 through December 2017, from January 1974 through November 2007, and from January 1974 through December 2010. Regarding the first subsample, recall that the baseline estimation uses data starting from January 1974. The motivation for extending the estimation period well before the period from which the purified surprises can be predicted from the neural network is the assumption that the precision of the impulse responses will be improved whilst the point estimates remain similar. In order to test this hypothesis, I restrict the estimation period to be as close to the sample size of the collected OPEC announcements and purified surprises, which is from July 1983 through November 2017. July 1982 was chosen as the subsample starting date due to the lag order of the VAR model being kept as 12. The findings are presented in Appendix Figure D.7. When comparing against the baseline impulse responses shown in Figure 4, the text shock yields responses that turn out to be weaker and less persistent for some variables. However, the results are qualitatively similar, such as world IP and oil inventories still contracting and expanding on impact, respectively, implying that the text shock still corroborates the dynamic responses to inventory demand shocks documented in the literature. The point estimate of the U.S. unemployment rate still unambiguously increases as well. Overall, the qualitative similarities support the aforementioned hypothesis.

Appendix Figures D.8 and D.9 present the responses when estimating with subsamples that exclude the Great Recession and shale oil revolution, respectively. The rationale behind the former subsample is to investigate the effects of the text shock about oil supply expectations whilst ignoring the recovery events and dynamics of the U.S. after the Great Financial Crisis and Great Recession. The qualitative and quantitative similarities between the responses and those from the baseline VAR model show that omitting either historical event does not meaningfully change the results. Most importantly are the facts that the disappearance of the output puzzles previously estimated for world output and the U.S. unemployment rate and the conformity to the oil inventory demand shock literature are both robust to the subsamples considered.

A.3.3 Differences in Wider Transmission Mechanisms

To better understand the differences between the text shock and Känzig (2021)'s oil supply news shock, I compare the impulse responses of various PCE components, CPI categories, and U.S. exchange rates estimated using both shocks. Appendix Figure D.3 presents the responses of PCE in total, energy, non-durables, durables, and services. Text shocks cause aggregate PCE to decline more severely through the channels of PCE in energy, durables, and services. In contrast to Känzig (2021), the point estimate of non-durables PCE contracts on impact and by twofold. Furthermore, durables PCE contracts for a longer time to the text shock. However, all other PCE categories respond with little differences to either shock.

The impulse responses for CPI components to both shocks are depicted in Appendix Figure D.4. Mostly small differences are present between the sets of responses. Inflation in energy, non-durables, and services have weaker point estimates in their responses to the text shock, particularly within the first year for services and non-durables. These differences do converge to zero, which explains the increasing similarity in the response of headline inflation to either shock at longer time horizons. However, one noticeable difference is the response of core inflation. Whilst the component increase slowly over time and are statistically significant when estimated using the news shock, the response to the text shock are insignificant and weaker. Interestingly, this response better align with previous findings, such as Kilian and Zhou (2023), who show that oil price shocks don't meaningfully increase U.S. core inflation.

I investigate the linkage between U.S. exchange rates and the real oil price because most crude oil is priced in U.S. dollars. Although the top row of Appendix Figure D.5 shows the narrow and broad U.S. NEERs immediately depreciating from either shock, the responses to the text shock are less negative in the near term. Nonetheless, both shocks produce similar responses.

More differences are found within bilateral exchange rates. From the bottom row of Appendix Figure D.5, we see that the Japanese Yen notably appreciates with greater severity against the dollar and for a longer duration in response to the text shock. Furthermore, Sweden's currency quickly depreciates against the dollar when hit with the text shock. In contrast, the exchange rate between the U.K. and U.S. responds little to the text shock. On the other side, currencies of major importers such as Russia, Nigeria, and Mexico depreciate for the entire horizon, although the magnitude of the responses differ between the two shocks. Despite this heterogeneity, the results from the text shock reinforce Känzig (2021) by reconciling the negative correlation found between the dollar and real oil price in Klitgaard et al. (2019).

A.3.4 The Heteroscedasticity-based Approach

Recall that one of the main refinement that neural networks such as XLNet can provide to event studies on the oil market is the removal of noise contamination. As such, it's important to investigate how the results compare to the standard approach in the literature used to address issues of noise contamination: The heteroscedasticity-based identification approach of

Rigobon and Sack (2004). Specifically, the approach theoretically filters out contamination in the oil supply surprise series by comparing variation in oil futures prices around OPEC announcements to movements observed within equally long and otherwise similar event windows not around OPEC announcements. The identifying assumptions are that the variance of oil supply expectations shocks increase around the time of OPEC announcements, that this variance does not change across different OPEC announcements, and that the variance of all other shocks are unchanged. The approach then complements the VAR residual covariance restrictions with the moment conditions for the heteroscedasticity-based estimator.

As shown in Appendix Figure D.10, the impulse responses estimated using the approach of Rigobon and Sack (2004) are fairly similar to those estimated from the text shock except one important distinction. Specifically, the latter is able to address the puzzling expansion of world IP in the near-term whilst the former cannot. Overall, the comparison supports the idea that neural networks for text analysis are a legitimate alternative for addressing issues of noise contamination when estimating oil supply expectations shocks. The method goes a step further by also purifying the oil supply surprises of information about oil demand and OPEC's endogenous response to global economic activity.

B Dates of OPEC Announcements Dates and Baseline VAR variables

This Data Appendix provides a chronological timeline of historical OPEC announcements used to calculate the oil supply surprises and visually depicts the variables used in the baseline VAR model. For full disclosure, all data series discussed in this appendix, such as oil futures prices, were provided by Känzig (2021) through his online replication package hosted on openICPSR, which is licensed under the CC BY 4.0 License.[18]

B.1 OPEC Announcements

Table B.1 below lists the date when each OPEC announcement is released. The specific control dates used in the comparison to the heteroscedasticity-based approach of Rigobon and Sack (2004) in Appendix A are also listed. Finally, a short description is provided for each OPEC announcement in the table.

For my text analysis, I collect all announcements from July 1983 through November 2017. The end date was chosen to properly compare impulse responses from vector autoregressions using my text shock to those estimated in Känzig (2021). All announcements dating back through 2002 were sourced from the official website and archive of OPEC.[19] I extend my sample of announcements back through July 1990 using the Wayback Machine.[20] Finally, announcements dating back through July 1983 are hand-typed from OPEC (1990).

[18] https://www.openicpsr.org/openicpsr/project/122886/version/V1/view

[19] https://www.opec.org/opec_web/en/press_room/28.htm

[20] A non-profit initiative by the Internet Archive that serves as a digital archive of the World Wide Web.

Month	Announcement Date	Control Date	Additional Information
1983M04		19/04/1983	
1983M05		17/05/1983	
1983M06		21/06/1983	
1983M07	19/07/1983		68th meeting of the OPEC conference
1983M08		12/08/1983	
1983M09		09/09/1983	
1983M10		07/10/1983	
1983M11		11/11/1983	
1983M12	09/12/1983		69th meeting of the OPEC conference
1984M01		11/01/1984	
1984M02		08/02/1984	
1984M03		14/03/1984	
1984M04		11/04/1984	
1984M05		09/05/1984	
1984M06		13/06/1984	
1984M07	11/07/1984		70th meeting of the OPEC conference
1984M08		29/08/1984	
1984M09		26/09/1984	
1984M10	31/10/1984		71st (extraordinary) meeting of the OPEC conference
1984M11		28/11/1984	
1984M12	29/12/1984		72nd meeting of the OPEC conference
1985M01	30/01/1985		73rd meeting of the OPEC conference
1985M02		11/02/1985	
1985M03		11/03/1985	
1985M04		08/04/1985	
1985M05		06/05/1985	
1985M06		10/06/1985	

Table B.1: OPEC announcement and control dates from April 1983 through December 2017.

Month	Announcement Date	Control Date	Additional Information
1985M07	07/07/1985,		Consultative meeting of the OPEC conference,
	25/07/1985		74th meeting of the OPEC conference
1985M08		02/08/1985	
1985M09		06/09/1985	
1985M10	04/10/1985		75th (extraordinary) meeting of the OPEC conference
1985M11		11/11/1985	
1985M12	09/12/1985		76th meeting of the OPEC conference
1986M01		20/01/1986	
1986M02		18/02/1986	
1986M03		24/03/1986	
1986M04	21/04/1986		77th meeting of the OPEC conference
1986M05		06/05/1986	
1986M06		03/06/1986	
1986M07		08/07/1986	
1986M08	05/08/1986		78th meeting of the OPEC conference
1986M09		24/09/1986	
1986M10	22/10/1986		79th meeting of the OPEC conference
1986M11		24/11/1986	
1986M12	20/12/1986		80th meeting of the OPEC conference
1987M01		26/01/1987	
1987M02		23/02/1987	
1987M03		30/03/1987	
1987M04		27/04/1987	
1987M05		26/05/1987	
1987M06	27/06/1987		81st meeting of the OPEC conference
1987M07		13/07/1987	
1987M08		17/08/1987	

Month	Announcement Date	Control Date	Additional Information
1987M09		14/09/1987	
1987M10		12/10/1987	
1987M11		16/11/1987	
1987M12	14/12/1987		82nd meeting of the OPEC conference
1988M01		12/01/1988	
1988M02		16/02/1988	
1988M03		15/03/1988	
1988M04		12/04/1988	
1988M05		17/05/1988	
1988M06	14/06/1988		83rd meeting of the OPEC conference
1988M07		25/07/1988	
1988M08		29/08/1988	
1988M09		26/09/1988	
1988M10		31/10/1988	
1988M11	28/11/1988		84th meeting of the OPEC conference
1988M12		07/12/1988	
1989M01		04/01/1989	
1989M02		08/02/1989	
1989M03		08/03/1989	
1989M04		05/04/1989	
1989M05		10/05/1989	
1989M06	07/06/1989		85th meeting of the OPEC conference
1989M07		26/07/1989	
1989M08		30/08/1989	
1989M09	27/09/1989		3rd meeting of the 8 ministerial monitoring committee
1989M10		31/10/1989	
1989M11	28/11/1989		86th meeting of the OPEC conference
1989M12		29/12/1989	
1990M01		26/01/1990	
1990M02		23/02/1990	
1990M03		30/03/1990	

Month	Announcement Date	Control Date	Additional Information
1990M04		27/04/1990	
1990M05		25/05/1990	
1990M06		29/06/1990	
1990M07	27/07/1990		87th meeting of the OPEC conference
1990M08		16/08/1990	
1990M09		13/09/1990	
1990M10		18/10/1990	
1990M11		15/11/1990	
1990M12	13/12/1990		88th meeting of the OPEC conference
1991M01		15/01/1991	
1991M02		12/02/1991	
1991M03	12/03/1991		3rd meeting
1991M04		02/04/1991	
1991M05		07/05/1991	
1991M06	04/06/1991		89th meeting of the OPEC conference
1991M07		24/07/1991	
1991M08		28/08/1991	
1991M09	25/09/1991		4th meeting of the ministerial monitoring committee
1991M10		23/10/1991	
1991M11	27/11/1991		90th meeting of the OPEC conference
1991M12		17/12/1991	
1992M01		21/01/1992	
1992M02	15/02/1992		6th meeting of the ministerial monitoring committee
1992M03		24/03/1992	
1992M04		28/04/1992	
1992M05	22/05/1992		91st meeting of the OPEC conference
1992M06		18/06/1992	
1992M07		16/07/1992	
1992M08		20/08/1992	

Month	Announcement Date	Control Date	Additional Information
1992M09	17/09/1992		9th meeting of the ministerial monitoring committee
1992M10		26/10/1992	
1992M11	27/11/1992		92nd meeting of the OPEC conference
1992M12		16/12/1992	
1993M01		20/01/1993	
1993M02	16/02/1993		10th meeting of the ministerial monitoring committee
1993M03		11/03/1993	
1993M04		08/04/1993	
1993M05		13/05/1993	
1993M06	10/06/1993		93rd meeting of the OPEC conference
1993M07		29/07/1993	
1993M08		26/08/1993	
1993M09	29/09/1993		94th (extraordinary) meeting of the OPEC conference
1993M10		25/10/1993	
1993M11	24/11/1993		95th meeting of the OPEC conference
1993M12		27/12/1993	
1994M01		31/01/1994	
1994M02		28/02/1994	
1994M03	26/03/1994		12th meeting of the ministerial monitoring committee
1994M04		14/04/1994	
1994M05		19/05/1994	
1994M06	16/06/1994		96th meeting of the OPEC conference
1994M07		19/07/1994	
1994M08		23/08/1994	
1994M09		20/09/1994	
1994M10		25/10/1994	

Month	Announcement Date	Control Date	Additional Information
1994M11	22/11/1994		97th meeting of the OPEC conference
1994M12		20/12/1994	
1995M01		17/01/1995	
1995M02		21/02/1995	
1995M03		21/03/1995	
1995M04		18/04/1995	
1995M05		23/05/1995	
1995M06	20/06/1995		98th meeting of the OPEC conference
1995M07		19/07/1995	
1995M08		23/08/1995	
1995M09		20/09/1995	
1995M10		25/10/1995	
1995M11	22/11/1995		99th meeting of the OPEC conference
1995M12		08/12/1995	
1996M01		05/01/1996	
1996M02		09/02/1996	
1996M03		08/03/1996	
1996M04		12/04/1996	
1996M05		10/05/1996	
1996M06	07/06/1996		100th meeting of the OPEC conference
1996M07		29/07/1996	
1996M08		26/08/1996	
1996M09		30/09/1996	
1996M10		28/10/1996	
1996M11	28/11/1996		101st meeting of the OPEC conference
1996M12		26/12/1996	
1997M01		23/01/1997	
1997M02		27/02/1997	
1997M03		27/03/1997	
1997M04		24/04/1997	
1997M05		29/05/1997	
1997M06	26/06/1997		102nd meeting of the OPEC conference

Month	Announcement Date	Control Date	Additional Information
1997M07		07/07/1997	
1997M08		04/08/1997	
1997M09		08/09/1997	
1997M10		06/10/1997	
1997M11		03/11/1997	
1997M12	01/12/1997		103rd meeting of the OPEC conference
1998M01		26/01/1998	
1998M02		23/02/1998	
1998M03	30/03/1998		104th (extraordinary) meeting of the OPEC conference
1998M04		22/04/1998	
1998M05		27/05/1998	
1998M06	24/06/1998		105th meeting of the OPEC conference
1998M07		27/07/1998	
1998M08		31/08/1998	
1998M09		28/09/1998	
1998M10		26/10/1998	
1998M11	26/11/1998		106th meeting of the OPEC conference
1998M12		22/12/1998	
1999M01		19/01/1999	
1999M02		23/02/1999	
1999M03	23/03/1999		107th meeting of the OPEC conference
1999M04		21/04/1999	
1999M05		26/05/1999	
1999M06		23/06/1999	
1999M07		21/07/1999	
1999M08		25/08/1999	
1999M09	22/09/1999		108th meeting of the OPEC conference
1999M10		27/10/1999	
1999M11		24/11/1999	
1999M12		29/12/1999	
2000M01		26/01/2000	

Month	Announcement Date	Control Date	Additional Information
2000M02		23/02/2000	
2000M03	29/03/2000		109th meeting of the OPEC conference
2000M04		19/04/2000	
2000M05		24/05/2000	
2000M06	21/06/2000		110th (extraordinary) meeting of the OPEC conference
2000M07		10/07/2000	
2000M08		14/08/2000	
2000M09	11/09/2000		111th meeting of the OPEC conference
2000M10		16/10/2000	
2000M11	13/11/2000		112th (extraordinary) meeting of the OPEC conference
2000M12		13/12/2000	
2001M01	17/01/2001		113th (extraordinary) meeting of the OPEC conference
2001M02		20/02/2001	
2001M03	17/03/2001		114th meeting of the OPEC conference
2001M04		03/04/2001	
2001M05		08/05/2001	
2001M06	05/06/2001		115th (extraordinary) meeting of the OPEC conference
2001M07	03/07/2001, 25/07/2001		116th (extraordinary) meeting of the OPEC conference
2001M08		30/08/2001	
2001M09	27/09/2001		117th meeting of the OPEC conference
2001M10		17/10/2001	
2001M11	14/11/2001		118th (extraordinary) meeting of the OPEC conference

Month	Announcement Date	Control Date	Additional Information
2001M12	28/12/2001		Consultative meeting of the OPEC conference
2002M01		11/01/2002	
2002M02		15/02/2002	
2002M03	15/03/2002		119th meeting of the OPEC conference
2002M04		24/04/2002	
2002M05		29/05/2002	
2002M06	26/06/2002		120th (extraordinary) meeting of the OPEC conference
2002M07		18/07/2002	
2002M08		22/08/2002	
2002M09	19/09/2002		121st meeting of the OPEC conference
2002M10		10/10/2002	
2002M11		14/11/2002	
2002M12	12/12/2002		122nd (extraordinary) meeting of the OPEC conferece
2003M01	12/01/2003		123rd (extraordinary) meeting of the OPEC conference
2003M02		11/02/2003	
2003M03	11/03/2003		124th meeting of the OPEC conference
2003M04	24/04/2003		Consultative meeting of the OPEC conference
2003M05		14/05/2003	
2003M06	11/06/2003		125th (extraordinary) meeting of the OPEC conference
2003M07	31/07/2003		126th (extraordinary) meeting of the OPEC conference
2003M08		27/08/2003	

Month	Announcement Date	Control Date	Additional Information
2003M09	24/09/2003		127th meeting of the OPEC conference
2003M10		02/10/2003	
2003M11		06/11/2003	
2003M12	04/12/2003		128th (extraordinary) meeting of the OPEC conference
2004M01		13/01/2004	
2004M02	10/02/2004		129th (extraordinary) meeting of the OPEC conference
2004M03	31/03/2004		130th meeting of the OPEC conference
2004M04		01/04/2004	
2004M05		06/05/2004	
2004M06	03/06/2004		131st (extraordinary) meeting of the OPEC conference
2004M07		14/07/2004	
2004M08		18/08/2004	
2004M09	15/09/2004		132nd meeting of the OPEC conference
2004M10		08/10/2004	
2004M11		12/11/2004	
2004M12	10/12/2004		133rd (extraordinary) meeting of the OPEC conference
2005M01	30/01/2005		134th (extraordinary) meeting of the OPEC conference
2005M02		16/02/2005	
2005M03	16/03/2005		135th meeting of the OPEC conference
2005M04		13/04/2005	
2005M05		18/05/2005	
2005M06	15/06/2005		136th meeting of the OPEC conference
2005M07		19/07/2005	

Month	Announcement Date	Control Date	Additional Information
2005M08		23/08/2005	
2005M09	20/09/2005		137th meeting of the OPEC conference
2005M10		10/10/2005	
2005M11		14/11/2005	
2005M12	12/12/2005		138th (extraordinary) meeting of the OPEC conference
2006M01	31/01/2006		139th (extraordinary) meeting of the OPEC conference
2006M02		08/02/2006	
2006M03	08/03/2006		140th meeting of the OPEC conference
2006M04		06/04/2006	
2006M05		04/05/2006	
2006M06	01/06/2006		141st (extraordinary) meeting of the OPEC conference
2006M07		10/07/2006	
2006M08		14/08/2006	
2006M09	11/09/2006		142nd meeting of the OPEC conference
2006M10	20/10/2006		Consultative meeting of the OPEC conference
2006M11		09/11/2006	
2006M12	14/12/2006		143rd (extraordinary) meeting of the OPEC conference
2007M01		18/01/2007	
2007M02		15/02/2007	
2007M03	15/03/2007		144th meeting of the OPEC conference
2007M04		10/04/2007	
2007M05		08/05/2007	
2007M06		12/06/2007	

Month	Announcement Date	Control Date	Additional Information
2007M07		10/07/2007	
2007M08		14/08/2007	
2007M09	11/09/2007		145th meeting of the OPEC conference
2007M10		03/10/2007	
2007M11		07/11/2007	
2007M12	05/12/2007		146th (extraordinary) meeting of the OPEC conference
2008M01		04/01/2008	
2008M02	01/02/2008		147th (extraordinary) meeting of the OPEC conference
2008M03	05/03/2008		148th meeting of the OPEC conference
2008M04		09/04/2008	
2008M05		07/05/2008	
2008M06		04/06/2008	
2008M07		09/07/2008	
2008M08		06/08/2008	
2008M09	10/09/2008		149th meeting of the OPEC conference
2008M10	24/10/2008		150th (extraordinary) meeting of the OPEC conference
2008M11		19/11/2008	
2008M12	17/12/2008		151st (extraordinary) meeting of the OPEC conference
2009M01		12/01/2009	
2009M02		09/02/2009	
2009M03	15/03/2009		152nd meeting of the OPEC conference
2009M04		30/04/2009	
2009M05	28/05/2009		153rd (extraordinary) meeting of the OPEC conference

Month	Announcement Date	Control Date	Additional Information
2009M06		11/06/2009	
2009M07		09/07/2009	
2009M08		13/08/2009	
2009M09	10/09/2009		154th meeting of the OPEC conference
2009M10		20/10/2009	
2009M11		24/11/2009	
2009M12	22/12/2009		155th (extraordinary) meeting of the OPEC conference
2010M01		13/01/2010	
2010M02		17/02/2010	
2010M03	17/03/2010		156th meeting of the OPEC conference
2010M04		15/04/2010	
2010M05		13/05/2010	
2010M06		10/06/2010	
2010M07		15/07/2010	
2010M08		12/08/2010	
2010M09		16/09/2010	
2010M10	14/10/2010		157th meeting of the OPEC conference
2010M11		15/11/2010	
2010M12	11/12/2010		158th (extraordinary) meeting of the OPEC conference
2011M01		05/01/2011	
2011M02		09/02/2011	
2011M03		09/03/2011	
2011M04		06/04/2011	
2011M05		11/05/2011	
2011M06	08/06/2011		159th meeting of the OPEC conference
2011M07		13/07/2011	
2011M08		10/08/2011	
2011M09		14/09/2011	
2011M10		12/10/2011	
2011M11		16/11/2011	

Month	Announcement Date	Control Date	Additional Information
2011M12	14/12/2011		160th meeting of the OPEC conference
2012M01		12/01/2012	
2012M02		16/02/2012	
2012M03		15/03/2012	
2012M04		12/04/2012	
2012M05		17/05/2012	
2012M06	14/06/2012		161st meeting of the OPEC conference
2012M07		11/07/2012	
2012M08		15/08/2012	
2012M09		12/09/2012	
2012M10		10/10/2012	
2012M11		14/11/2012	
2012M12	12/12/2012		162nd meeting of the OPEC conference
2013M01		25/01/2013	
2013M02		22/02/2013	
2013M03		22/03/2013	
2013M04		26/04/2013	
2013M05	31/05/2013		163rd meeting of the OPEC conference
2013M06		05/06/2013	
2013M07		03/07/2013	
2013M08		07/08/2013	
2013M09		04/09/2013	
2013M10		02/10/2013	
2013M11		06/11/2013	
2013M12	04/12/2013		164th meeting of the OPEC conference
2014M01		08/01/2014	
2014M02		12/02/2014	
2014M03		12/03/2014	
2014M04		09/04/2014	
2014M05		14/05/2014	
2014M06	11/06/2014		165th meeting of the OPEC conference
2014M07		25/07/2014	

Month	Announcement Date	Control Date	Additional Information
2014M08		29/08/2014	
2014M09		26/09/2014	
2014M10		31/10/2014	
2014M11	27/11/2014		166th meeting of the OPEC conference
2014M12		05/12/2014	
2015M01		02/01/2015	
2015M02		06/02/2015	
2015M03		06/03/2015	
2015M04		10/04/2015	
2015M05		08/05/2015	
2015M06	05/06/2015		167th meeting of the OPEC conference
2015M07		10/07/2015	
2015M08		07/08/2015	
2015M09		04/09/2015	
2015M10		02/10/2015	
2015M11		06/11/2015	
2015M12	04/12/2015		168th meeting of the OPEC conference
2016M01		07/01/2016	
2016M02		04/02/2016	
2016M03		03/03/2016	
2016M04		07/04/2016	
2016M05		05/05/2016	
2016M06	02/06/2016		169th meeting of the OPEC conference
2016M07		28/07/2016	
2016M08		25/08/2016	
2016M09	28/09/2016		170th (extraordinary) meeting of the OPEC conference
2016M10		26/10/2016	
2016M11	30/11/2016		171st meeting of the OPEC conference
2016M12	10/12/2016		OPEC and non-OPEC ministerial meeting

Month	Announcement Date	Control Date	Additional Information
2017M01		26/01/2017	
2017M02		23/02/2017	
2017M03		23/03/2017	
2017M04		27/04/2017	
2017M05	25/05/2017		172nd meeting of the OPEC conference
2017M06		29/06/2017	
2017M07		27/07/2017	
2017M08		31/08/2017	
2017M09		28/09/2017	
2017M10		26/10/2017	
2017M11	30/11/2017		173rd meeting of the OPEC conference
2017M12		28/12/2017	

B.2 Baseline VAR Variables

Figure B.1 graphs all of the series included in the baseline VAR model over the sample period from January 1974 through December 2017. All variables are depicted in logs multiplied by 100.

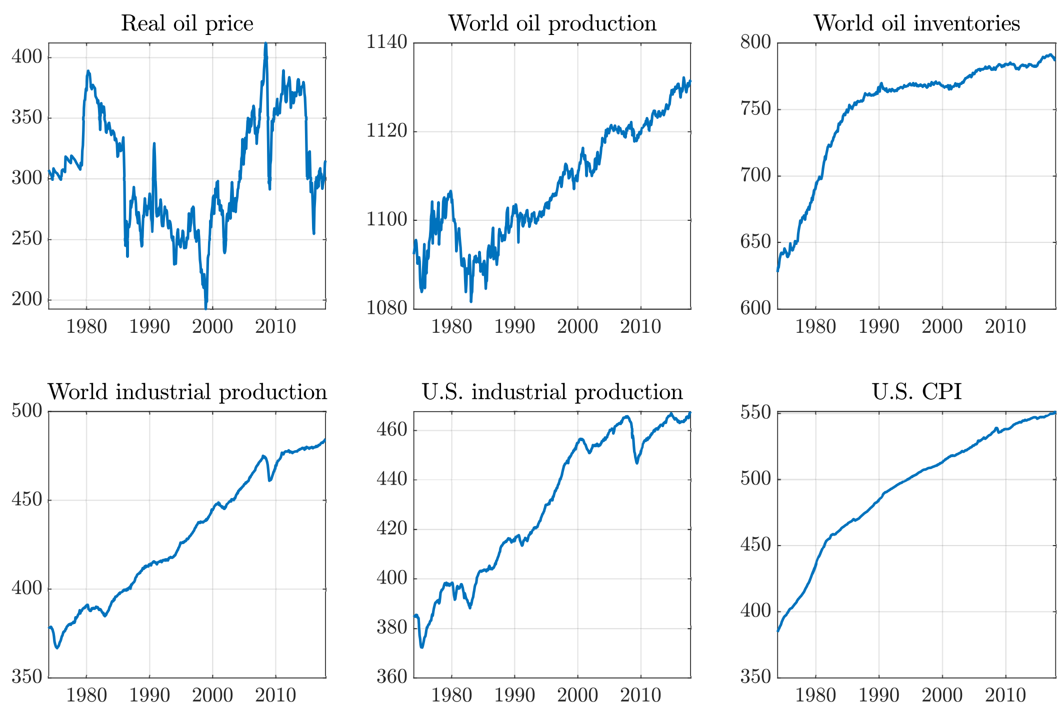


Figure B.1: Transformed data series used in the baseline VAR model, from January 1974 through December 2017.

C Additional Figures

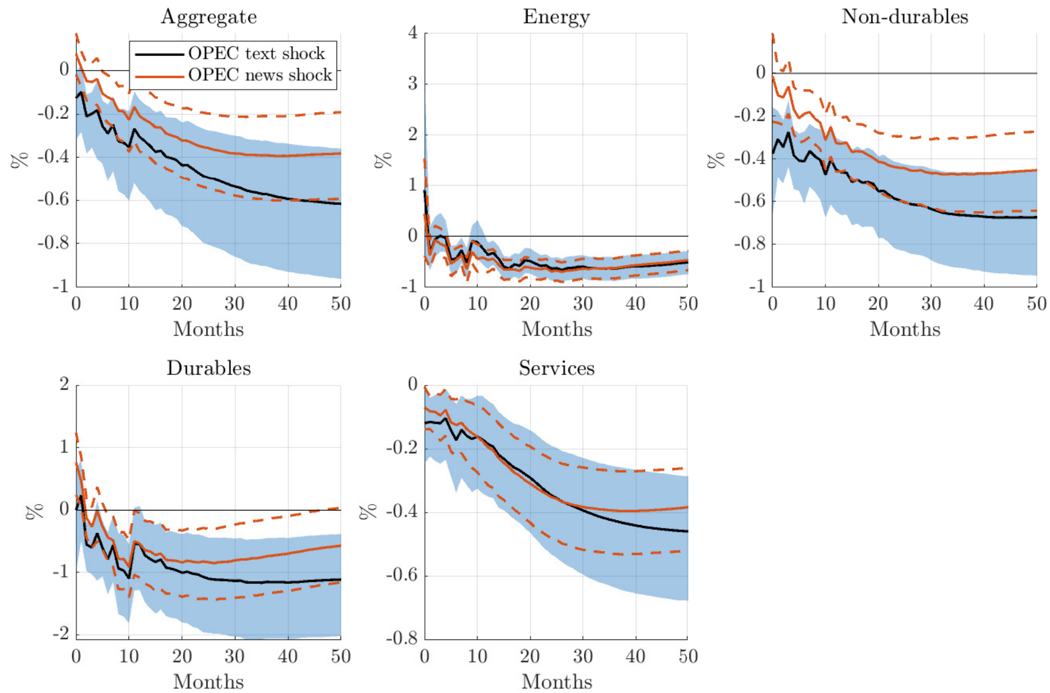


Figure C.1: Impulse responses of PCE categories to text shocks v. to oil supply news shocks

The impulse responses are normalised to increase the real price of oil by 10% on impact (not shown). The solid black (red) lines are the point estimates made using the text shock (oil supply news shock). The shaded areas (dashed lines) are 68% confidence bands.

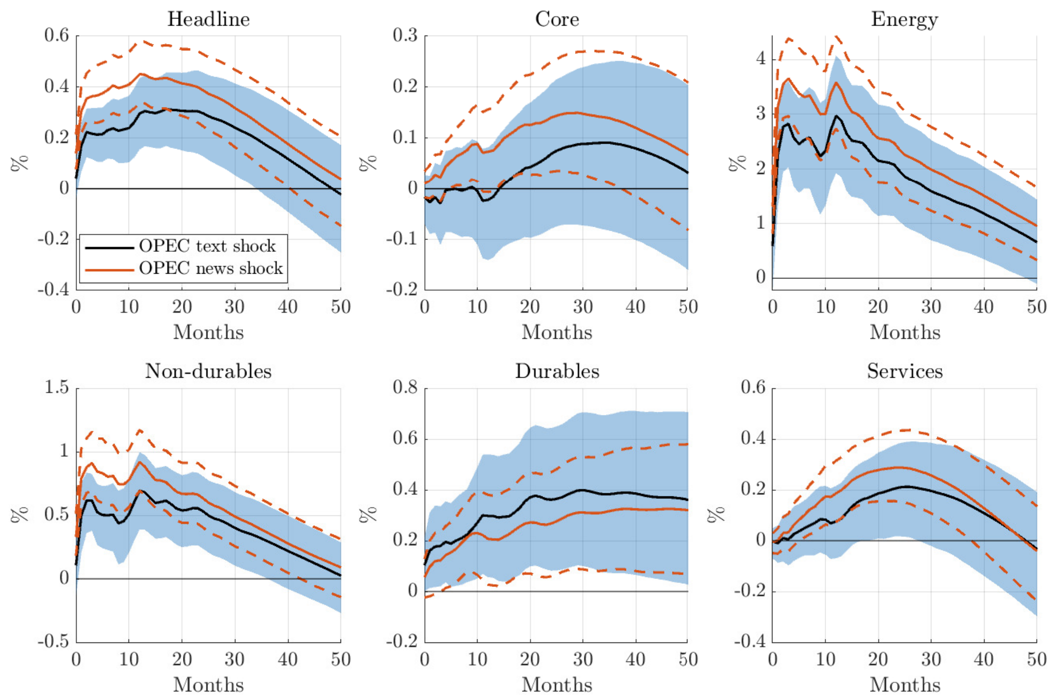


Figure C.2: Impulse responses of CPI inflation categories to text shocks v. to oil supply news shocks

The impulse responses are normalised to increase the real price of oil by 10% on impact (not shown). The solid black (red) lines are the point estimates made using the text shock (oil supply news shock). The shaded areas (dashed lines) are 68% confidence bands.

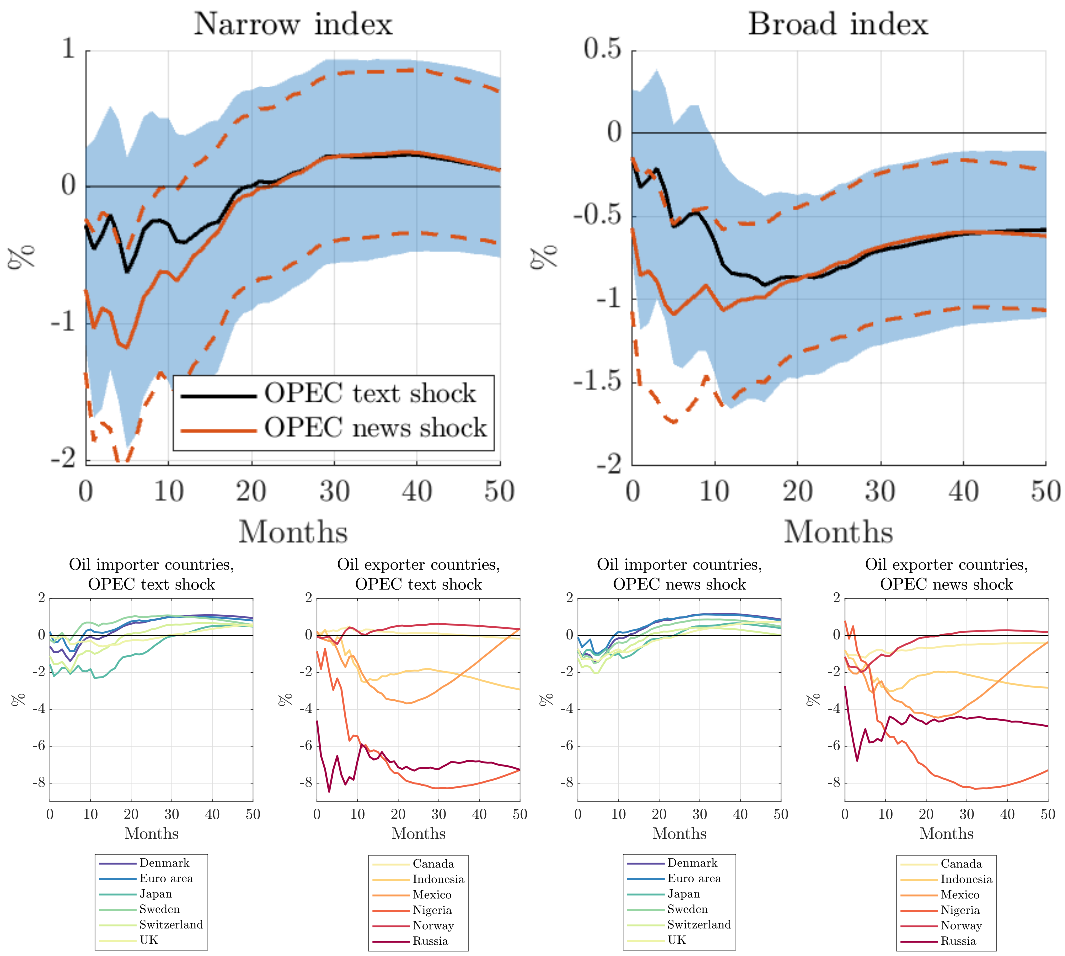
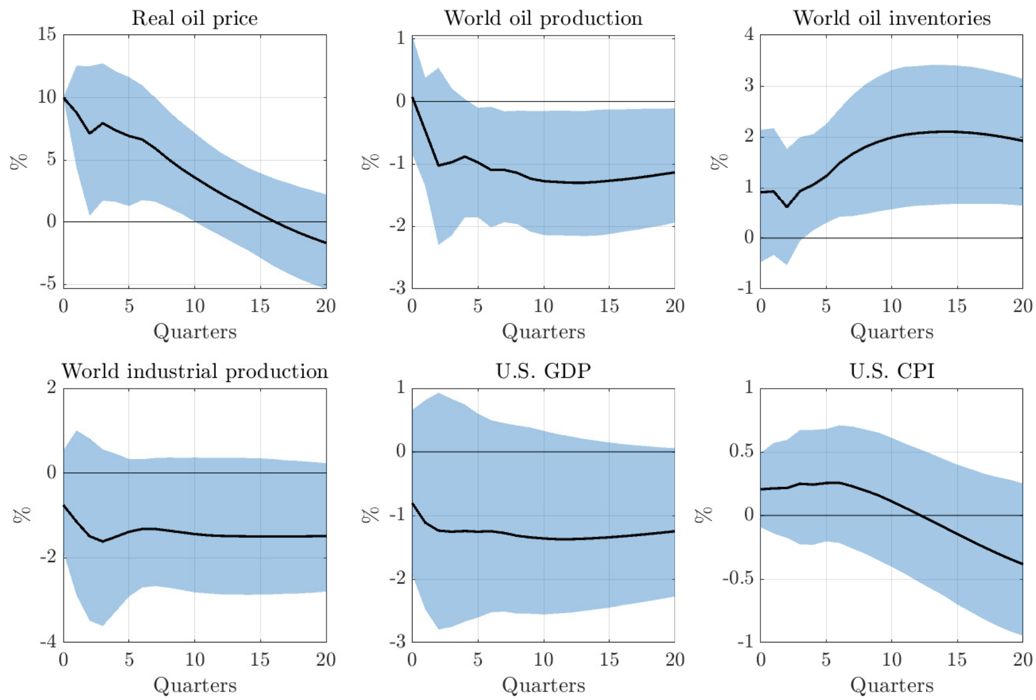


Figure C.3: Impulse responses of narrow and broad U.S. NEER (top row) and bilateral exchange rates (bottom row) to text shocks v. to oil supply news shocks

The impulse responses are normalised to increase the real price of oil by 10% on impact (not shown). The solid black (red) lines are the point estimates made using the text shock (oil supply news shock). The shaded areas (dashed lines) are 68% confidence bands. The narrow index incorporates the Eurozone, Canada, Japan, the United Kingdom, Switzerland, Australia, and Sweden. The broad index further includes Mexico, China, Taiwan, South Korea, Singapore, Hong Kong, Malaysia, Brazil, Thailand, the Philippines, Indonesia, India, Israel, Saudi Arabia, Russia, Argentina, Venezuela, Chile, and Colombia.



First stage regression: F: 0.82, Robust F: 0.63, R^2: 0.48%, Adjusted R^2: -0.10%

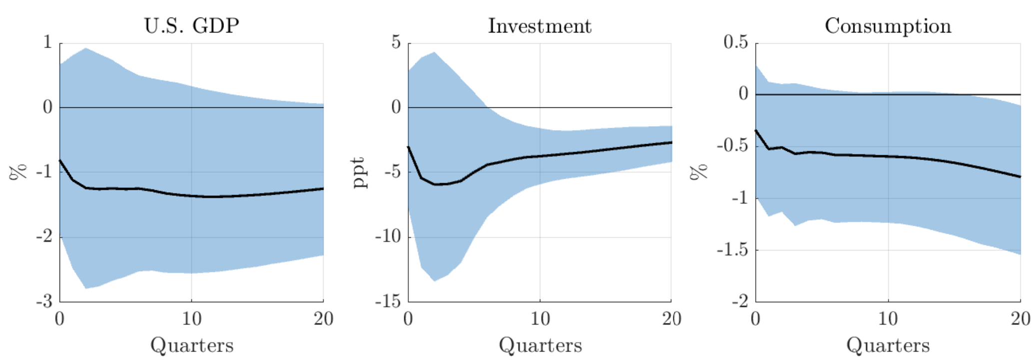
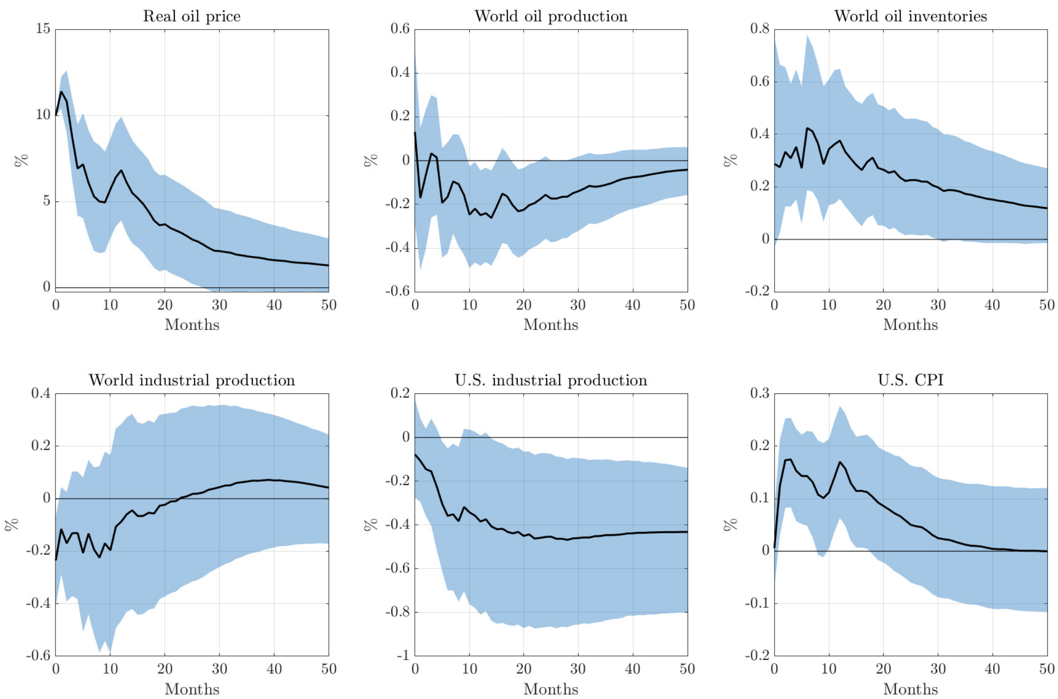


Figure C.4: Impulse responses to a negative oil supply expectations shock (i.e., positive text shock), quarterly frequency

The impulse responses are normalised to increase the real price of oil by 10% on impact. The solid black lines are the point estimates and the shaded areas are 68% confidence bands.



First stage regression: F: 11.48, Robust F: 9.54, R^2: 2.71%, Adjusted R^2: 2.48%

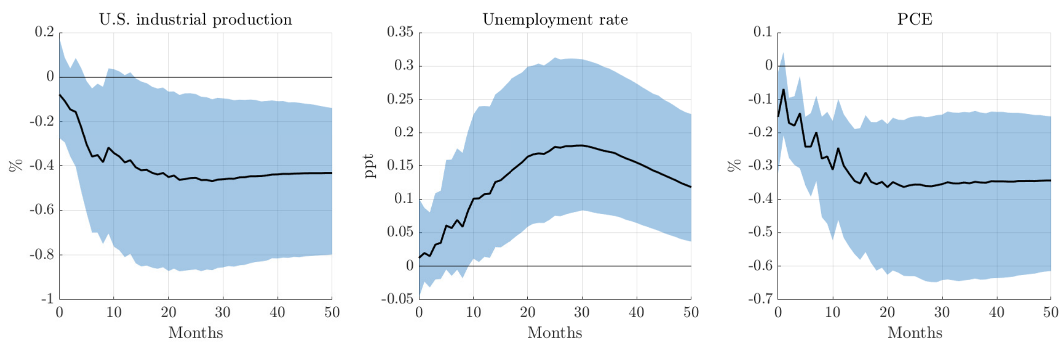
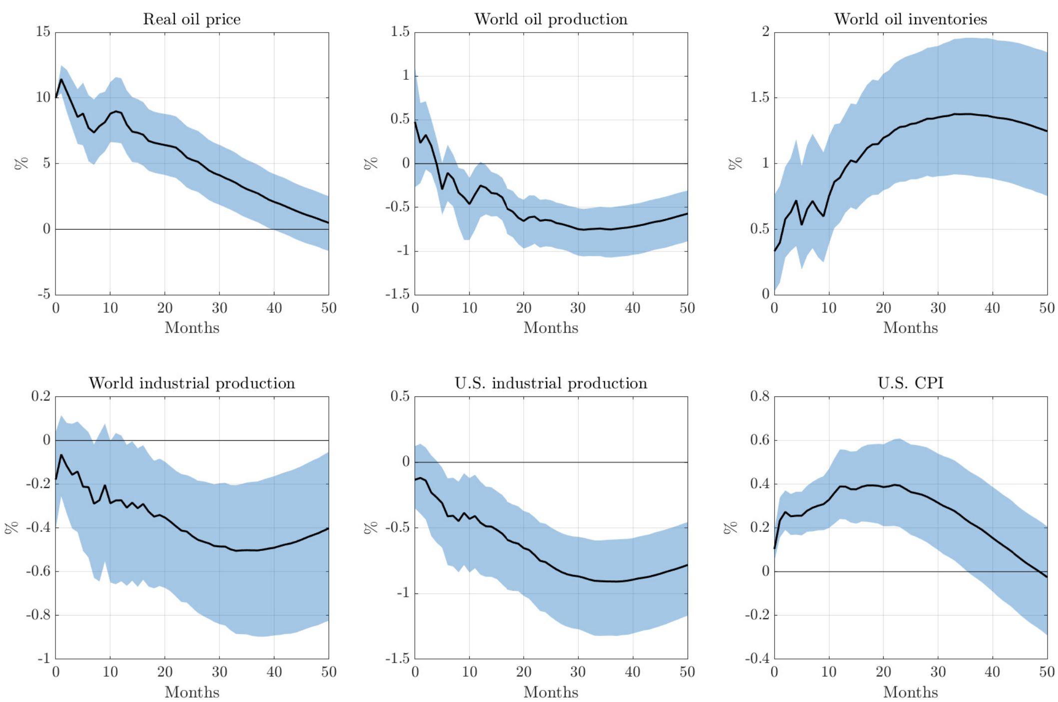


Figure C.5: Impulse responses to a negative oil supply expectations shock (i.e., positive text shock), from July 1982

The impulse responses are normalised to increase the real price of oil by 10% on impact. The solid black lines are the point estimates and the shaded areas are 68% confidence bands.



First stage regression: F: 14.02, Robust F: 8.11, R^2: 3.44%, Adjusted R^2: 3.20%

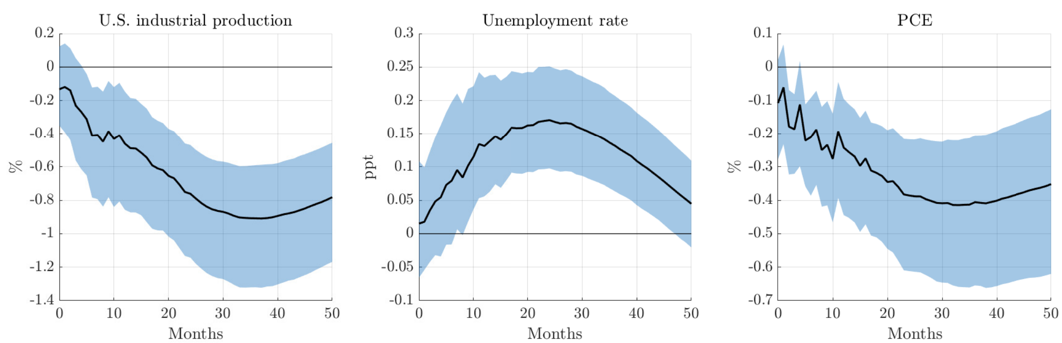
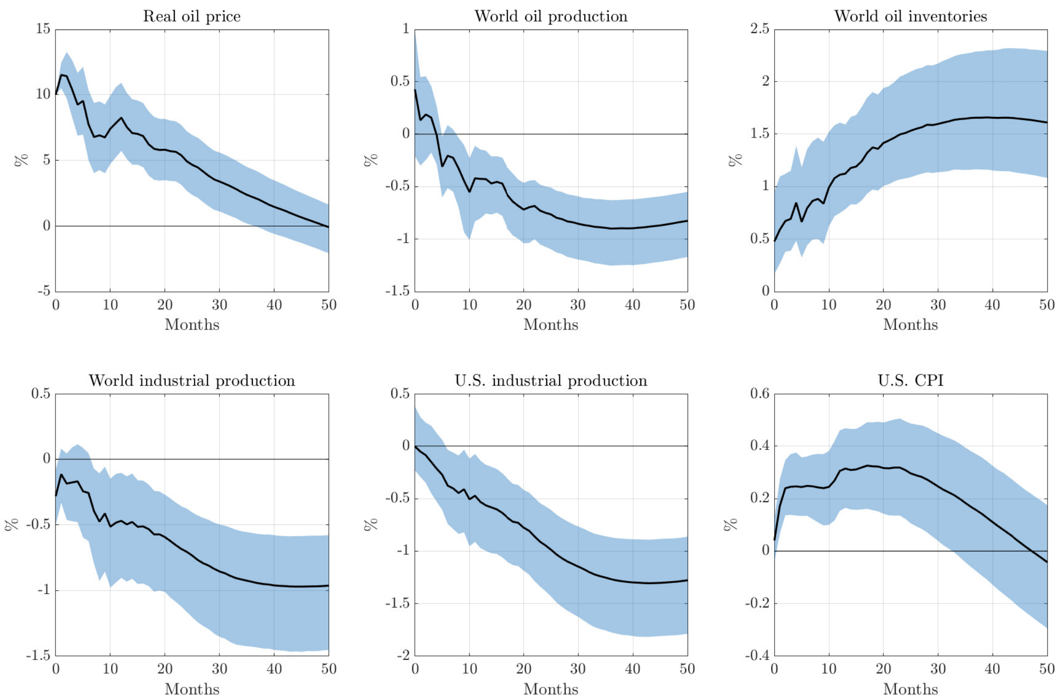


Figure C.6: Impulse responses to a negative oil supply expectations shock (i.e., positive text shock), through November 2007

The impulse responses are normalised to increase the real price of oil by 10% on impact. The solid black lines are the point estimates and the shaded areas are 68% confidence bands.



First stage regression: F: 10.29, Robust F: 5.98, R^2: 2.34%, Adjusted R^2: 2.11%

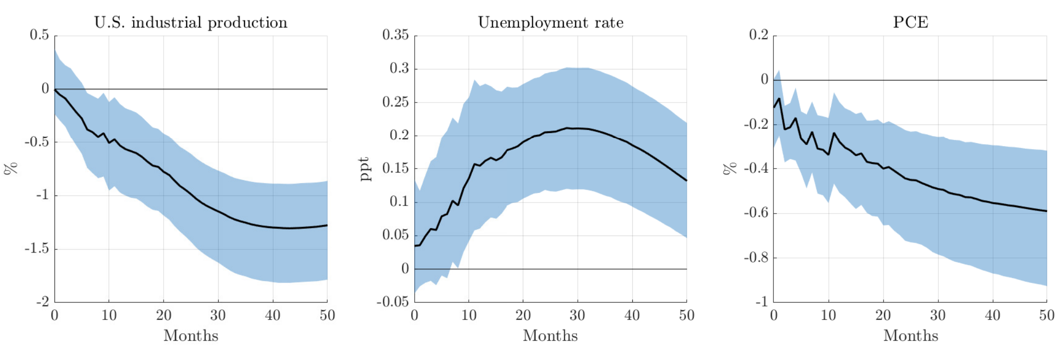


Figure C.7: Impulse responses to a negative oil supply expectations shock (i.e., positive text shock), through December 2010

The impulse responses are normalised to increase the real price of oil by 10% on impact. The solid black lines are the point estimates and the shaded areas are 68% confidence bands.

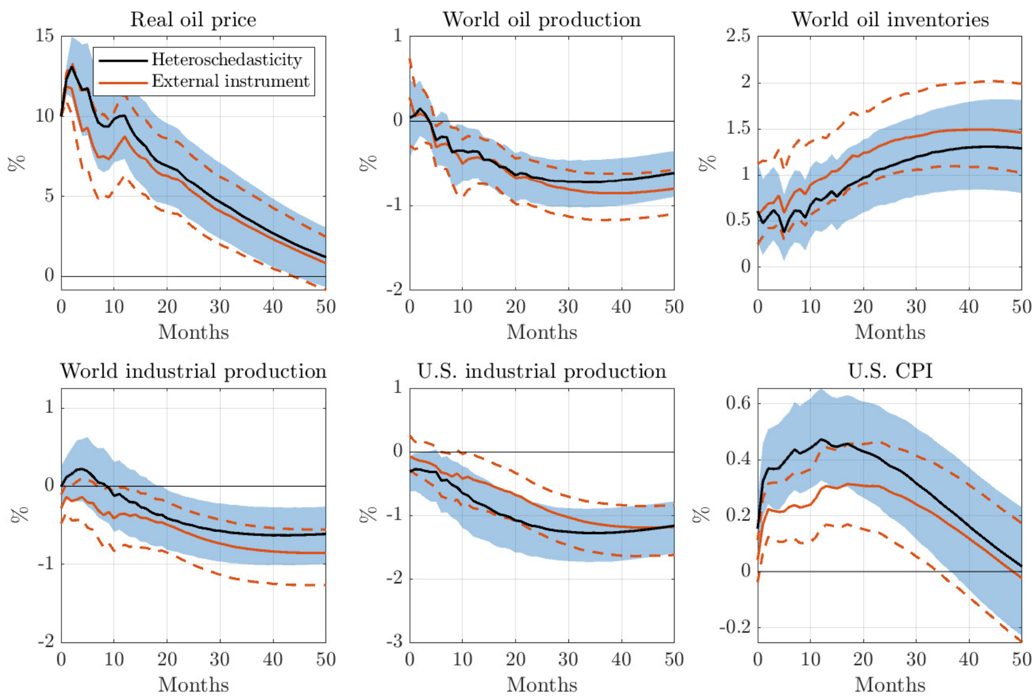


Figure C.8: Impulse responses to purified oil supply surprise series as an external instrument v. to observed oil supply surprise series in heteroscedasticity-based identification

The impulse responses are normalised to increase the real price of oil by 10% on impact. The solid black (red) lines are the point estimates made using the oil supply surprise series in the heteroscedasticity-based approach (XLNet's purified surprises as an external instrument). The shaded areas (dashed lines) are 68% confidence bands.