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Global financial markets and oil price shocks in real time

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Global financial markets and oil price shocks in real time

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Abstract

The role that the price of oil plays in economic analysis in central banks as well as in financial markets has evolved over time. Oil is not seen anymore just as a input to production but also as a barometer of global economic activity as well as a financial asset. A high frequency structural decomposition of the price of oil can therefore inform on the state of the global business cycle as well as on global financial market sentiment. In this paper we develop a method to identify structural sources of oil price fluctuations at the daily frequency and in real time. The identification strategy blends sign, narrative restrictions and instrumental variable techniques. By using data on asset prices, oil production and global economic activity we account for the double nature of oil: a financial asset as well as a physical commodity. The model offers novel insights on the relationship between the price of oil and asset prices. We also illustrate how the model could have been used in real time to interpret oil price movements in periods of high geopolitical tensions between the US and Iran and to read the drop of crude prices due to fears related to the Corona virus.

JEL classification: Q43, C32, E32, C53

Keywords: Oil prices, VAR, Proxy-SVAR, Sign Restrictions.

Non Technical Summary

Disentangling the structural drivers of the price of oil is crucial both for policy makers as well as for market participants. First, oil is an important input into economic production and sustained (supply driven) price increases can throw the global economy into recession. Second, oil prices impact directly inflation and consumer spending through energy prices, as oil prices are passed on (one to one) to gasoline prices within a week. Third, commodity prices, move strongly in sync with the global business cycle. Finally, in recent years, oil has become an important financial asset. However, the models that are most frequently used for assessing the structural drivers of oil prices typically rely on low-frequency variables that are only available with a substantial delay. As a result, these models typically paint an outdated picture of the state of the economy, and are not particularly useful when more timely information is needed.

In this paper we develop a new method for decomposing the price of oil into its structural drivers *in real time at the daily frequency*, exploiting the relationship between oil prices and global financial markets. Using a daily structural Vector Autoregression (VAR), in which we jointly model spot and futures oil prices as well as stock prices, we decompose the price of oil in three structural shocks. The first shock is a forward looking demand shock, which captures the impact on the oil price of changes in expectations about future economic activity. We label this shock, *risk sentiment shock*, as it embodies unexpected changes in the risk sentiment of market participants on the outlook of global activity. The second shock is an unexpected change in the *current state* of the business cycle and, as a consequence, in commodities demand more broadly. The third shock is a *supply shock*, which captures but current and expected changes in oil supply.

We use the model to analyze fluctuations in the oil price and their relationship with global financial markets (equities, bonds, inflation swaps and currencies) using data between June 2007 and February 2020. We find that risk sentiment shocks induce a parallel shift of the oil futures curve: a one percent increase in the price of oil due to a risk sentiment shock is associated with a rise of about one percent in 12 months ahead futures prices. More generally, a positive risk sentiment shock raises global stock prices, reduces volatility, raises interest rates as well as inflation expectations and leads to a depreciation of typical safe haven currencies, namely the USD, the Japanese yen and the Swiss franc. The effects of current demand shocks are qualitatively similar to, but quantitatively very different from, those of

risk sentiment shocks. They have very small effects on oil prices futures and, as consequence, a strong negative impact on the slope of the futures curve. The response of financial asset prices to a positive current demand shock is consistent with an improved macroeconomic environment. Stock prices and bond yields rise, while volatility falls. Safe haven currencies depreciate, but less than in response to risk sentiment shocks. Importantly long-term market based inflation expectations do not respond to these shocks, suggesting that the information content of risk sentiment and current demand shocks is indeed different. Finally, an increase in the price of oil due to a negative scarcity shocks is associated with a fall in risky asset prices, an increase in financial volatility and a depreciation of the dollar. In general, however, the effect of scarcity shocks on financial asset prices is quantitatively very limited. Long-term inflation expectations constitute an important exception, as they respond significantly, albeit with a delay, also to scarcity shocks, suggesting that the latter might shift inflation risk premia.

As a final exercise, we illustrate how the model could have been used in real time to analyze the structural drivers of oil price developments between January and February 2020. This period was characterized first by a marked increase in crude prices, as geopolitical tensions between the US and Iran spiked following the killing of the Iranian general Soleimani by a US drone, then by a collapse of oil (and financial) markets due to the Corona virus. Our model neatly distinguishes the main drivers of the price of oil around these episodes, attributing the rise in early January to scarcity shocks and the bulk of the Corona virus related collapse to a combination of risk sentiment and current demand shocks.

As I said, we are monitoring the data. [...] The market sends a signal that it expects the rate hike to be much later than what we have said. It's too early to have the discussion because we are still (in the process of) understanding the nature of the shock.

B. Cœuré.[a]

[a]Interview with Mr Benoît Cœuré, Member of the Executive Board of the European Central Bank, and Bloomberg TV, conducted by Ms Francine Lacqua on 25 January 2019. Available at https://www.bis.org/review/r190128a.htm

1 Introduction

Every day policy makers inspect the behaviour of financial markets and macroeconomic data releases to learn about the structural shocks that move asset prices and macroeconomic aggregates. The task is not trivial. Macroeconomic data are only available with a significant lag and are subject to non-negligible revisions. Financial asset prices, on the other hand, are available in real time but are only imperfectly related to the macroeconomic variables that policy makers ultimately care about, namely output and inflation. The tension between using information that is timely but noisy and information that is accurate but lagging is the key challenge for economic analysis in real time. Although "the economy does not cease to exist in between observations" (Bartlett, 1946) understanding the nature of the shocks driving its current state is inherently difficult. The problem that the publication lag poses for real time economic analysis has been extensively analyzed in the context of forecasting (Banbura, Giannone, Modugno, and Reichlin, 2013). Yet, exactly the same problem arises when trying to understand *in real time* the nature of the structural shocks that shape macroeconomic developments. The models that are most frequently used for this purpose, i.e. Structural Vector Autoregressions, typically rely on low-frequency variables that are only available with a substantial delay. As a result, the decomposition of economic data into structural shocks that these models provide typically paints an outdated picture of the state of the economy.

The price of oil plays, in this context, a crucial role for four reasons. First, oil is an important input into economic production and a sustained (supply driven) increase in its price can potentially throw the global economy into a recession (Kanzig, 2018). Second, the price of oil impacts directly inflation and consumer spending through energy prices, as oil prices are passed on (one to one) to gasoline prices within a week (Venditti, 2013). Third,

the price of oil, and more generally commodity prices, are strongly correlated with the global business cycle, and provide a timely gauge of the state of the economy (Delle Chiaie, Ferrara, and Giannone, 2017; Sockin and Xiong, 2015); developments in the oil market also play an important role in how business news ultimately impact financial markets, and can therefore help in measuring the overall state of the economy (Bybee, Kelly, Manela, and Xiu, 2020). Finally, in recent years, oil has become an important financial asset, which can be traded either as a risky asset, given its positive correlation with the business cycle, or to hedge against geopolitical risk that involves oil producing countries.

Since Kilian (2009) opened the box of structural identification in global oil markets, distinguishing the relative role of demand and supply in driving the price of oil has been at the center of a lively debate in the literature. Such a distinction has far reaching policy implications, especially for monetary policy makers. The source of the shock matters for its transmission to inflation, as well as to inflation expectations at different horizons, a key piece of information for central banks and especially for those following an inflation targeting strategy. While demand shocks call for determined policy action, supply shocks usually require a smoother and more protracted policy response (Schnabel, 2020). A real time structural decomposition of the price of oil would, therefore, allow policy makers and financial market observers to gauge the nature of the shocks that hit the real economy and that shape the relationship between oil and financial markets. However structural models of the oil market, like those put forward by Kilian and Murphy (2014), Caldara, Cavallo, and Iacoviello (2019), Baumeister and Hamilton (2019), are only available at the monthly frequency and rely on data that are published with between two to three months delay with respect to the reference period.

The main motivation of this paper, and its main contribution to the literature, is to fill this gap by providing a method for decomposing the price of oil into its structural drivers in real time. The core of the method is a daily structural VAR that jointly models the price of oil, stock prices and the price of 12 months ahead oil futures. In constructing this model, one issue that we face is which measure of equity prices to use. The few papers that look at the high frequency correlation between oil prices and the stock market typically look at a broad market index for the US, for instance the S&P 500 index. This, however, has a number of shortcomings. The S&P 500 index is a float-adjusted index weighted by market

capitalization and a quick look at the weights used in the index reveals that the largest companies operate in sectors (Information Technology or Financial Services) in which the direct impact of oil price fluctuations is negligible. We therefore take a different approach and rely on a particular sector to extract high frequency information on structural shocks, namely the airline sector. We pick this sector because of the direct relevance that energy costs have for the profitability of transport companies. We can, therefore, confidently assume that a negative oil supply shock will raise operating costs for airlines, denting their profitability and weakening their equity prices. Implicitly, we are also making a second identification assumption, i.e. that following a demand shock, the increase in operating costs is more than offset by a rise in revenues due to a stronger demand for transport and for other services that are offered by airline companies.[1]

A quick look at the raw data shows that, over the sample that we consider (2007-2020), changes in the price of oil have been positively correlated with changes in global airlines stock prices as measured by the MSCI World Airlines index (Figure 1, left hand side panel) and negatively correlated with the slope of the oil futures curve (Figure 1, right hand side panel) constructed as the difference between the 12-months ahead oil price futures and the current price of oil.[2] In other words, news that have moved the price of oil have been mostly also good news for risky asset prices (hence the positive correlation with stock returns) and have generally moved the short end of the futures curve more than the long end (hence the negative correlation with the slope). Of course this correlation is not perfect. There are instances in which oil price changes have moved in the opposite direction with respect to stock prices, plausibly because of bad news about oil supply, and cases in which the slope of the oil futures has been positively correlated with spot price changes.

We capture these patterns with three separate structural shocks. The first shock embodies unexpected changes in the risk sentiment of market participants, and moves spot and futures oil prices much as if they were equity prices. To identify this shock we use an external instrument. The instrument is the change in implied volatility in the US equity

[1] As a possible alternative to airline stock prices, we propose the use of a synthetic global stock market factor, obtained by extracting the common component from a large panel of country wide stock returns. The results obtained with this alternative measure of global stock prices, reported in Appendix E, are remarkably similar.

[2] For the spot price we use the nearby ICE Brent Crude Futures contract; the 12-months ahead oil price futures refers to the contract month expiring 12 calendar months later in the ICE Brent Crude Futures contract series.

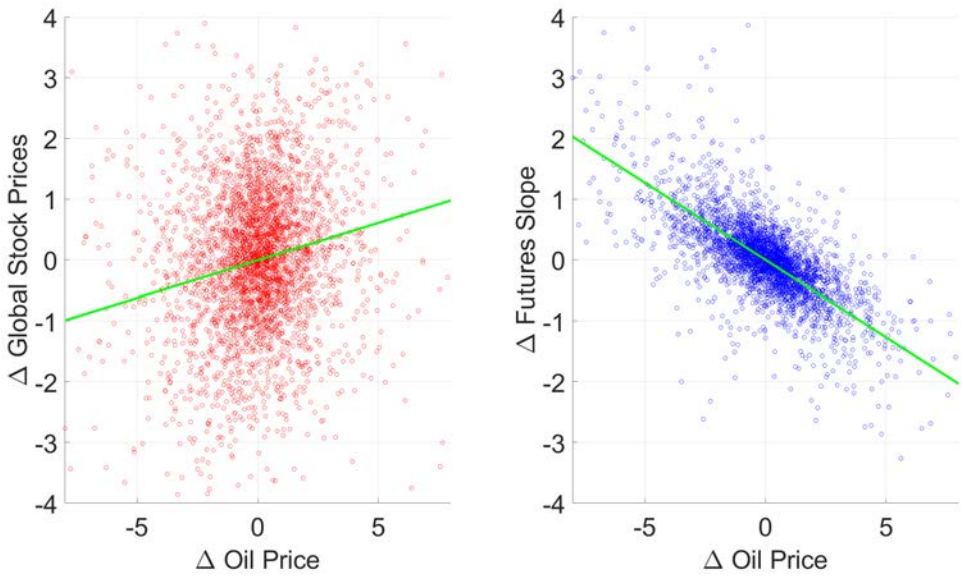

Figure 1: Oil Prices, global stock returns and slope of the futures curve

Notes: The scatter reports the daily percentage change of the oil price (Brent quality) on the horizontal axis versus the daily percentage changes in global airline stock prices (vertical axis, left hand side panel) and the difference between the percentage change of futures and spot oil prices (vertical axis, right hand side panel).

market in days when this change is (i) large, (ii) negatively correlated with changes in the price of oil (iii) positively correlated with the price of gold and with implied volatility in the oil market.[3] These are days when, in response to negative news on the global economy, market participants run to safety, volatility in oil and stock markets spikes and the price of oil plunges (alternatively, these are days in which positive news about global growth raise oil prices and suppress volatility in financial markets).[4] The external instrument has, by construction, a sparse structure as it presents many zeros.[5] The second shock is an unexpected change in the current state of the business cycle and, as consequence, in the demand for commodities. We identify this shock by conjecturing that it induces a *positive* correlation between oil (both spot and futures) and stock prices but a *negative*

[3]Volatility in equity markets is measured by the VIX, that is the CBOE Volatility Index. Implied volatility in oil markets is captured by the OVX, which measures the market's expectation of 30-day volatility of crude oil prices by applying the same methodology used for the VIX to options on crude oil futures. As shown by (Robe and Wallen, 2016) the VIX index is positively associated with the OVX, as generalized financial uncertainty and oil market uncertainty indeed tend to move together.

[4]Although the VIX is specific to the US $S\&P500$, it has a correlation as high as 0.9 with implied volatility in European and Asian stock markets (Londono and Wilson, 2019). By using the VIX to gauge risk sentiment in global markets we also follow a growing literature in applied macroeconomics (Kalemli-Ozcan, 2019).

[5]The potential challenge from using sparse instruments is discussed in Budnik and Gerhard (2020), who suggest resorting to Bayesian proxy VAR approaches.

correlation between the price of oil and the slope of the futures curve. In other words, conditional on this shock, spot and futures oil prices move in the same direction as stock prices, but spot prices move more than futures prices. These two shocks (risk sentiment and current demand) have broadly similar macroeconomic consequences, in that they both raise economic activity and oil prices at the same time. In Schnabel (2020) parlance they are both "demand" shocks. There are three good reasons for separating them. The first is that risk sentiment shocks induce a much stronger positive correlation between oil, risky asset prices and long-term bond yields. The second is that they have different implications for the slope of the futures curve. The slope is broadly unaffected by risk sentiment shocks (that raise current and futures prices by a similar amount) but is negatively related to current demand shocks (that affect current prices more than futures prices). The third is that risk sentiment shocks are found to have a much stronger impact on the price of inflation swaps, from which popular measures of long-term inflation expectations are derived. These shocks, therefore, help us in shedding some light on the somewhat puzzling link between the price of oil and long-term inflation expectations, a point to which we return in Section 5. The last shock that we identify is a stagflationary disturbance, conditional on which oil prices co-move *negatively* with stock prices. We term this structural disturbance a "scarcity" shock. This shock conflates two structural shocks that have been studied extensively in the oil price literature. The first is a supply shock, that is an unexpected exogenous fall in the production of oil. This would raise the price of oil and induce a fall in economic activity and also affect negatively stock returns (Kilian and Park, 2009). The second is a shock to the precautionary demand for oil, due for instance to worries about future oil availability. This is related more to uncertainty about the outlook for oil supply rather than to current supply conditions, and has been typically associated with geopolitical tensions involving large oil producing countries. Differently from the oil supply shock, uncertainty about future oil supply leads to an increase in current oil production (Kilian and Murphy, 2014). This additional oil production, however, does not reach consumers and firms but feeds higher inventories, leading again to a contraction in economic activity, and to a fall in stock prices (Anzuini, Pagano, and Pisani, 2015). While we see some merits in trying to distinguish these two sources of oil price fluctuations, we prefer treating them as a single shock for two reasons. First, many episodes of geopolitical tensions involving large

oil producers tend to include a combination of both actual oil supply disruptions as well as worries about future oil availability. For instance, on the 14th of September 2019 oil production facilities in Saudi Arabia were struck by drones and missiles and forced to shut down. Besides causing a significant loss in actual production (about 5% of global output) the attack also raised fears of further geopolitical tensions, increasing uncertainty on future oil supply. In such a case, trying to separate the effects of actual supply shortfalls from precautionary demand is challenging. Second, the macroeconomic implications of these two shocks are not easily distinguishable. In fact, following both a negative oil supply as well as a precautionary demand shock, oil is both scarcer and more expensive for both consumers and producers, either because of lower production or because of higher storage needs. As a result, economic activity and stock prices fall and the inflationary pressure due to higher energy prices is somewhat offset by lower aggregate demand. These effects, and their real time assessment, is what ultimately matters both for monetary policy makers, as well as for market participants.

The method described so far provides a daily decomposition of the price of oil in structural shocks. However, nothing ensures that the shocks that we obtain from such a daily VAR are consistent with the behaviour of prices and quantities in the *physical oil market*. In particular, we would expect both demand shocks in our model to be associated with an expansion in global economic activity and to induce an increase in oil production. At the same time, the scarcity shock should cause a reduction in global economic activity. Yet, it is not possible to have control over these effects when considering only the variables in our daily VAR. By moving from traditional models of the physical oil market to a framework in which oil is related to financial asset prices, we gain a real-time estimate of the shocks, but lose touch with the fact that oil is a physical commodity. We re-establish such consistency by introducing a second step in our identification procedure. For each candidate structural model in the daily VAR, we extract the structural shocks and take their monthly average. Conditional on demand shocks we require oil production and economic activity to be positively correlated with the price of oil, while scarcity shocks need to induce a negative correlation between oil prices and economic activity. Crucially, this second step is only used to select, across all the candidate structural shocks derived in the first step, the ones that have reasonable macroeconomic consequences and does not hinder the real time

nature of the structural decomposition.

We use the model to analyze fluctuations in the oil price and their relationship with global financial markets (equities, bonds, inflation swaps and currencies) using data between June 2007 and February 2020. We find that risk sentiment shocks induce a parallel shift of the oil futures curve: a one percent increase in the price of oil due to a risk sentiment shock is associated with a rise of about one percent in 12 months ahead futures prices. More generally, a positive risk sentiment shock raises global stock prices, reduces volatility, raises interest rates as well as inflation expectations and leads to a depreciation of typical safe haven currencies, namely the USD, the Japanese yen and the Swiss franc. The effects of current demand shocks are qualitatively similar to, but quantitatively very different from, those of risk sentiment shocks. They have very small effects on oil prices futures and, as consequence, a strong negative impact on the slope of the futures curve, explaining most of the negative correlation shown in the right hand panel of Figure 1. The response of financial asset prices to a positive current demand shock is consistent with an improved macroeconomic environment. Stock prices and bond yields rise, while volatility falls. Safe haven currencies depreciate, but less than in response to risk sentiment shocks. Importantly long-term market based inflation expectations do not respond to these shocks, suggesting that the information content of risk sentiment and current demand shocks is indeed different. Finally, an increase in the price of oil due to a negative scarcity shocks is associated with a fall in risky asset prices, an increase in financial volatility and a depreciation of the dollar. In general, however, the effect of scarcity shocks on financial asset prices is quantitatively very limited. Long-term inflation expectations constitute an important exception, as they respond significantly, albeit with a delay, also to scarcity shocks, suggesting that the latter might shift inflation risk premia.

As a final exercise, we illustrate how the model could have been used in real time to analyze the structural drivers of oil price developments between January and February 2020. This period was characterized first by a marked increase in crude prices, as geopolitical tensions between the US and Iran spiked following the killing of the Iranian general Soleimani by a US drone, then by a collapse of oil (and financial) markets due to the Corona virus. Our model neatly distinguishes the main drivers of the price of oil around these episodes, attributing the rise in early January to scarcity shocks and the bulk of the Corona virus

related collapse to a combination of risk sentiment and current demand shocks.

The paper is structured as follows. Section 2 places our paper in the context of the relevant literature. Section 3 describes the empirical model and the identification strategy. Section 4 briefly discusses model estimation, deferring most of the details to a technical Appendix. Section 5 presents the empirical results. Section 6 concludes.

2 Relationship with the literature

The first strand of the literature to which we relate includes a set of papers that use Structural Vector Autoregressions to study global oil markets dynamics. Challenging the conventional wisdom that viewed oil prices as largely exogenous to global macroeconomic developments, Kilian (2009) is the first to notice that the macroeconomic consequences of oil prices fluctuations cannot be assessed separately from the underlying shocks that cause them. Subsequent contributions have built on this idea and explored different identification strategies, see for instance Lippi and Nobili (2012), Kilian and Murphy (2014), Anzuini, Pagano, and Pisani (2015) and Juvenal and Petrella (2015). In recent years, the debate has shifted on the relationship between identifying restrictions and demand and supply elasticities in oil markets. Using two different approaches, both Caldara, Cavallo, and Iacoviello (2019) and Baumeister and Hamilton (2019) argue that the price elasticity of supply is higher than previously estimated, and emphasize the role that oil supply shocks have in explaining oil price changes in the past forty years.

We add to this literature by developing a high frequency model that provides a bridge between the global oil market and financial markets.[6] Unsurprisingly, we are not the first ones to think about the identification of oil price shocks at the daily frequency. Since oil prices convey signals on global growth, real time information on their structural drivers can be used, for instance, for portfolio allocation. For this reason, financial market practitioners and academics have recently studied the nexus between oil prices and financial markets, typically relying on a simple rule of thumb that classifies daily changes of oil prices as

[6] Kilian and Park (2009) investigate the role of oil supply and oil demand shocks in determining fluctuations of the US stock market, but at the monthly frequency. They find that the effects of supply shocks on stock returns are negligible. Oil demand shocks, on the other hand, provide a direct stimulus for the U.S. economy that outweighs, at least in the short run, the negative effects of higher oil prices.

either demand or supply driven, depending on whether they are positively or negatively correlated with stock returns (Rapaport, 2014; Perez-Segura and Vigfusson, 2016). A similar identification philosophy, but in the context of a dynamic factor model, underlies the New York Fed Oil Market Report by Groen, McNeil, and Middeldorp (2013). A central contribution to this literature is the one by Ready (2017), where oil production is connected to appetite for risk and equity prices in a theoretical model. In his model the comovement between oil prices, stock market returns and implied volatility in equity markets is determined by exogenous shifts in risk aversion, global demand for oil and supply shocks. These shocks are then estimated in a SVAR with recursive ordering based exclusively on asset prices (equity returns of oil producing firms, the VIX and oil prices). While the philosophy of our identification scheme is similar to the one in Ready (2017), we go beyond the recursive ordering, hardly tenable in a daily setting with financial market variables. We construct a more credible identification scheme in which exogenous changes in the risk attitude of investors are inferred from information contained in the joint movement of volatilities in the stock and in the oil market, complemented with a narrative approach. The fact that in our model all the variables can react contemporaneously to structural shocks makes the resulting structural decomposition more credible. Importantly, none of these high frequency papers tries to establish some consistency between the role that oil plays in financial markets and the fact that oil is a physical commodity.

3 Shocks Identification

Our daily model is a three-variate Vector Autoregression that includes the price of oil, airline stock prices and the price of the 12 months ahead oil futures. Our measure of the price of oil is the log of Brent (1st futures delivery price). Global equity prices are the log of the MSCI World Airline index[7]. Futures prices are the log of the 12 months ahead Brent futures. The sample runs from the 1st of June 2007 to the 28th of February 2020. Collecting the n variables in the vector y_t, we can write the structural representation of the

[7]The MSCI World Index is a market cap weighted stock market index of the major world airlines.

model, which allows for contemporaneous interaction of the variables:

$$A_0 y_t = A_+ x_t + e_t, \qquad e_t \sim i.i.d.\ N(0, I), \tag{1}$$

where $A_+ = [A_1, A_2, ..., A_p, c]$ and $x_t = [y'_{t-1}, y'_{t-2}, ..., y'_{t-p}, 1]'$. A_0 is an $n \times n$ matrix of contemporaneous interactions, the p matrices A_j $(j = 1, 2, ..., p)$ of dimension $n \times n$ collect the autoregressive coefficients, c is an intercept term and e_t is an n dimensional vector of structural shocks. The reduced form model has a compact representation:

$$y_t = \Phi_+ x_t + u_t, \qquad u_t \sim i.i.d.\ N(0, \Sigma),$$

where $\Phi_+ = {A_0}^{-1} A_+$ and reduced form and structural shocks are related as follows:

$$u_t = A_0^{-1} e_t = B e_t, \tag{2}$$

$$\Sigma = (A_0' A_0)^{-1}. \tag{3}$$

The matrix B, the structural impact matrix, is the crucial object of interest in structural identification. To estimate this matrix we place three types of restrictions: restrictions on the response of daily data to the shocks; restrictions on the response of monthly data to the shocks; an upper bound on the elasticity of oil supply; narrative sign restrictions.

3.1 Identification restrictions on daily data

Risk sentiment shock. Motivated by Ready (2017), the first structural shock that we analyze can be seen as a change in the willingness of market participants to bear risk due to a substantial change in their assessment about future economic conditions. The importance of investors' sentiment in driving the high-frequency correlation between stock and oil prices appears often in market commentaries and is also used by policymakers to rationalize, in real time, the nature of the shocks that hit the economy. Bernanke (2016), for instance, explicitly makes this point in his Brookings blog discussing the positive correlation between stock returns and the price of oil: *"[...] recent market moves have been accompanied by elevated volatility. If investors retreat from commodities as well as stocks during periods*

of high uncertainty and risk aversion, then shocks to volatility may be another reason for the observed tendency of stocks and oil prices to move together." The Brexit referendum offers a concrete example of the type of shock we are after. On the first trading day after the referendum (24th of June 2016) markets were shaken by increased uncertainty and higher pessimism on future economic activity; implied volatility in the US stock market jumped by 8.5 percentage points and world equities and the price of oil plunged by 5%. Our first structural shock is designed to catch exactly episodes of this type, characterized by a tight positive (negative) correlation between the price of oil and stock returns (financial volatility).

While financial market participants agree that this is an important driver of the correlation between the price of oil and asset prices, most economists would disagree on the exact definition of such a shock. Arguably, one could think that such a co-movement in asset prices could be prompted by *first moment shocks* like for instance the news shocks identified by Kurmann and Otrok (2013), but also by *second moment* shocks, like for instance the uncertainty shocks studied by Bloom (2014), Caldara, Cavallo, and Iacoviello (2019), Alessandri and Mumtaz (2019) and Cesa-Bianchi, Pesaran, and Rebucci (2018). All these different shocks are combined by Bluwstein and Yung (2019) in a "risk perceptions" shock, that is an exogenous increase in the risk-premium that investors require to bear risk. This shock depresses output and credit and raises implied volatility in stock markets. Such a shock could originate from (i) a revision of expectations about future growth or (ii) revisions of the balance of risks on growth or (iii) a combination of the two. We see this shock as a disturbance that would induce investors to treat commodities in their portfolios as if they were a risky asset (i.e. an asset whose returns are positively correlated with future consumption).

To identify this shock we use an external instrument, in the spirit of Mertens and Ravn (2013) and Stock and Watson (2012). The construction of the instrument proceeds in two steps. First, we select, through a statistical procedure, days in which we observe a large increase (decrease) of volatility in oil and equity markets and in the price of gold, and a large decrease (increase) in the price of oil. Changes in the price of gold have been used to isolate shocks to uncertainty (Piffer and Podstawski, 2018) and can be used as an indicator of risk on/off mood in financial markets. Specifically, we consider, for each year in our

sample, the joint empirical distribution of daily gold and oil price returns and changes in the VIX and in the OVX. We then select the days in which the change in *all* these variables is large, based on a subjective statistical criterion. By 'large' we mean that they fall, respectively, either below their 10th percentile or above their 90th percentile. In the second step, we rely on market commentaries to assess the origin of such shock according to financial market sources (Bloomberg, private sector newsletters and the IMF daily Global Markets Monitor). This cross-check reveals that these specific days were characterized by important revisions of global growth prospects. Operationally, we define our external instrument as a variable equal to the actual change in the VIX in these days, and zero on all other days in the sample.

After auditing the candidate dates through market commentaries, we are left with 15 days (see Table 1).[8] In 2008-2019 we select five days, central in the unfolding of the global financial crisis, with marked financial volatility and large moves in gold prices. In August 2011 a reduction of the US credit rating by Standard & Poor's fueled concerns that the ongoing economic slowdown could worsen. Ten days later the eruption of the euro area crisis led to another spike in financial volatility that also negatively impacted oil prices. Days of market turmoil in 2012 were dominated by disappointing news on growth prospects for the US and for the euro area. Finally, in 2016 and in 2018 we identify as risk off episodes the day of the Brexit referendum and a specific day in April 2018 when trade tensions between the United States and China concretely intensified. In 2019 the trade war escalation is picked up by several dates, following specific Trump tweets and the threat of China retaliation. Finally, the 24th of February is picked up as the outbreak of the corona virus shock.

Current oil demand. Our second shock of interest is an unexpected change in the *current* state of the business cycle and, as a consequence, in the current demand for oil. We identify this shock through sign and magnitude restrictions. First, we assume that an increase in the demand for oil has a positive impact on the spot price of oil as well as on equity prices. Second, we assume that a shock to current demand affects the price of oil at all maturities, i.e. not only the spot price but also futures prices, but that its impact is

[8] In Appendix A we report a full account, sourced from these market commentaries, of the key events that, in each of these days, triggered a change in global risk appetite.

Table 1: **Selected dates defining the external instrument**

event date	*key headline*	OVX	VIX	Gold	Oil
30-Sep-2008	Rescue package hopes	-4.7	-7.3	-2.3	4.4
06-Oct-2008	Global growth fears	8.6	6.9	2.7	-7.6
17-Feb-2009	Global growth fears	10.1	5.7	2.8	-5.3
20-Apr-2009	Global growth fears	4.7	5.2	1.8	-6.8
01-Jun-2010	Global growth fears	5.6	3.5	2.0	-2.6
08-Aug-2011	US sovereign downgrade	13.8	16.0	2.5	-5.3
18-Aug-2011	Euro sovereign	14.8	11.1	2.2	-3.3
07-Sep-2011	Global growth rebound	-2.5	-3.6	-4.3	2.6
01-Jun-2012	Global growth fears	6.8	2.6	2.9	-3.4
24-Jun-2016	Brexit	3.2	8.5	3.9	-5.0
02-Apr-2018	Trade tensions	2.5	3.7	1.2	-3.8
23-May-2019	Trade tensions	5.6	2.2	0.9	-4.7
31-May-2019	Trade tensions	7.3	1.4	0.9	-3.6
14-Aug-2019	Global growth fears	2.6	4.6	1.1	-3.0
24-Feb-2020	Corona virus shock	3.7	8.0	1.9	-3.8

Notes: From left to right: *event date* reports the specific date from our combination statistical and narrative selection criteria for the "risk dates"; *key headline* reports the main risk driver identified from our reading of the daily market commentaries; OVX, VIX, Gold and Oil, report the daily change for the variable indicated (log change for Gold and Oil). Source: authors' compilation from Bloomberg, Refinitiv, and other news reports.

relatively stronger for shorter than for longer maturities. This translates into an identifying assumption on the slope of the futures curve, which we expect to go relatively more in "backwardation" (i.e. sloping downwards) following a positive current demand shock and more in "contango" (i.e. sloping upwards) following a negative demand shock. In other words, conditional on a current demand shock, the spot price is negatively correlated with the slope of the futures curve. Our assumption is that, everything else equal, a current demand shock changes the market balance relatively more in the present than in the future, so that the spot price has to adjust more than futures prices to clear the market.

Oil scarcity shock. The third structural shock is a supply driven exogenous tightening of the oil market. This can occur for two reasons. The first is an exogenous disruption in

oil production, due for instance to geopolitical tensions, a natural disaster or a decision of oil producers to cut production independently from demand conditions. These are not rare events; Caldara, Cavallo, and Iacoviello (2019), for instance, identify 29 such episodes between 1985 and 2011. There is a large consensus in the literature that such a shock has stagflationary macroeconomic consequences, i.e. it yields higher oil prices and higher inflation while leading to a contraction in economic activity. Yet scarcity of oil for consumers and producers can also stem from higher demand for oil storage, i.e. from a precautionary demand for oil driven by uncertainty about future oil supply (Anzuini, Pagano, and Pisani, 2015). As explained in the Introduction, we conflate these two shocks into a single stagflationary disturbance, a "scarcity" shock, which we identify by assuming that it induces a negative conditional correlation between the price of oil and equity prices. This assumption resonates with similar assumptions in the high frequency literature (Perez-Segura and Vigfusson, 2016; Rapaport, 2014) and is supported by the theoretical model in Ready (2017).

Narrative restrictions on the scarcity shock. We further sharpen the identification of the scarcity shock with two additional narrative restrictions, in the spirit of Antolîn-Dîaz and Rubio-Ramîrez (2018). On the 14th of September 2019, a drone attack hit the state-owned Saudi Aramco oil processing facilities in Saudi Arabia. The damage to the production facility led to a substantial, albeit temporary, cut of Saudi Arabia's oil production, amounting to about 5% of global oil output. As a result, as markets opened the following Monday (the 16th of September) the price of oil jumped by 13 percent, from 60 to 68 USD per barrel. We use this episode to place two identifying narrative restrictions on the scarcity shock.

- *Narrative Restriction #1: sign of the shock.* On the 14th of September 2019 the scarcity shock gave a positive contribution to the increase in the price of oil.
- *Narrative Restriction #2: contribution of the shock.* On the 14th of September 2019 the scarcity shock accounted for most of the change in the price of oil.[9]

[9] In the following days worries about oil supply quickly retreated, as Saudi Arabia's energy minister pledged the use of strategic reserves to stabilise oil exports. Since we use daily data this does not represent a problem for our identification strategy.

3.2 Restrictions on monthly variables and elasticity bounds

So far, we have sought to identify primitive shocks to the price of oil by using information exclusively from daily financial market data. Although we claim that the identification restrictions that we have placed on daily data are plausible, one may wonder whether the shocks that this identification scheme delivers have sensible implications for macroeconomic variables as well as for the physical oil market. For instance, current demand shocks should induce a positive correlation between oil prices, global economic activity and oil production. We have also motivated our identification of scarcity shocks by arguing that they should move oil prices and global economic activity in opposite directions. To ensure that our shocks have these desired properties, we need to impose additional identifying assumptions on the response of monthly variables (namely oil production and global economic activity) on the structural shocks. A second, related point is that sign restrictions by themselves are not sufficient to identify structural shocks in the *physical* oil market (Kilian and Murphy, 2012) and that imposing credible bounds on the elasticities of demand and supply narrows down the set of plausible structural models.

We address both of these points. First, we add a set of identifying assumptions on the response of oil production and global economic activity to demand and scarcity shocks. At each point in time we compute an aggregate "macro demand" shock as the sum of the risk sentiment and current demand shock. We then require both oil production as well as global industrial production to co-move positively with the price of oil conditional on this shock.[10] In response to a scarcity shock, on the other hand, we require global industrial production to co-move negatively with oil prices. Second, we place an upper bound on the elasticity of oil supply to limit the range of acceptable structural models. We place this upper bound at 0.1. This value strikes a balance between the very low bound of 0.0258 set by Kilian and Murphy (2014) and the evidence presented by Caldara, Cavallo, and Iacoviello (2019) that this elasticity might be as high as 0.08. In our sample, results are not particularly sensitive to the value chosen for this upper bound, as the posterior distribution of this supply elasticity is concentrated towards the lower end of these values. A summary of the

[10] We measure oil production as the world production of crude taken from the International Energy Agency. As a proxy for global economic activity we use the industrial production based measure developed by Baumeister and Hamilton (2019).

identification restrictions is presented in Table 2. We have populated the first column of this table, which relates to the impact of the risk sentiment shock on the high and low frequency variables, with the word '*Proxy*', to clarify that the response of both the daily and monthly variables to this shock is determined by the external instrument.

Table 2: **Summary of the Identifying Restrictions**

	Risk sentiment	Current demand	Scarcity
		Daily Model	
Oil Price	*Proxy*	+	+
Equity Prices	*Proxy*	+	-
Oil price futures (12m)	*Proxy*	+	
		Monthly Model	
Oil Production	*Proxy*	+	
Global IP	*Proxy*	+	-
		Additional Restrictions	
- Magnitude restriction: current demand shocks affect spot more than futures oil prices			
- Narrative restrictions on the scarcity shock (14th of September)			
- Upper bound (0.1) on the elasticity of oil supply			

4 Model Estimation

The model is estimated using Bayesian methods. Here we briefly explain the main estimation steps and refer the reader to Appendix B for all the technical details.

Shocks identification requires the estimation of the reduced form parameters Φ_+ and Σ and of the three columns of the structural impact matrix $B = [b_1, b_2, b_3]$. The estimation of these parameters is conceptually split in three steps. The first step consist of estimating the reduced form parameters and the first column b_1 using the external instrument described in Section 3.1. We draw on the literature on Proxy-SVARs to estimate these parameters, and in particular on the method developed by Caldara and Herbst (2019).

In the second step we use sign restrictions to set-identify b_2 and b_3 conditional on the estimate for b_1 obtained in the first step. Methods that tackle this problem have been developed by Cesa Bianchi and Sokol (2017), Braun and Brggemann (2017) and Arias,

Rubio-Ramirez, and Waggoner (2019). In Appendix B we provide a detailed description of how we adapt the procedure by Cesa Bianchi and Sokol (2017) to the Bayesian framework of Caldara and Herbst (2019). In this step we also implement narrative sign restrictions on the scarcity shock, rejecting all the candidate structural models in which scarcity shocks are not the predominant contributors to the spike in the price of oil on the 14th of September 2019.

The final step consists of adding identification restrictions on lower frequency variables. These are implemented by estimating the effects of the shocks (identified on daily data and then averaged at the monthly frequency) on two monthly variables, namely global oil production and global industrial production, and by discarding the candidate structural shocks that do not satisfy either the sign restrictions on the monthly variables or the elasticity bounds. Intuitively, this final step requires nothing more than a local projection of the monthly variables on the identified shocks, and is performed along the lines of Jarocinski and Karadi (2019), Paul (2017) and Gazzani and Vicondoa (2020). Crucially, this last step does not hinder the real time nature of the structural decomposition, as the information sets in the daily and in the monthly data do not need to be aligned. To give a concrete example, in our empirical analysis the daily information set runs from the 1st of June 2007 to the 28th of February 2020, while data on global industrial production and on oil production are only available up until November 2019. From the daily model we obtain a range of candidate structural shocks up to the 28th of February 2020. For each of these candidate shocks we run the (monthly) local projections with data up to November 2019. Finally, out of the daily candidate shocks, we only keep those for which the (monthly) local projections satisfy the sign restrictions and the elasticity bounds. In other words, monthly information is only used to select, among the daily candidate shocks, those that have reasonable macroeconomic implications.

5 Results of the empirical analysis

We organize the empirical section in four parts. We start by looking at Impulse Response Functions for daily data. We then analyze the response of a wide array of financial variables to our structural shocks. Then, we zoom in on some specific episodes of particular interest

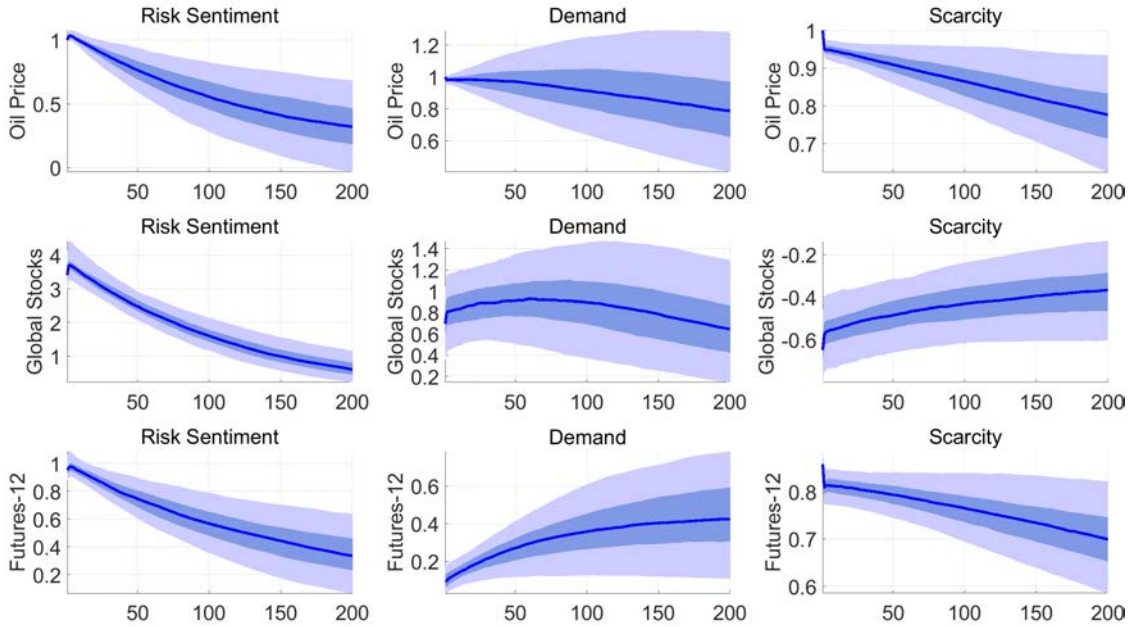

Figure 2: Impulse Response Functions for the daily VAR

Note. 68 percent confidence bands. Both parameter and identification uncertainty is reflected in the confidence bands. Impulse response functions are standardized so as to lead to a 1 percent increase in the price of oil.

for the interplay between oil and financial markets and interpret them through the lens of our model. Finally, we describe how the model could have been used in real time do understand oil price dynamics in a longer period, between January and February 2020, when the killing of the Iranian general Soleimani by US forces first, and the spreading of the corona virus afterwards, lead to pronounced volatility in oil markets.

5.1 Impulse Response Functions

Figure 2 shows the response of the endogenous variables included in the daily VAR to the three structural shocks. Impulse response functions are normalized to generate a 1 percent increase in the price of oil.

The risk sentiment shock. Since the IRFs are normalized so as to generate a rise in oil prices, the first column of Figure 2 shows the effects of a positive risk sentiment shock. It is worth remarking that these are estimated through an external instrument, so that neither the sign nor the magnitude of these responses is, a priori, constrained. A striking result is that a 1 percent increase in the spot price of oil is associated with a 1 percent increase in the price of oil futures as well as in airlines stock prices. Two implications follow. The first is that this shock captures indeed episodes of strong contemporaneous co-movement between oil and stock prices. The second is that, in response to a risk sentiment shock,

the slope of the futures curve barely changes. This means that the shock that we are capturing through our exogenous instrument is strongly forward looking and induces an almost parallel shift of the futures curve.[11]

Current demand shock. The second source of positive correlation between oil and stock prices is the current demand shock. There are three major differences in the way this shock affects oil and stock prices as compared to the risk sentiment shock.[12] First, the increase in oil and stock prices is much slower and more persistent than what observed after a risk sentiment shock. Second, oil prices rise relatively more than (about three times as much as) stock prices. Third, this shock has a much stronger impact on spot than futures oil prices. As the spot price of oil rises on impact by 1%, oil price futures only rise by around 0.1 percent, and thus the slope of the futures curve declines significantly. As a result, this is the shock that is mostly responsible for the negative correlation between spot and futures prices shown in the right hand side panel of Figure 1.

Scarcity shock. Conditional on a scarcity shock, a 1 percent increase in the price of oil is associated with a significant fall in stock prices (-0.45 percent). Futures prices also respond strongly to this shock, although their reaction is milder than that of spot prices (0.8 percent). This implies that part of the negative relationship between spot prices and the slope of the futures curve in Figure 1 is also due to supply side shocks.

In Appendix C we describe in details the effects of the structural shocks on monthly variables, in particular oil production and the measure of global industrial production developed by Baumeister and Hamilton (2019). This analysis shows that risk sentiment and current demand shocks have broadly similar macroeconomic consequences, as they raise persistently both industrial production and oil production. The latter responds to risk sentiment shocks only with a lag, suggesting that this disturbance anticipates macroeconomic developments that lead to higher demand for oil, which in turn is accommodated by higher oil production. Scarcity shocks, on the other hand, have a significant recessionary impact but do not have a significant effect on oil production, as they blend shocks (supply and

[11] Understanding whether this is due to risk premia or to changes in the convenience yields rather than to expectations would require a term structure model. While this question is of great interest it a beyond the scope of our analysis.

[12] We should note that, despite the same pattern of *signs* for the risk sentiment and demand shocks estimated from our IRFs, we are still able to separately identify the the demand shock from the risk shock: demand shocks are, by assumption, orthogonal to the proxy used for the identification of risk sentiment shock (Arias, Rubio-Ramirez, and Waggoner, 2019).

precautionary demand) that move production in opposite directions.[13]

5.2 Impact on financial variables

This section, the heart of our empirical analysis, illustrates how our identified structural shocks shape the relationship between the price of oil and global financial markets. To this end, we run a battery of local projections of various asset prices on the identified structural shocks. The exercise follows in spirit Kilian (2008) and Kilian, Rebucci, and Spatafora (2009), who study the effects of oil price shocks on output, inflation and external balances.

To measure the dynamic effect of the shock S_t on a particular asset price y_t, h days after the shock, we estimate regressions of this form:

$$y_{t+h} = \alpha_h + \beta_h Z_{t-1} + \gamma_h S_t + u_t^h, \qquad h = 0, 1, \ldots, H, \tag{4}$$

where Z_t is a set of controls and u_t^h is a residual. The parameter γ_h is an estimate of the impulse response function of the variable y_t to the shock S_t at horizon h (Jorda, 2005). In all of our specifications the controls Z_t include p lags of the endogenous variable[14] together with the variables included in the daily VAR, namely spot and futures oil price and global airline stock prices. Since shocks are identified up to a sign, we standardize the coefficient γ_h by the contemporaneous effect of the shock S_t on the percentage change in the price of oil. This makes these regression coefficients directly comparable to the impulse response functions shown in figure 2, which are similarly standardized. For each asset price, and for each shock, we estimate local projections up to 90 days following the shock, namely $h = 1, \ldots 90$.[15] We analyze five markets: equity, sovereign bonds, inflation swaps, foreign exchange, and other commodities.

Equity markets. We start by analyzing the response to the identified structural shocks of several (log) equity market indices (US, China, Euro area, UK, Japan, a global

[13]Forecast error variance decomposition are not reported for the sake of brevity, but are available upon request.

[14]The projection regressions are estimated using Bayesian methods. We report results for $p = 1$. Adding further lags does not change the outcome of the analysis.

[15]Notice that S_t is a generated regressor. We therefore estimate its effects using the following algorithm. First, we obtain a draw of S_t from the posterior distribution of the daily VAR. Then, conditional on this draw, we draw 100 estimates of γ_h using a standard regression model with conjugate, uninformative, priors. We repeat this procedure 250 times and thus obtain an empirical distribution for γ_h.

aggregate), of implied volatility in the US (the VIX) and of implied volatility in Europe (the VSTOXXI, see Figure 3). The first, important, result is the strong response of equity prices to a risk sentiment shock. Strikingly, equity prices for China (and also, not shown in the chart for brevity, for EMEs) rise by 1 percent on impact, given a 1 percent increase in the price of oil, revealing a tight link between investors sentiment on Emerging markets and oil prices. Current oil demand shocks also have a strong, positive effects on equity prices, but their impact response is around one third that of risk sentiment shocks, confirming that it is the latter shock that captures the bulk of the positive co-movement between equity and oil prices. Equity prices tend to respond negatively to scarcity shocks across the board, but the effect is smaller and less precisely estimated (significant only for Europe, Japan and China).

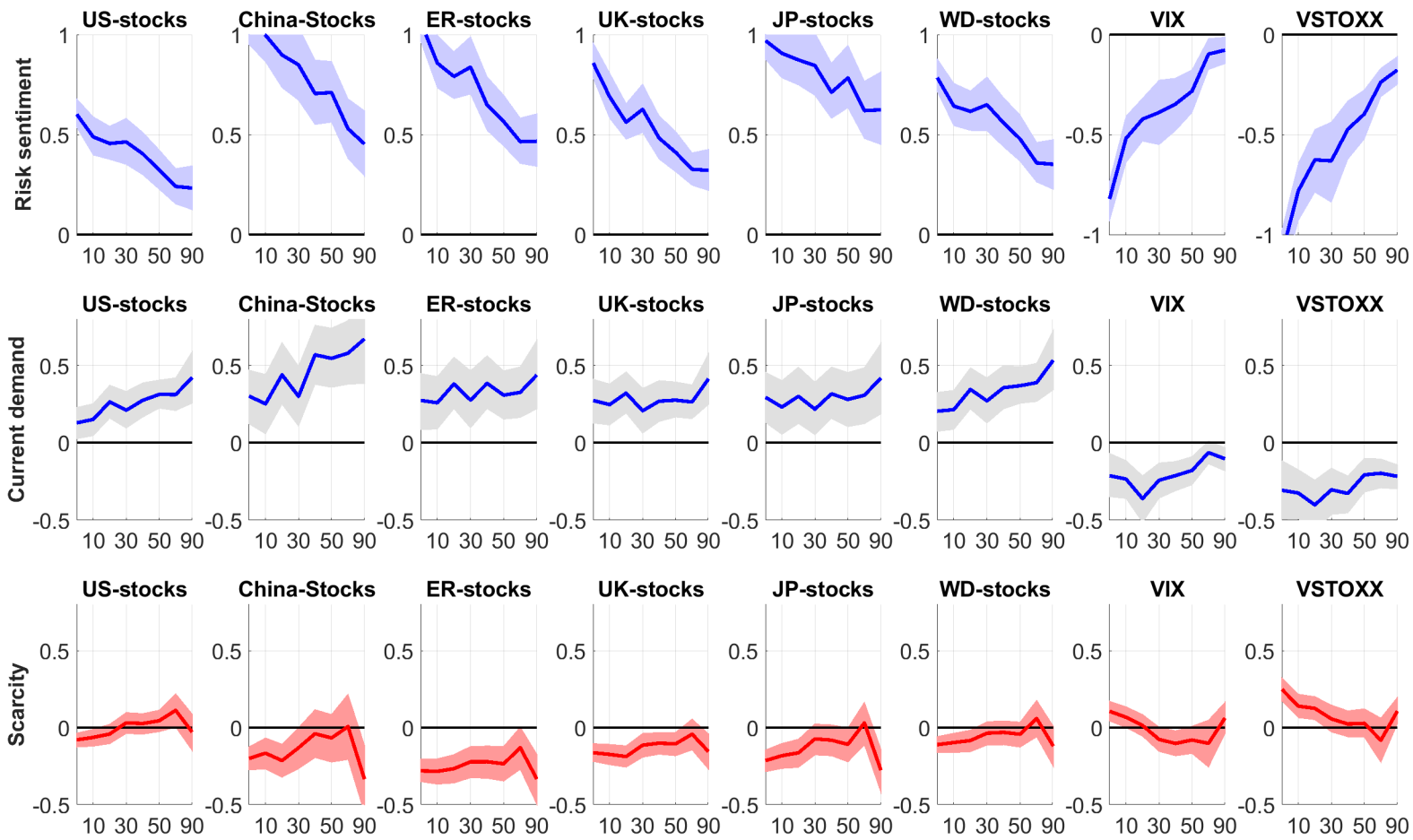

Figure 3: Response of stock prices and equity volatility to structural shocks

Note. IRFs are estimated using local projections as in equation (4). Error bands are 90 percent confidence intervals obtained by simulation techniques taking into account both uncertainty on the estimation of the shock as well as uncertainty on the parameters of the local projections. They are adjusted to account for autocorrelation of the residuals via a Newey-West correction. The horizontal axis measures working days after the shock.

Importantly, US stock prices barely respond to scarcity shock. This is not surprising given the large weight that tech companies, for which oil does not play an important role as an input, have on the $S\&P500$. It also reflects the fact that increased domestic oil production shelters the US stock market (and the US economy) from energy price shocks.[16] Finally, volatility moves in the opposite direction with respect to stock prices, in particular in response to risk sentiment shocks, as the leverage effect makes options cheaper when the price of the underlying stock increases (Geske, 1979). The VIX, consistently with the muted response of US equity prices, is not affected by scarcity shocks. Overall, these results are broadly in line with those obtained by Kilian and Park (2009) on US stock markets. Yet, the broader scope of our analysis allows us to uncover significant heterogeneity across markets and reveals that the strong episodic co-movement between oil and risky asset prices observed in financial markets is mainly due to unexpected changes in investors sentiment.

Sovereign bond markets. We next turn to the response of long-term yields (see Figure 4). Oil price shocks affect long-term yields via two channels. First, by affecting inflation and growth, they change the term premium, that is the compensation that investors require to hold a fixed income long-term investment. Second, they affect the expected path of short term interest rates, as investors expect central banks to react to the shocks that move oil prices. Of course, the nature of the shock matters greatly both for the reaction of term premia as well as for that of rates expectations. Risk sentiment and demand shocks move inflation and output in the same direction, raising the term premium and calling for a pro-cyclical response of monetary policy. Scarcity shocks, on the other hand, induce a negative correlation between inflation and output. They therefore have, in principle, an ambiguous effect on the term premium, as long-term bonds provide a hedge against a recession but are negatively affected by unexpected inflation. Also, their impact on expected rates will depend on the relative weight placed by policy makers on inflation and output. Figure 4 shows the response of 10y government bond yields in the US, Germany and in the UK to our structural shocks. Two robust results emerge. First, when oil prices rise because of a reflationary shocks (that is a positive risk sentiment or current demand

[16] These results also provide further support for the choice of using airline equity prices in the baseline daily VAR, rather than an aggregate stock market index, which would fail to capture the high frequency effects of oil supply shocks on stock returns. The response of airline stock stock prices to supply shock (around -0.45 percent on impact, see figure 2) is indeed substantially stronger than that of aggregate indices.

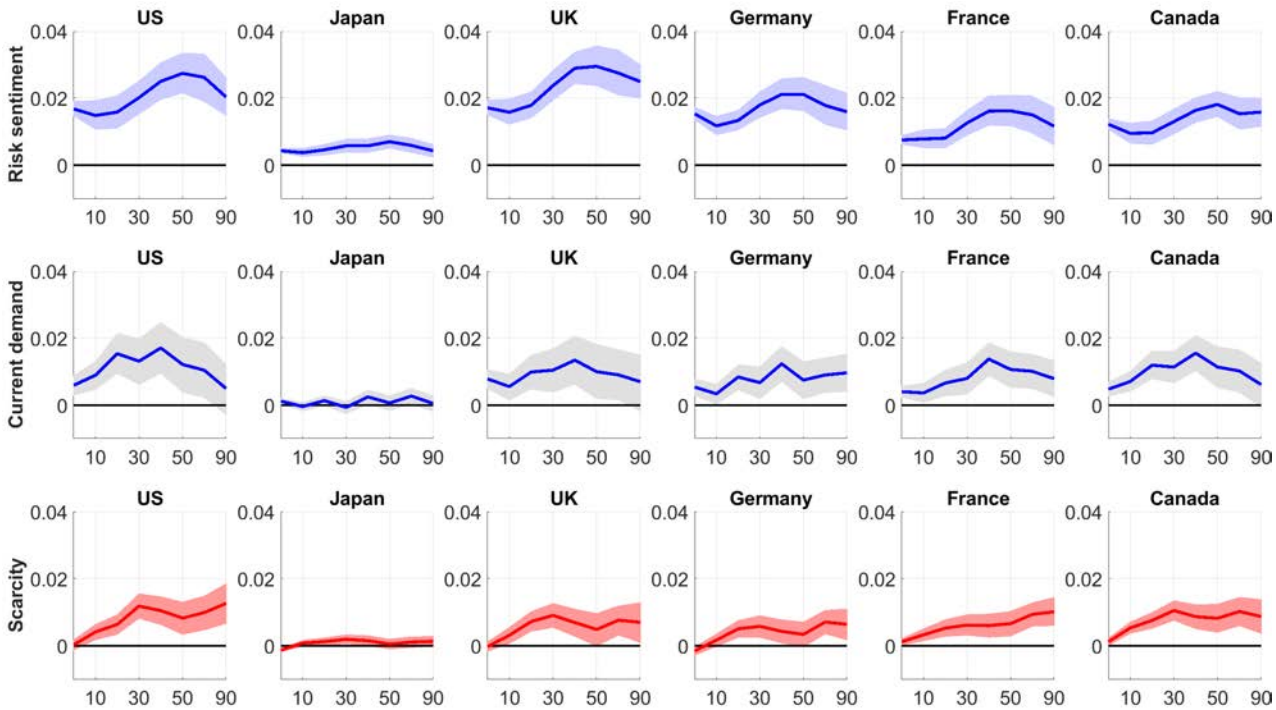

Figure 4: Response of bond yields to structural shocks

Note. IRFs are estimated using local projections as in equation (4). Error bands are 90 percent confidence intervals obtained by simulation techniques taking into account both uncertainty on the estimation of the shock as well as uncertainty on the parameters of the local projections. They are adjusted to account for autocorrelation of the residuals via a Newey-West correction. The horizontal axis measures working days after the shock.

shock), investors sell safe assets (and rotate to risky assets, as shown in Figure 3). As a result, bond yields increase significantly. Second, scarcity shocks raise long-term bond yields, indicating that the inflationary impact of these shocks is a significant concern for bond holders, although their effect is smaller and less precisely estimated.

Inflation swaps. Next, we consider the derivative market for inflation compensation. The price of inflation-linked swaps (ILSs) is often used by central banks to obtain measures of long-term inflation expectations. One such popular measure is, for instance, the 5 to 10 years expectations, that is the average inflation rate over a five year period, starting in five years time, as implied by ILS rates (Böninghausen, Kidd, and de Vincent-Humphreys, 2018). The strong co-movement between the price of oil and such measures of long-term inflation expectations (for instance, 0.43 between 2007 and 2020 for the US) is a long-standing puzzle, given the notion that oil price shocks have only temporary effects on consumer prices

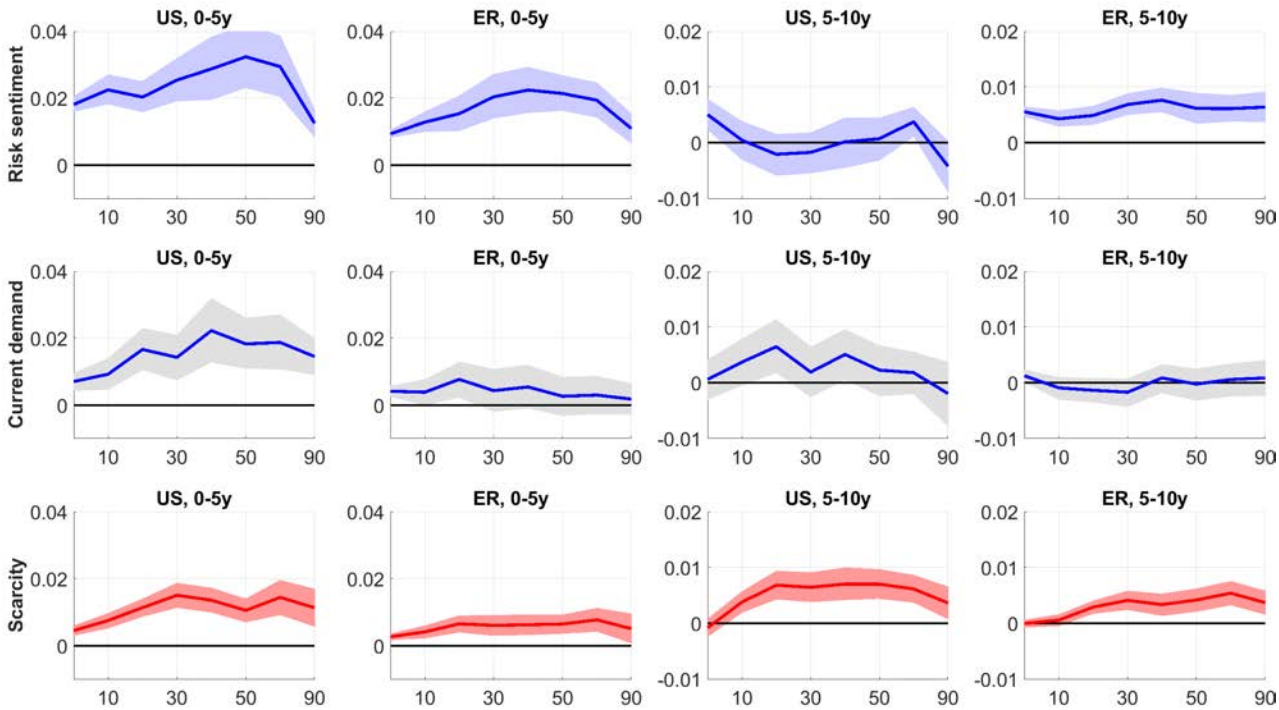

Figure 5: Response of Market based inflation expectations to structural shocks

Note. The chart shows the IRFs to the identified structural shocks. IRFs are estimated using local projections. Error bands are obtained by simulation techniques taking into account both uncertainty on the estimation of the shock as well as uncertainty on the parameters of the local projections. They are adjusted to account for autocorrelation of the residuals via a Newey-West correction. The horizontal axis measures working days after the shock.

and, therefore, should not affect expectations at distant time horizons (Perez-Segura and Vigfusson, 2016). A plausible explanation is that inflation expectations and oil prices are moved by common shocks, which might also be related to the compensation that risk-averse investors demand because of uncertainty about future inflation (Böninghausen, Kidd, and de Vincent-Humphreys, 2018). In our analysis, we consider two measures of market-based inflation expectations for the US and for the euro area, that is 0-5 years ahead and 5-10 years ahead inflation. Figure 5 shows that shorter term expectations (0 to 5 years ahead) respond to all the three shocks in which we decompose the price of oil. This reflects simply the fact that any change in the price of oil also impacts current inflation (directly via energy prices, but also indirectly via second round effects) and this is priced in the shorter leg of the 0-5 years inflation swaps. The picture looks different for expectations at the 5 to 10 years horizon. First, most of the contemporaneous co-movement between oil prices

and inflation expectations is accounted for by the risk sentiment shock. For instance, an increase of the price of oil by 1 percentage point due to a risk sentiment shock results in an increase of 5 to 10 years inflation expectations of 1 basis point in the US and of 0.5 basis points in the euro area one day after the shock. This effect dies out quickly in the US but remains more persistent in the euro area. Demand shocks have some delayed effects in the US, but no impact whatsoever in the euro area. This, again, confirms that risk sentiment and demand shocks convey different information related to different time horizons. Finally, scarcity shocks have a negligible effect at short horizons but their impact builds over time, suggesting that also these shocks, when left unattended, could dislodge longer term inflation expectations.

Foreign exchange and commodities. The price of oil has historically tended to move in the opposite direction with respect to the dollar, that is to strengthen when the value of the dollar weakens against other major currencies, and vice versa. Within our sample, the unconditional correlation between the US dollar and the price of oil is -0.78. According to some authors, this relationship might arise from the fact that oil affects the dollar through the terms of trade (Backus and Crucini, 2000) a view that, however, clashes against the empirical disconnect between macroeconomic fundamentals and the exchange rate. More likely, the US dollar and the exchange rate share a common component related to current and expected changes in economic conditions (Kilian and Zhou, 2019). This could also be related to fluctuations in global risk, which would influence simultaneously exchange rates and asset prices (Gabaix and Maggiori, 2015).

In the first three columns of Figure 6 we show the response of traditional safe haven currencies (the US dollar, the Swiss franc and the Japanese Yen) to our identified structural shocks. All these currencies lose value in response to a positive risk sentiment shock. Consistently with the financial frictions view of the exchange rate, as markets are dominated by increased appetite for risk, investors move away from traditional safe currencies (Lille, Maggiori, Neiman, and Schreger, 2019; Kalemli-Ozcan, 2019; Habib and Stracca, 2012). The dollar, however, has a special relationship with the price of oil as, unlike the other currencies herein analyzed, it depreciates also in response to a current demand and to a scarcity shock, a result that, despite the methodological differences in the identification of the structural shocks, echoes that of Kilian and Zhou (2019).

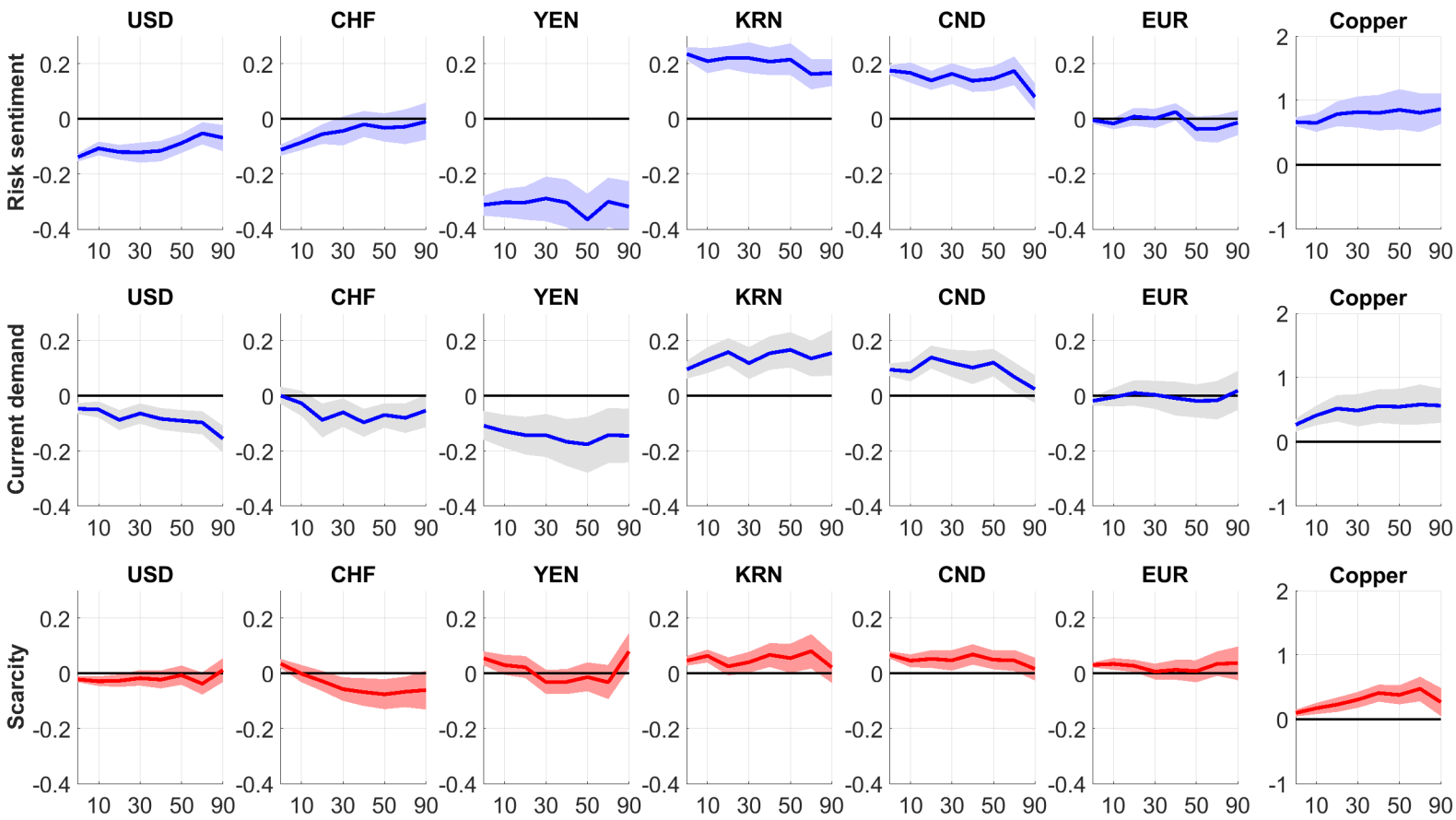

Figure 6: Response of exchange rates, copper and Baltic index to structural shocks

Note. The chart shows the IRFs to the identified structural shocks. IRFs are estimated using local projections. Error bands are obtained by simulation techniques taking into account both uncertainty on the estimation of the shock as well as uncertainty on the parameters of the local projections. They are adjusted to account for autocorrelation of the residuals via a Newey-West correction. The horizontal axis measures working days after the shock.

In contrast, currencies of advanced oil exporting economies, such as the Canadian dollar (CND) and the Norwegian Krona (KRN), appreciate in response to an increase in the price of oil, regardless of the underlying structural shocks. Remarkably, for the Canadian dollar (Norwegian Krone), the effect is about four (two) times as strong when crude prices are moved by risk sentiment shocks rather than by scarcity shocks. This result is in line with the literature on oil exporter currencies, dating back to Akram (2004), and gives some structural content to the predictive relationship between commodity prices and exchange rates studied by Ferraro, Rogoff, and Rossi (2015). Finally, the euro (EUR) does not present any significant correlation with the identified structural shocks. In the last chart, on the right hand side, we look at the response of copper. The price of copper, often used as a proxy for the global business cycle, responds positively and significantly to all the three shocks. The strong positive spillovers of commodity prices, independently of the structural shock driving them, has been also documented by Peersman, Rüth, and der Veken (2019), who rationalize this result as the outcome of information discovery in globalized and financialized commodity markets.

5.3 Zooming into specific episodes

Given the daily frequency of the analysis, we can interpret high frequency movements in the oil price through the lens of our structural identification. We examine some examples that provide the flavor of the method and the potential usefulness of the tool in providing policy makers with a description of oil market developments and their drivers in real-time. For each identified shock we present a particular day or set of days, in which its contribution to the daily movement in the oil price stands out as starkly dominant with respect to the the one of the other shocks.[17]

We start by considering risk sentiment shocks. Not surprisingly, one day identified by our statistical procedure as being characterized by large risk sentiment shocks is the 8th of August 2011, when US credit rating was downgraded and markets were dominated by a

[17]Specifically, we look for days when the contribution of each shock to the historical decomposition is larger (in absolute value) than the largest contribution of any other shock, or than the joint contribution (in absolute value) of other shocks. This resonates with the idea of the narrative identification proposed in Antolîn-Dîaz and Rubio-Ramîrez (2018), but we do not use these results to restrict the set of admissible models, but rather to evaluate ex-post if our identification method is plausible in explaining some noteworthy episodes.

large risk-off move. On Friday the 5th of August 2011, the credit rating agency Standard and Poor's stripped the US of its AAA status, judging US debt dynamics to be on an unsustainable path. On Monday, when markets opened, risky assets sold off, on the back of concerns that a slowing global economy would weaken further. US stocks sank the most since December 2008, while Treasuries rallied and gold surged to a record. The VIX experienced the biggest jump since 2007. Consistently with growing worries about the global economy, oil prices also plunged. And indeed our model decomposition intuitively attributes this fall in the price of crude around this episode to a large negative risk sentiment shock (Figure 7).

Next, we turn to an example of trading days dominated by scarcity shocks. Our model decomposition identifies the 27th of November 2014 as a day in which this shock played a major role in the oil market. With oil prices sliding due to an oversupplied market, some OPEC members (like Venezuela and Algeria) called for production cuts to stop the slide in crude prices. Saudi Arabia, however, stopped the initiative, cognizant of the fact that persistently low oil prices would hurt the Iranian economy as well as shale oil producers. As a result, the price of oil plunged to a four year low.[18] Our model correctly assigns both the preceding slide, as well as the sharp fall on the 27th of November to the glut in the physical oil market (i.e. a positive scarcity shock).

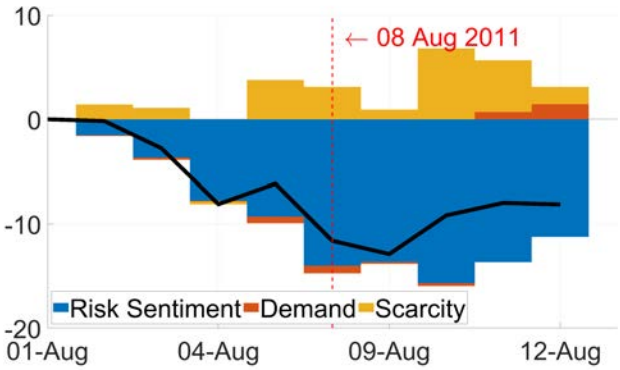

Figure 7: August 2011, US downgrade

Note. The chart shows the contribution of the structural shocks to the cumulative percentage change of the price of oil in the days indicated.

As to demand shocks, we zoom into April 2019 when, for several days, their contribution to the oil price change was dominant. At the beginning of the month oil prices staged

[18] See here Reuters article, accessed on the 26th of January 2020.

a recovery, buoyed by several positive macroeconomic data releases, namely the Chinese and US manufacturing PMI indicators (April 1st) and the employment report in the US (April 5th), which some oil analysts welcomed as "green shoots". The same period is characterized by an intermittent contribution stemming from scarcity shocks, consistent with the contradictory news coming from the physical oil market.[19]

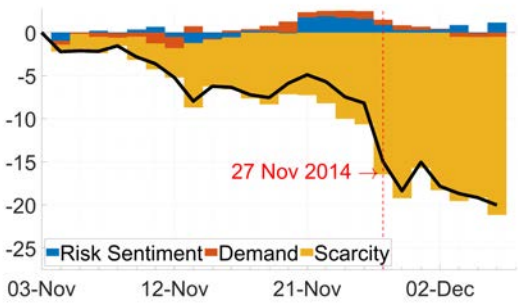

Figure 8: November 2014: the oil glut

Note. The chart shows the contribution of the structural shocks to the cumulative percentage change of the price of oil in the days indicated.

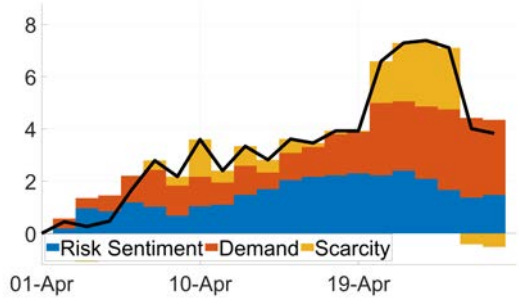

Figure 9: April 2019: green shoots

Note. The chart shows the contribution of the structural shocks to the cumulative percentage change of the price of oil in the days indicated.

5.4 The model at work: a narrative for central bank monetary policy meetings

We close by providing an example of how the model could have been used (and was actually used both at the Bank of Italy and at the European Central Bank) to analyze oil price developments at the beginning of 2020. This period is noteworthy for two reasons. First, on January the 3rd a top Iranian official, general Soleimani, was killed by a US drone. Increased geopolitical risk, also due to a brief retaliation by Iran, raised temporarily oil prices. Figure 10 reveals that our model picks the increase of oil prices in early January as the sequence

[19]For example, on April 3 US oil inventories surprised with a large stock build, while market analyst had foreseen a draw-down. On April 11 the International Energy Agency (IEA) was portraying a picture of global oil markets tightening as OPEC supply fell, but on the other hand it was warning that its demand forecasts could be lowered significantly because of economic threats. Later in the month, according to our model, scarcity shocks play an important role in driving the temporary blip in the oil price. Examining the news commentary, it is evident that oil prices spiked up on April 22nd, with the US threat of eliminating the sanction waivers for imports of Iranian crude. However, the impact on the oil price was quickly offset by a scarcity shock of the opposite sign, which the model rightly identifies on April 26th, a day when the oil market reacted negatively to President Trump urging Saudi Arabia and other countries to increase the oil supply so to offset the shortfall of Iranian crude

of negative scarcity shocks, as worries about oil supply rose together with geopolitical risk. These tensions were defused a few days later, as both President Trump as well as the Iranian government issued statements that no further escalation was to be expected on either side. Fading fears about oil scarcity led to a quick drop of the crude price, which returned to the levels recorded at the end of December 2019. Second, following the outbreak of the Corona-virus epidemic in China, oil prices plunged. From the third week of January, with the outbreak of the Corona-virus epidemic in China, oil prices dropped by almost 20%, before stabilizing in early February. At the time, lacking timely hard data on the Chinese and on the global economy, the plunge of the price of oil was interpreted as evidence of the economic scars due to higher uncertainty and to supply chains disruptions. Indeed, our model estimates attribute almost two thirds of the oil price fall to a deterioration of risk sentiment in global financial markets. In the first three weeks of February, however, a contribution came also from the current oil demand and scarcity shocks. The latter reflected increasing disagreement among OPEC and other large oil producer on how to respond to the corona virus shock (with some members suggested slowing production to accommodate the shock, and Russia opposing this view). The increased role of these two shocks shows up also in the behaviour of the term structure of oil futures. The futures curve kept shifting almost in a parallel fashion in January and remained in backwardation (see Figure 11). In the following week, the futures curve switched to "contango", i.e. the futures for nearby delivery started selling at a discount compared to deliveries for the following months. This behaviour is consistent with the different effect of risk sentiment, current demand, and scarcity shocks on the slope of the futures curve, as discussed in Section 5.1. Finally, from the 24th of February onward, as the virus spread to Europe, the sudden worsening of expectations about global economic prospects, captured by our risk sentiment shock, lead to a concurrent collapse of stock markets and crude prices.

Finally, in Appendix D we revisit the behaviour of the price of oil in longer historical periods. The narrative obtained for these periods lines up with conventional wisdom on the main drivers of oil price movements between 2007 and 2020, lending further support to the credibility of our new method.

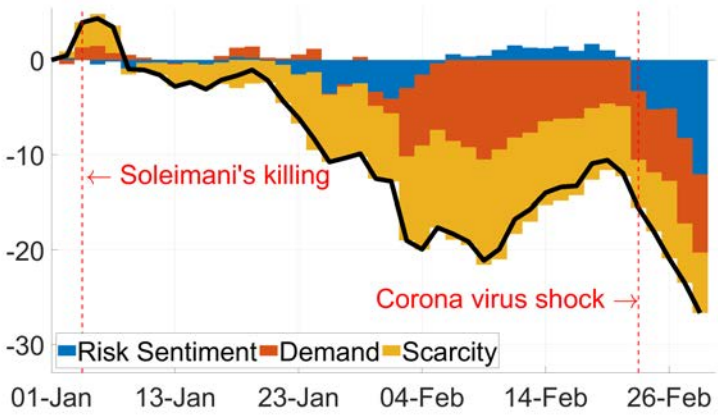

Figure 10: Iran tensions and corona-virus fears

Note. The chart shows the contribution of the structural shocks to the cumulative percentage change of the price of oil in the days indicated.

6 Conclusion

In this paper we have provided a method for decomposing the price of oil into its structural drivers at the daily frequency and studied the relationship between oil prices and global financial markets. Using a daily Vector Autoregression (VAR), in which we jointly model spot and futures oil prices and stock prices, we identify three structural shocks, namely a risk sentiment shock that captures fluctuations in oil prices that originate from revisions that market participants make on the global economic outlook, an unexpected change in the current demand for commodities and a scarcity shock, conditional on which oil prices co-move negatively with stock prices. Consistency of the shocks identified on financial asset prices with the physical oil market is ensured by further restricting the response of two lower frequency variables, i.e. oil production and global activity, to the identified shocks. The model offers novel insights on the relationship between the price of oil and global asset prices and provides a real-time reading of the shocks that jointly affect financial markets as well as the global oil market.

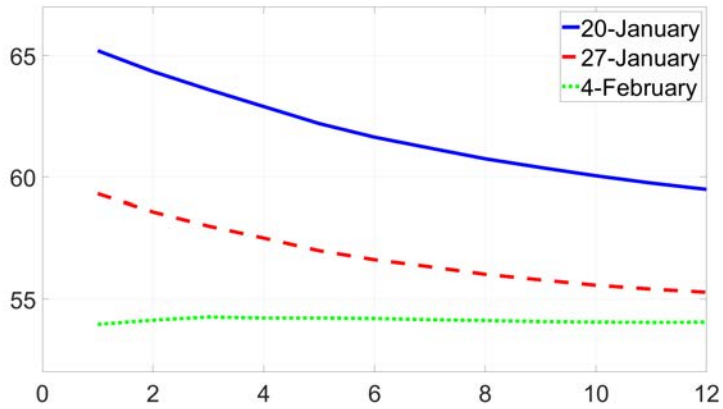

Figure 11: Futures during the corona-virus outbreak

Note. The chart shows the term structure of oil price futures in the indicated days.

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A News commentaries on instrument days

30-Sep-2008

Crude oil rose, rebounding from its biggest drop in seven years, after US lawmakers said they intend to salvage a $700 billion bank-rescue package that may avert an economic slowdown. "The market is being totally driven by what is happening in Washington", said Nauman Barakat, senior vice president of global energy futures at Macquarie Futures USA Inc. in New York. "What happens to oil prices depends completely on whether the rescue package is approved or not".

06-Oct-2008

U.S. stocks dropped, driving the Dow Jones Industrial Average below 10,000 for the first time in four years, after commodities producers slid on concern global growth is slowing. Equities fell worldwide. Bank of America Corp. and Citigroup Inc. sank more than 5% after the German government led a bailout of Hypo Real Estate Holding AG and BNP Paribas SA bought parts of Belgium's Fortis. Chevron Corp. lost 3.2 percent as oil declined to the lowest since February. The CBOE VIX surged to a record intraday high of 58.24. "It's a financial panic, total dislocation in the financial industry across the board," said Ralph Shive, chief investment officer at 1st Source Corp. Investment Advisors. Every company in the Dow average and all 10 industries in the S&P 500 retreated. Treasury securities rose and gold jumped 4 percent as investors sought the safest assets.

17-Feb-2009

Stocks slumped from Tokyo to London and New York as growing signs of a deepening recession sent the MSCI World Index lower for a sixth day. Bank of America Corp., Citigroup JP Morgan Chase & Co. lost at least 12 percent as US markets opened after a three-day weekend. General Motors Corp. retreated 13 percent before taking its case. The MSCI World Index decreased 4.1 percent, extending its 2009 retreat to 13 percent. Gold futures for April delivery reached $975.9 an ounce, the highest since July 22. Concern that a deepening U.S. recession will curb fuel demand pushed oil below $35 a barrel. Shares of metal producers and energy companies declined after commodities sank to the lowest since June 2002 on concern the global recession will reduce demand for raw materials.

20-Apr-2009

Equity indexes tumbled in New York on mounting concern that credit losses are worsening. The Conference Board's U.S. index of leading economic indicators fell more than forecast in March, indicating any recovery from what may be the longest postwar recession isn't in sight. Gold rose the most in a month as the slide in European and U.S. equities boosted demand for precious metals as a store of value. Crude oil and copper plunged, leading commodities to the biggest slump in seven weeks, as the outlook for the global economy dimmed and the dollar's rally eroded demand for raw materials. The dollar climbed to the highest in a month against a weighted basket of six major currencies. "There is growing concern that the economy really isn't turning around yet, and that would be concurrent with weak demand for commodities," said Walter Bucky-Hellwig, who helps oversee $30 billion at Morgan Asset Management in Birmingham, Alabama.

01-Jun-2010

Stocks and oil dropped, while the dollar and Treasuries rose, as a report that Lebanon fired on Israeli warplanes spurred concern tensions in the Middle East are escalating. Energy companies led declines in equities after BP Plc failed to halt the biggest oil spill in U.S. history. The Dow Jones Industrial Average slumped after last week completing a 7.9 percent monthly tumble, its worst May since 1940. Oil fell 1.9 percent to settle at $72.58 a barrel and extended losses in after-hours electronic trading. The Dollar Index climbed 0.2 percent to 86.737. The 10-year Treasury yield slipped 4 basis points to 3.26 percent. "We're in anxiety mode," said Bruce McCain, chief investment strategist at Cleveland-based Key Private Bank, which manages $25 billion. "There are already too many international and geopolitical things to worry about. What happens in the Middle East definitely gets investors worried especially because of all the concern about energy. A continuing re-pricing of risk appears to be the order of the day for now, with markets across asset classes moving from oversold to rally mode and back again", John Stoltzfus, senior market strategist at Ticonderoga Securities LLC, said in a note to clients.

08-Aug-2011

U.S. stocks sank the most since December 2008, while Treasuries rallied and gold surged to a record, as Standard & Poors reduction of the nations credit rating fueled concern the

economic slowdown will worsen. The Dow Jones Industrial Average plunged 634.76 points as approximately $2.5 trillion was erased from global equities. The S&P 500 Index lost 6.7 percent to 1,119.46 at 4 p.m. in New York, its lowest level since September, as all 500 stocks fell for the first time since Bloomberg began tracking the data in 1996. The Stoxx Europe 600 Index slid 4.1 percent to extend a drop from its 2011 high to 21 percent. A surge in Treasuries, benchmarks of the nation's $34 trillion debt market that is more than twice the value of American equities, sent the 10-year note yield down 22 basis points to 2.34 percent, the lowest since January 2009, and the two-year rate slid to a record low. The S&P GSCI commodities index lost 3.9 percent. Equities extended losses after the ratings cut prompted S&P to also lower debt rankings on Fannie Mae, Freddie Mac and other lenders backed by the government and reduce the credit outlook on Warren Buffett's Berkshire Hathaway Inc. to negative. President Barack Obama, breaking his silence on the downgrade, said the main obstacle facing the U.S. is "lack of political will in Washington" to solve the countrys problems. Investors retreated from riskier assets on concern the global economy will slow further. They poured money into haven assets such as Treasuries, gold, and the Swiss franc, while benchmark equity indexes for Europe, Australia, China extended losses. "This is fear and panic" Don Wordell, a fund manager for Atlanta-based RidgeWorth Capital Management, said in a telephone interview. The VIX surged 50 percent 48, the biggest jump since 2007 and the highest level since the day the S&P 500 bottomed on March 9, 2009.

18-Aug-2011

Stocks plunged while Treasuries rallied, pushing yields to record lows, amid growing signs the economy is slowing and speculation that European banks lack sufficient capital. Gold climbed to a record, while oil led commodities lower. The Standard & Poor's 500 Index tumbled 4.5 percent to 1,140.74 at 4 p.m. in New York. The Stoxx Europe 600 Index lost 4.8 percent in its worst plunge since March 2009. Ten-year Treasury yields fell as much as 19 basis points to 1.97 percent as rates on similar-maturity Canadian and British debt also reached all-time lows. The dollar gained versus 15 of 16 major peers. Gold futures rallied as much as 2.1 percent to $1,832 an ounce, while oil slid 5.9 percent. "The massive exodus from risk markets reflects heightened concerns with a possible recession and the accelerated loss of trust in policy makers," Mohamed El-Erian, chief executive officer and co-chief

investment officer at Pacific Investment Management Co., the worlds biggest manager of bond funds, wrote in an e-mail today. "The risk is of a rapidly deteriorating negative feedback loop of weakening fundamentals, inadequate policies and bad technicals. It's a combination of concern of a potential recession and the lack of policy tools to fight it. Until people see a bottom, they are not going to buy stocks. There will be pressure on the equity market until we see a solid policy response."

07-Sep-2011

Commodities posted the biggest gain in almost four weeks, led by industrial metals and energy, on **speculation that more economic stimulus** in the US and low interest rates will bolster demand for raw materials. "The market is following the 'risk-on' pattern," Stanley Crouch, who helps oversee $2 billion as the chief investment officer of Aegis Capital Corp. in New York, said in an e-mail. "Gold, on the other hand, is the obvious loser from the risk-on trade". The MSCI All-Country World Index of shares rose as much as 2.8 percent. The Standard & Poor's 500 Index gained 2.9 percent, snapping a three-session decline.

01-Jun-2012

Treasuries rallied, driving 10-year yields below 1.50 percent for the first time, while the Dow Jones Industrial Average erased its 2012 gain after U.S. employers created the fewest jobs in a year and reports signaled manufacturing growth was slowing. Commodities slumped. Yields on 10-year Treasuries dropped 10 basis points. The Standard & Poors 500 Index sank 2.5 percent, its biggest drop since November, to a four-month low of 1,278.04. The S&P GSCI gauge of 24 commodities slipped to the lowest level since October as oil plunged 3.8 percent to an eight-month low. Germanys two-year note yield turned negative during the day for the first time ever. Gold and silver rallied. "The bond market has reacted to every rainstorm as if its a hurricane," David Kelly, chief market strategist at JPMorgan Funds, told Bloomberg Television. "What's happened in markets over the last few years is valuations have gotten more and more extreme. In fact I dont think that there's been a more extreme day in the relative valuations of stocks and bonds in the last 50 years." Gold for August delivery rose as much as 4.3 percent to $1,632 an ounce.

24-Jun-2016

Global markets buckled as Britain's vote to leave the European Union drove the pound to the lowest in more than 30 years and wiped about $3 trillion from stock market values while sparking demand for haven assets from U.S. Treasuries to gold. MSCI's global stock index plunged 4.8 percent in the biggest slide since August 2011. The Dow Jones Industrial Average sank more than 600 points, or 3.7 percent, to erase gains for the year, while European stocks slid 7 percent in its worst day since 2008. The yen briefly strengthened past 100 per dollar. Treasury yields had their biggest drop in more than four years and gold rallied. Volatility surged, the VIX jumping 43 percent. "There were a lot of surprise positions that had be unwound very, very quickly. This is a legitimate risk-off event, and there are concerns about what's going to happen. We're likely to see weaker growth as a result of this, and it's appropriate that markets are reacting to this." said Dean Maki, chief economist of investment firm Point72 Asset Management.

02-Apr-2018

Shares deepened and volatility soared. Havens like the yen and gold rose. The S&P 500 Index closed at the lowest level since early February and finished below its average price for the past 200 days for the first time since June 2016 with fresh presidential criticism of Amazon and retaliatory tariffs from China rattling investors. The Cboe VIX jumped to 23. After the worst three months for global stocks in more than two years, the second quarter started on the back foot as trade-tension worries festered and technology shares got slammed. The risk-off tone comes two weeks before earnings season begins, with investors still anticipating a strong showing there, though watchful for signs of any slowdown in the synchronized global expansion and strains from Federal Reserve tightening. Fanning the rout in tech, the biggest gainers of the bull run, U.S. President Donald Trump renewed his attack on Amazon, sending shares of the online retailer down the most in more than two years. Elsewhere, crude slid the most in almost two months as fears of a trade war prompted investors to dump commodities.

23-May-2019

U.S. stocks retreated further on Thursday and investors sought refuge in gold and bonds as the world's two largest economies hardened their trade-war stances. The yen gained against the dollar, while 10-year Treasury yields fell to their lowest since 2017. The S&P 500 Index dropped for a fourth session in five, and the Dow Jones Industrial Average lost

286 points, after the Chinese Communist Partys flagship newspaper published two commentaries assailing U.S. moves to curb Chinese companies. Stocks in industries seen as susceptible to trade disruptions – including semiconductors, automobiles and energy – retreated. Emerging-market shares slid and West Texas crude fell below $60 a barrel, while yields on bunds and gilts hit two-year lows. Risky assets remain under pressure and havens in demand as investors dig in for what looks like a protracted trade dispute. Goldman Sachs Group Inc. now sees higher odds of a stalemate between the two nations, and Nomura Holdings Inc. has shifted to forecasting a full-blown escalation of tariffs.

31-May-2019

The latest move by the self-described Tariff Man would put 5% American duties on all Mexican imports on June 10, rising to 25% in October unless Mexico halts illegal migrants heading to the U.S. Trump's Mexico declaration and a Bloomberg report that China is planning to restrict rare-earths exports leave markets set for a turbulent end to what's been a rough month for global stocks. Treasuries have benefited from haven demand, with yields on 10-year notes down to 2.15% Friday compared with 2.50% at the start of the month. These announcement exacerbated the global risk-off sentiment and led to a selloff in risk assets globally. Conversely, safe haven assets have been strongly bid with the 10Y Treasury yield dropping to 2.14% and the 10Y Bund yield dipping below -0.2%, its lowest level on record. The Japanese yen was also bid, appreciating by about 0.8%, while the US dollar slightly weakened against major currencies this morning. Gold gained 1.3% to $1,304.81 an ounce, the highest in seven weeks.

14-Aug-2019

Oil stocks gave up Tuesday's gains to tumble toward an almost two-year low amid a global selloff. Stocks in Asia were poised to join a global sell-off after U.S. equities tumbled and a closely watched part of the Treasury yield curve inverted, raising recession fears. Treasuries surged. The S&P 500 tumbled almost 3% on Wednesday as the 10-year Treasury rate slid below the two-year for the first time since 2007. Bonds also climbed across Europe, with the U.K. yield curve inverting for the first time since the financial crisis and Bund yields sliding to a fresh record low. Gold surged and crude oil slumped. Warnings flashing in bond markets are spooking investors who are already seeking shelter

from the fraught geopolitical climate and the impact of the global trade war. "You no longer have anything anchoring markets, you no longer have the Feds ability to repress financial volatility," Mohamed El-Erian, Allianz Chief Economic Advisor & Bloomberg Opinion columnist, told Bloomberg TV.

24-Feb-2020

Investor fears are intensifying following multiple signs that COVID-19 is spreading rapidly outside China. Global equities are almost 2.5% lower this morning, adding to last weeks losses, with the VIX implied volatility index jumping to almost 24. Benchmark global bond yields have tumbled amid surging haven demand, with key US tenors trading below or near all-time lows, as reports indicate that virus cases are surging in multiple continents. European stocks have been hit hardest, down around 3.5 percent this morning, led by Italy (-4.9%) after authorities announced lockdowns of sections of Northern Italy in response to a surge in COVID-19 cases. While most Italian assets have seen sell-offs with sovereign spreads to Bunds widening and bank CDS rising the moves are still partially unwinding impressive gains in recent quarters. Emerging markets are also affected this morning, with currencies sharply weaker versus the greenback and equities off 4%.

B Model estimation: details

For convenience, let us rewrite the expressions for the VAR. The structural form can be written as :

$$A_0 y_t = A_+ x_t + e_t, \qquad e_t \sim i.i.d.\ N(0, I), \tag{5}$$

where $A_+ = [A_1, A_2, ..., A_p, c]$ and $x_t = [y'_{t-1}, y'_{t-2}, ..., y'_{t-p}, 1]'$. A_0 is an $n \times n$ matrix of contemporaneous interactions, the p matrices A_j, $j = 1, 2, ..., p$ of dimension $n \times n$ collect the autoregressive coefficients, e_t is a n dimensional vector of structural shocks and c is an intercept term. The reduced form model is:

$$y_t = \Phi_+ x_t + u_t, \qquad u_t \sim i.i.d.\ N(0, \Sigma),$$

where $\Phi_+ = {A_0}^{-1} A_+$ and reduced form and structural shocks are related as follows:

$$u_t = A_0^{-1} e_t = B e_t, \tag{6}$$

$$\Sigma = (A'_0 A_0)^{-1} = BB'. \tag{7}$$

Let us partition the 3×3 structural impact matrix B in columns, $B = [b_1, b_2, b_3]$. Given our identification strategy, we seek to estimate the elements of the first columns b_1 using the external instrument that we have described in Section 3.1. The elements of the remaining two columns b_2 and b_3 are only set-identified, i.e. they need to fulfil the sign restrictions, the narrative restrictions as well as the elasticity bounds in Table 2.
We estimate the model using Bayesian methods. Conceptually the estimation is divided in three steps. The first step involves estimating the reduced form parameters and the first column of B. In the second step we estimate the remaining columns of B. In the third step we take care of the restrictions on the monthly variables and of the elasticity bounds.

B.1 Estimating Φ_+, Σ and b_1

Our first step consists of estimating Φ_+ Σ and the first column of B, that is b_1 using the Bayesian procedure proposed by Caldara and Herbst (2019). To understand how the method works, let us consider the relationship between the external instrument z_t and the

shock that we want to identify using this instrument (without loss of generality let us assume that this is the first shock, i.e. e_1). If z_t is a *valid* and *relevant* instrument[20] then the relationship between the shock and the instrument can be consistently estimated with the following regression:

$$z_t = \beta e_{1,t} + \sigma_\nu \nu_t, \quad \nu_t \sim N(0,1) \tag{8}$$

Equation (8) shows that if we had available an estimate of β and σ_ν, then we could recover the first shock $e_{1,t}$ and, consequently, estimate its effect on the variables in the VAR, i.e. the column b_1. Caldara and Herbst (2019) develop a sampler that delivers a joint posterior distribution for Φ_+, Σ, β and σ_ν, and therefore provides an estimate of b_1. In sub-section B.5 we analyze the strength of the instrument used for estimating b_1.

We apply some shrinkage on the model parameters through a standard Minnesota prior. Priors are implemented via dummy observations, see Geweke, Koop, Dijk, and del Negro (2012) section 2.2. Data are in levels, so the priors on the autoregressive coefficients are centered around 1 for first lag and 0 for the remaining lags. Let us collect the hyper-parameters in the vector $\lambda = [\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5]$. The parameters λ_1 and λ_2 set the tightness of the prior on the coefficients for first and for the remaining lags, respectively. The prior for the covariance matrix is centered at a matrix that is diagonal with elements equal to the pre-sample variance of the data, with tightness λ_3. Finally, λ_4 and λ_5 regulate the tightness of the sum of coefficients prior and of the co-persistence priors. Values for these hyperparameters are set at conventional levels, $\lambda = [0.5, 1, 0.5, 0.5, 1]$. For σ_v we set an inverse Gamma prior $\mathcal{IG}(s_1, s_2)$, with $s_1 = 2$ degrees of freedom and scale $s_2 = 0.002$.

B.2 Estimating b_2 and b_3

To *set identify* the two remaining shocks we need to find values of b_2 and b_3 that respect the restrictions in Table 2 and that, conditional on the values for b_1, ensure that $BB' = \Sigma$. Methods that tackle this problem have been developed by Cesa Bianchi and Sokol (2017), Braun and Brggemann (2017) and Arias, Rubio-Ramirez, and Waggoner (2019). We briefly describe how we adapt the procedure by Cesa Bianchi and Sokol (2017) to the Bayesian

[20] Validity implies that the instrument is correlated with the shock of interest but uncorrelated with the remaining shocks. Relevance implies that the correlation between the instrument and the shock of interest is significantly different from zero.

framework of Caldara and Herbst (2019). Identification via sign restriction consists of finding an orthonormal matrix Ω (i.e. a matrix such that $\Omega^{-1} = \Omega'$) that rotates the reduced form residuals and makes them consistent with structural shocks that have the desired economic interpretation. In other words given the Choleski factor Σ_{tr} of Σ such that $\Sigma_{tr}\Sigma_{tr}' = \Sigma$ the problem consists of finding a particular Ω such that:

$$\begin{aligned} B &= [b_1, b_2, .., b_n] \\ &= \Sigma_{tr}\Omega \\ &= \Sigma_{tr}[\omega_1, \omega_2, ..., \omega_n] \\ &= [\Sigma_{tr}\omega_1, \Sigma_{tr}\omega_2, ..., \Sigma_{tr}\omega_n] \end{aligned} \tag{9}$$

Equation (9) shows that conditioning on b_1 implies a restriction on the first column of Ω $\omega_1 = \Sigma_{tr}^{-1}b_1$.[21] Then, in order to find a rotation matrix Ω such that the remaining columns satisfy the sign restrictions in Table 2, we implement the following algorithm:

1. Draw Φ_+, Σ and b_1 using the method in Caldara and Herbst (2019).
2. Compute Σ_{tr} and $\hat{\omega}_1 = \Sigma_{tr}^{-1}b_1$.
3. Draw a candidate $n \times n$ orthonormal Ω matrix using the algorithm in Rubio-Ramirez, Waggoner, and Zha (2010).
4. Replace ω_1 in Ω with $\hat{\omega}_1$.
5. Orthogonalize columns from 2 to n of Ω with respect to $\hat{\omega}_1$.[22] Call this matrix $\Omega^\star$
6. Compute $B = \Sigma_{tr}\Omega^\star$ and daily structural shocks $e_t = Bu_t$.
7. If columns b_2 and b_3 satisfy the sign restrictions in the top panel of Table 2 and if the scarcity shock $e_{t,3}$ satisfies the the narrative restriction in the bottom panel of Table 2 store this draw, otherwise discard it and return to step 1.

B.3 Identification restrictions on monthly variables

Finally, we need to ensure that the shocks that are identified on the basis of daily data have sensible implications for the physical side of the oil market. To add identification restrictions on lower frequency variables we need to estimate the effects of the shocks

[21] The intuition is that since the orthonormal matrix Ω spans $\boldsymbol{R}^n$ the first vector can be picked arbitrarily.
[22] This is done using the Grahm-Schmidt procedure.

(identified on daily data) on two monthly variables, namely global oil production and global industrial production. To implement this step we draw on Jarocinski and Karadi (2019), Paul (2017) and Gazzani and Vicondoa (2020). Suppose that we are interested in studying the effects of a given structural shock $\eta_{t,m}$ on a set of $(n-1)$ macroeconomic variables $Y_{t,m}$ and that either an external instrument or an external measure of the shock $\eta_{t,m}$ is available. First, we set up the following VAR:

$$\begin{pmatrix} \eta_{t,m} \\ Y_{t,m} \end{pmatrix} = \sum_{j=1}^{p} \Gamma_j \begin{pmatrix} \eta_{t-j,m} \\ Y_{t-j,m} \end{pmatrix} + \begin{pmatrix} \epsilon_{t,\eta} \\ \epsilon_{t,Y} \end{pmatrix}, \quad \begin{pmatrix} \epsilon_{t,\eta} \\ \epsilon_{t,Y} \end{pmatrix} \sim N(0, \Sigma_m \Sigma_m'), \tag{10}$$

where Σ_m is a (lower) Choleski factor. An estimate of the effects of $\eta_{t,m}$ on $Y_{t,m}$ is then obtained by assuming that $\eta_{t,m}$ is *predetermined* with respect to $Y_{t,m}$, i.e. that it affects contemporaneously $Y_{t,m}$ but that is unaffected on impact by other shocks in the model. This is a plausible assumption, considering that $\eta_{t,m}$ is a structural shock, and therefore unaffected at the contemporaneous lag, by other shocks.

The j periods ahead response of the ith element of $Y_{t,m}$ to $\eta_{t,m}$ is then obtained as:

$$IRF_{j,i,\eta_{t,m}} = e_i \Gamma_c^j \Sigma e_1' \tag{11}$$

where e_i is an $np \times 1$ selection row vector that has all zeros and 1 in the $i_{th}+1$ position, Γ_c is the $np \times np$ companion matrix that collects the dynamic multipliers $\Gamma_1, \Gamma_2, ..., \Gamma_p$ and Σ is a $np \times np$ block diagonal matrix with blocks $[\Sigma_m, 0_{n\times n}, \ldots, 0_{n\times n}]$.

This framework conveniently allows us to verify the impact on monthly macroeconomic variables of the shocks identified in the daily model, and to discard candidate shocks that do not have the desired effect. More in detail, we collect in the vector $Y_{t,m}$ four macroeconomic variables conventionally used to study the physical oil market, namely oil production, the real monthly price of oil, a measure of global economic activity and oil inventories.

Sign restrictions for current demand and scarcity shocks on monthly variables. We assume that, conditional on an overall demand shock, oil production, economic activity and oil prices need to rise. An important point is that we define an overall demand shock

as the sum of the risk sentiment and current demand shocks, so that the individual impact of these two shocks is not a-priori restricted. Conditional on a scarcity shock that raises oil prices, instead, economic activity needs to fall. We do not impose any restrictions on oil production conditional on scarcity shocks since production might either rise or fall depending on whether this is driven by a supply shock or by a precautionary demand shock. These additional identifying assumptions allow us to further restrict the set of admissible structural shocks estimated on the daily model.

Elasticity bounds on oil supply. Next, we impose a bound on the elasticity of supply. First define the overall oil demand shock as the *sum* of the risk sentiment and current demand shocks, let us call it $e_t^{m,dem}$. Then, we obtain the response of oil production and of the price of oil at the monthly frequency as in (11). Let us define the log of oil production as Q_{oil} and the log of the price of oil as P_{oil}. The oil price supply elasticity can then be computed as:

$$\beta_s = IRF_{0,Q_{oil},\eta_{m,dem}} / IRF_{0,P_{oil},\eta_{m,dem}} \tag{12}$$

that is the response of oil production to a demand shock, scaled by a one percent change in the price of oil. In our empirical application, we constrain the elasticity of the supply curve to lie between 0 and 0.1. This range strikes a balance between the very tight bound (0.0258) set by Kilian and Murphy (2014) and the findings of a supply elasticity of 0.081 in Caldara, Cavallo, and Iacoviello (2019).

Figure B.12 shows the posterior distributions of oil supply elasticity obtained with our model.

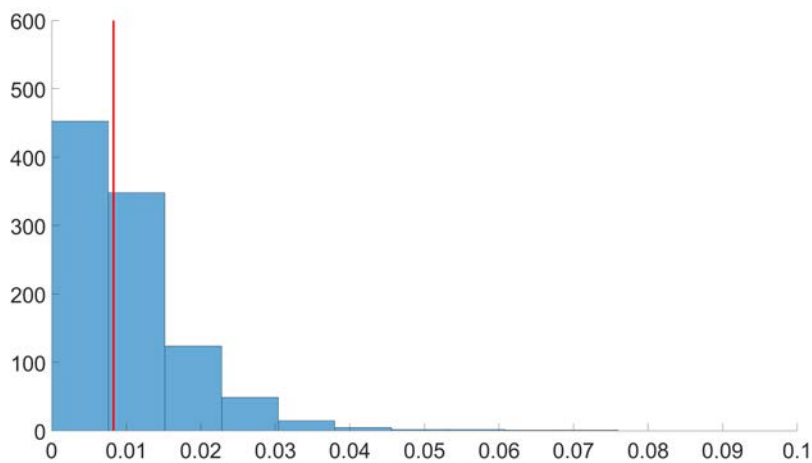

Figure B.12: Estimated Oil supply Elasticity

Kilian and Murphy (2014) also recommend imposing elasticity bounds on the demand for oil schedule. Since we conflate supply and precautionary demand shocks in a single "scarcity" shock , we do not estimate a clear shift in the supply of oil and therefore cannot identify through the impulse response functions the elasticity of oil demand.

B.4 The full estimation algorithm

We can now state the full estimation algorithm :

1. Draw Φ_+, Σ and b_1 using the method in Caldara and Herbst (2019).
2. Compute Σ_{tr} and $\hat{\omega}_1 = \Sigma_{tr}^{-1} b_1$.
3. Draw a candidate $n \times n$ orthonormal Ω matrix using the algorithm in Rubio-Ramirez, Waggoner, and Zha (2010).
4. Replace ω_1 in Ω with $\hat{\omega}_1$.
5. Orthogonalize columns from 2 to n of Ω with respect to $\hat{\omega}_1$.[23] Call this matrix $\Omega^\star$
6. Compute $B = \Sigma_{tr}\Omega^\star$ and daily structural shocks $e_t = Bu_t$.
7. If columns b_2 and b_3 satisfy the sign restrictions in the top panel of Table 2 and if the scarcity shock $e_{t,3}$ satisfies the the narrative restriction in the bottom panel of Table 2 go to the next step, otherwise discard this draw and return to step 1.
8. Take a monthly average of the daily structural shocks e_t^m. Take a draw from the monthly Proxy-SVAR. If the response of oil production and global economic activity to these structural shocks is consistent (i) with the sign restrictions in the bottom panel of Table 2 and (ii) with the elasticity bounds on oil supply, retain this draw, otherwise discard it and return to step 1.

B.5 Instruments strength

In this Section we assess the strength of the instrument proposed in the paper, and compare it to alternative choices devised from simpler basic statistical criteria. We explored different criteria to select event dates, as well as different candidate proxy variables to be used as instruments. Of course in our final selection we also made sure that the dates identified could be characterized as indeed markedly risk-on or risk-off events,

[23] This is done using the Grahm-Schmidt procedure.

resorting to the actual daily commentaries from several media sources. Specifically, we looked for proxies strongly correlated with the reduced form innovations of the VAR model, most prominently in correspondence to the first equation that features the crude oil price as the dependent variable.

We take as dependent variable the reduced form residuals from equation 6:

$$\hat{u}_t = \alpha + \beta z_t + \nu_t$$

A high F-statistic for the null hypothesis that $\beta = 0$ suggests that the candidate proxy indeed reflects variations in the developments in oil prices, in a sufficient strong way to label the candidate the candidate proxy as a strong instrument. The results of the tests considering different choices of the proxy are shown in Table 3.

Table 3: **Alternative instruments: relevance F-test**

instrument	Oil price		Airlines		Futures 12th	
	F-test	pval	F-test	pval	F-test	pval
VIX	82.073	0	167.54	0	83.156	0
Gold	20.076	0	4.594	0.032	26.601	0
OVX	30.672	0	4.962	0.026	43.036	0
USD	61.908	0	124.88	0	71.763	0
CHF	0.487	0.485	0.507	0.477	2.328	0.127
JPY	7.81	0.005	50.805	0	10.455	0.001
US10Y	45.464	0	68.692	0	44.042	0
VIX+Gold	11.868	0.001	104.57	0	20.359	0
VIX+OVX	153.56	0	209.15	0	175.58	0
VIX+USD	96.959	0	263.26	0	124.1	0
baseline	36.322	0	92.401	0	45.961	0

Notes: The table reports the F-test of the regression of reduced form residuals from the base VAR on alternative instruments. For each variable the median from the draws of the reduced from residuals are reported along the first column, the corresponding p-value in the second column.

We build from several variables to arrive at proxies of our risk shocks: the VIX, the price of gold, the US dollar nominal effective exchange rate, the yield on the benchmark 10 year US Treasury note, and the OVX. First, we considered each variable in isolation, identifying

dates displaying extreme movements implying a major risk shock.[24] In each of these cases the proxy is set equal to the change of the VIX upon these days and equal to zero on all other days. Second, we refined the search for risk-off days, by considering the joint behavior of each variable with the VIX, selecting only days when both variables display extreme movements in the same direction. As we can see from the Table, as soon as we pool information from at least two sources the strength of the instrument does not seem to be an issue for the oil price equation residual (first variable in our VAR). Finally, we considered the joint behavior of the VIX with any of the two other variables, holding the VIX change upon the resulting days as our proxy. Results for these other combinations are not reported here for the sake of brevity. We report instead the strength statistics for the baseline proxy used in our application (see last row in Table 3): as discussed in Section 3.1 it is inspired from the latter approach, where the risk variables used are the OVX, the VIX and price of gold, and the VIX is used as the proxy variable.

[24] We consider the empirical distribution of each variable and select extreme dates as those in its tails. The thresholds are the 5% and 95% percentile when considering joint behavior of 2 or three variables at a time, or the 1% and 99% percentile, when considering a single variable in isolation.

C The effects on monthly variables

Figure C.13 displays the dynamic effects of the three identified structural shocks on three additional monthly variables, namely oil production, the measure of global industrial production developed by Baumeister and Hamilton (2019) and oil inventories. Details on how these are obtained can be found in Appendix B. Risk sentiment shocks have significant and persistent effects both on global economic activity and on oil production. The latter only responds with a lag to this shock, suggesting that the shock identified by our external instrument genuinely anticipates macroeconomic developments that lead to higher demand for oil. Current demand shocks also raise persistently economic activity and oil production. Finally, scarcity shocks have a recessionary impact but do not move significantly oil production.

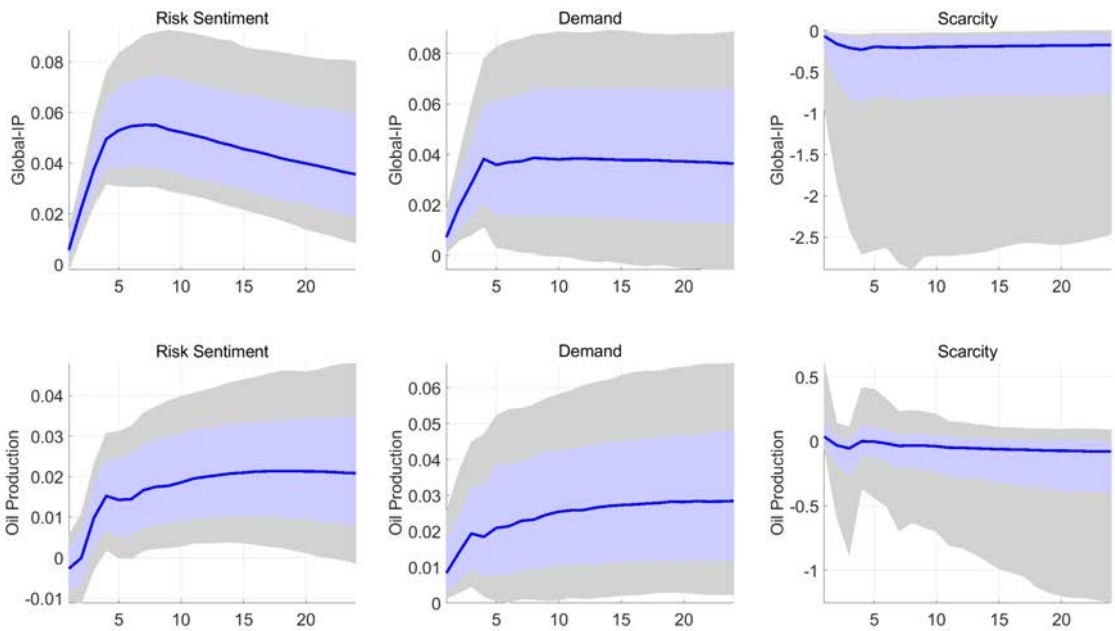

Figure C.13: Impulse Response Functions: monthly variables

Note. 68 percent confidence bands. Both parameter and identification uncertainty is reflected in the confidence bands. Impulse response functions are standardized so as to lead to a 1 percent increase in the price of oil.

D Longer historical decompositions

In this Appendix we describe the historical decomposition of the actual path of the price of oil that can be attributed to our structural shocks. We focus on three specific longer time periods, namely the global financial crisis, the months between 2014 and 2015 when oil prices slumped, and the turn of the 2018-2019 years, when oil prices were affected by increased worries about the global business cycle and difficulties of OPEC in agreeing on a credible strategy to put a floor to oil prices.

The global financial crisis. Movements in the price of oil around the global financial crisis, i.e. the slump observed in 2008 and the subsequent recovery in 2009, are dominated by a fall and a recovery in global risk appetite, see Figures D.14 and D.15, consistently with the financial nature of the shock that hit global financial markets in that period. In contrast, the role of supply shocks, albeit positive, is barely visible and becomes more relevant in the last part of 2008 and the first half of 2009, possibly reflecting news on the production cuts being implemented by the OPEC cartel.[25]

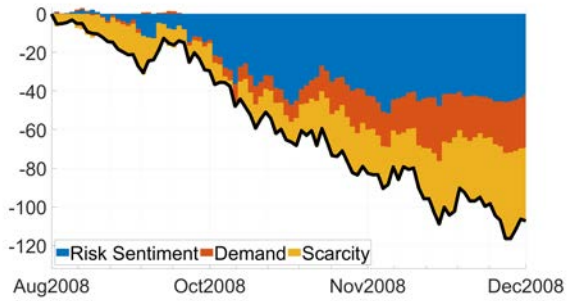

Figure D.14: The Global Financial Crisis oil price slump

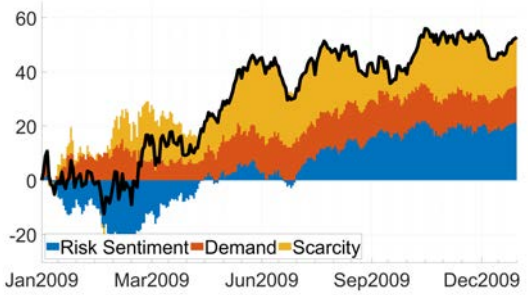

Figure D.15: the post Global Financial Crisis oil price recovery

The 2014-2015 slump. The reasons behind the long slump in the price of oil over this biennium are the object of long discussions among academics and practitioners. Part of the story is related to the supply side of the global oil market. Since 2011, advances in the shale oil extraction technology (together with investments in pipeline systems and rail capacity) had allowed the US to compete, in terms of daily extraction volumes, with two of the worlds largest oil producers, Russia and Saudi Arabia. In 2014 OPEC reacted to the

[25] OPEC cuts were announced on 24 Oct. 2008 and on 17 Dec. 2009, but effective implementation was gradual and took place during the first months of 2009.

production boom in the US by abandoning production quotas and expanding production. This strategy aimed at crowding out US competitors by driving oil prices below the levels at which US shale oil producers could be profitable. Despite a substantial fall in the price of oil, US production did not fall dramatically, as shale producers improved their competitiveness through mergers and acquisitions. A second factor was the worsening of global economic prospects, due in particular to worries about growth in China. Such worries triggered a rise in risk aversion with a concurrent tightening of financial conditions in December 2015, a shock of proportions large enough to persuade the Fed, which had started normalizing rates, to remain on hold for a whole year. Reading these episodes through the lens of the model reveals that both factors show up as important ingredients of the oil price fall, albeit with different timings. The protracted fall in the price of oil observed between 2014 and the beginning 2015 was induced, according to the model, by an interplay between falling demand, which played a role at the beginning of 2014, see Figure D.16, and increased supply. The effect of the latter became particularly strong in late 2014 –in response to the OPEC surprise announcement to maintain production on 27 Nov. 2014 despite the ongoing slump in prices– and again in the second half of 2015, see Figure D.17.

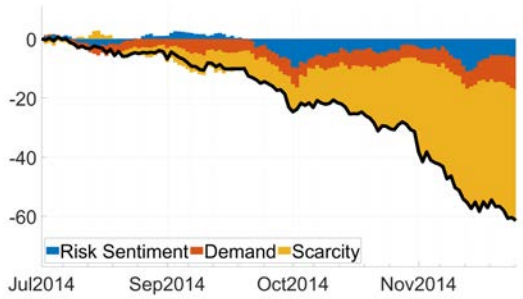

Figure D.16: The 2014 oil price slump

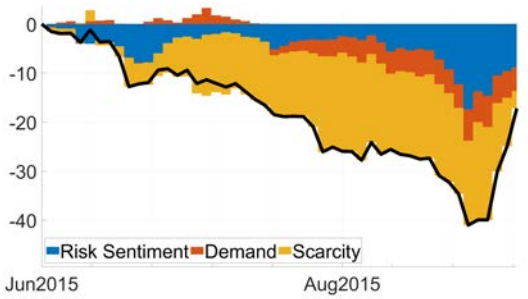

Figure D.17: The 2015 oil price slump

Opec new strategy and the 2017-2018 recovery. OPEC's strategy to regain market shares turned out to be more costly than expected in terms of fiscal revenues. Shale oil producers, in fact, proved able to reorganize their production processes, enhance extraction techniques and overall lower their break even prices, leading OPEC to revert its strategy to price stabilization. In late 2016, OPEC reconsidered its approach by returning to a policy of price stabilisation and forging alliance with some major non-OPEC countries. OPEC+,

as the alliance between OPEC and major non-OPEC countries is called, announced an agreement in November 2016 to cut production by 1.8 million barrels per day, effective from January 2017 (around 2 percent of global production). In its attempt to preserve its market power, OPEC+ faced a number of challenges. First, technical advances in the production of shale oil allow producers to easily stop and reactivate production. Such degree of flexibility makes it more challenging for OPEC+ to affect prices. Second, due to the oversupply and to weaker global demand in 2014-2016, oil inventories had reached historical peaks, making oil prices less responsive to changes in supply flows. Indeed, the initial reaction of oil prices to the OPEC+ production cuts was relatively muted, and prices only started rising in mid 2017, when global demand inventories thinned out as the recovery in global demand picked up speed. This narrative is well captured by our model, which attributes a large share of the oil price rally between July 2017 and January 2018 to demand shocks (Figure D.18). For most of 2018 risky asset prices and the price of oil showed contrasting trends. As market sentiment suffered from rising trade tensions between the US and China, global stock prices kept on a downward trajectory for most of the year. Oil prices, however, were sustained by tight supply conditions (Figure D.19).

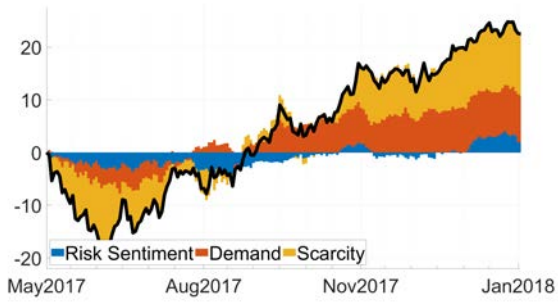

Figure D.18: The 2017 oil price recovery

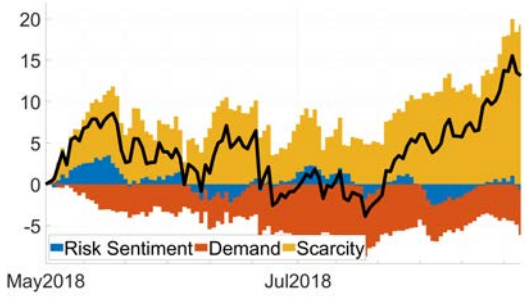

Figure D.19: 2018: contrasting forces

2018-2019 volatility. Towards the end of 2018, amid downward revisions for global demand, compliance of key producers (including the two largest producers Saudi Arabia and Russia) worsened, casting some doubts on the stability of the coalition. At the same time, stock prices and inflation expectations fell precipitously, as markets became more and more concerned about a possible catching down of the US business cycle on a weakening global business cycle. At its policy meeting in mid-December, the FOMC

increased the Fed Fund Rates and reiterated its intention to reduce the size of its balance sheet using an auto-pilot approach. The tone of the FOMC communication was perceived by the market as unduly hawkish, adding to the tightening in financial conditions. Tensions abated only in early January, when the Fed calmed investors by signalling a pause in further interest rates increases and global markets took some comfort from positive news on US-China trade talks. Moreover, in order to dispel doubts over its cohesion, the alliance between OPEC and their partners confirmed their pledge to curtail production and further decreased their individual production targets (effective from January 2019 for half a year). This narrative is well captured by the daily structural model. According to the model, the fall in oil prices at the end of 2018 was indeed mainly driven by a marked worsening of sentiment in financial market as well as by excess supply in oil markets, see Figure D.20. As OPEC and some non-OPEC countries (notably Russia) reinforced their decision to keep supply tight, and economic activity benefitted from stimulus in the US and in China, prices recovered over the course of 2019, see Figure D.21.

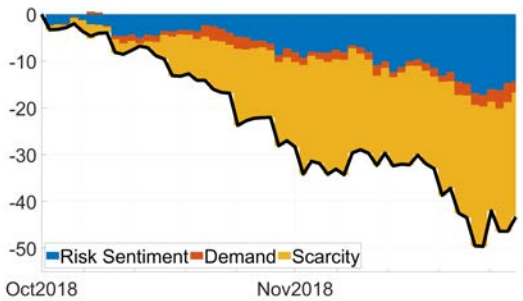

Figure D.20: The 2018 collapse

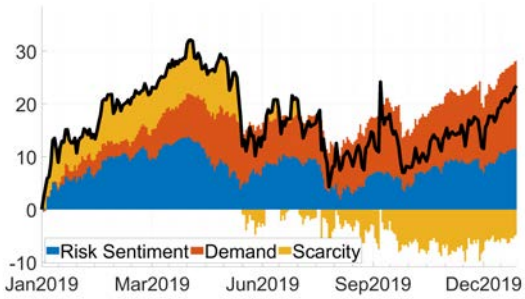

Figure D.21: The 2019 recovery

E Replacing airline stock prices with a Global Stock Market Factor

As an alternative to the stock prices of global airlines, we construct a *global* equity factor, along the lines on the risky asset price factor constructed by Miranda-Agrippino and Rey (2015) and Habib and Venditti (2019). We rely on a dataset of daily stock market returns for 57 advanced and emerging market economies excluding relatively large oil producers.[26] and model co-movement across stock returns in the $j = 1, 2, ..., 63$ countries in our sample as follows:

$$r_{j,t} = \lambda_j f_t^{global} + \xi_{j,t} \tag{13}$$

where $\xi_{j,t}$ collects both idiosyncratic terms as well as other common dynamic components (like for instance local/regional factors). Given its heterogeneity, the panel is unbalanced and presents missing observations. We follow Stock and Watson (2002) and use standard principal components analysis coupled with the EM algorithm to extract the latent component f_t^{global}. The resulting global stock market factor is the cumulative sum of f_t^{global}. We exclude from the analysis a number of large oil producers.

The following charts replicate the main analysis in the paper replacing global airlines with the global stock market factor. For the local projections of financial asset prices on daily shocks we report in red the impulse response functions obtained with airline stock prices, in blue those obtained with the global stock market factor described above. Results are remarkably similar.

[26] Stock market returns are taken from Global Financial Data. The countries included are Mexico, Australia, Canada, Finland, Netherlands, Spain, France, United States, Hong Kong, Japan, United Kingdom, Argentina, India, Chile, Sri Lanka, Ireland, Italy, Pakistan, Malaysia, Austria, Mauritius, Philippines, Peru, Egypt, Bangladesh, Belgium, Slovak Republic, Republic Of Korea, Turkey, Czech Republic, Thailand, Iceland, China, Portugal, Venezuela, New Zealand, Switzerland, Croatia, Zambia, Hungary, Singapore, Israel, Europe, Ukraine, Luxembourg, Vietnam, Denmark, Colombia, Sweden, Brazil, Bulgaria, South Africa, Lebanon, Germany, Montenegro, Slovenia. We explicitly exclude large oil producers like for instance Iran, Venezuela, Indonesia, Kuwait, Russia, Norway, Saudi Arabia.

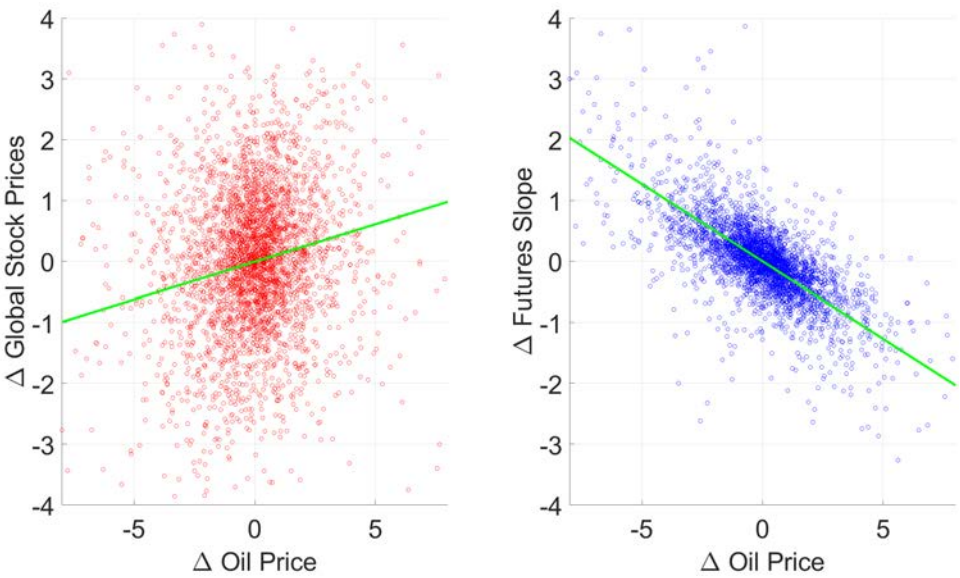

Figure E.22: Oil Prices, global stock returns and slope of the futures curve

Notes: The scatter reports daily percentage changes of the oil price (Brent quality) on the horizontal axis versus daily percentage changes in global airline stock prices (vertical axis, left hand side panel) and difference between the percentage change 12 months ahead futures prices and spot prices (vertical axis, right hand side panel).

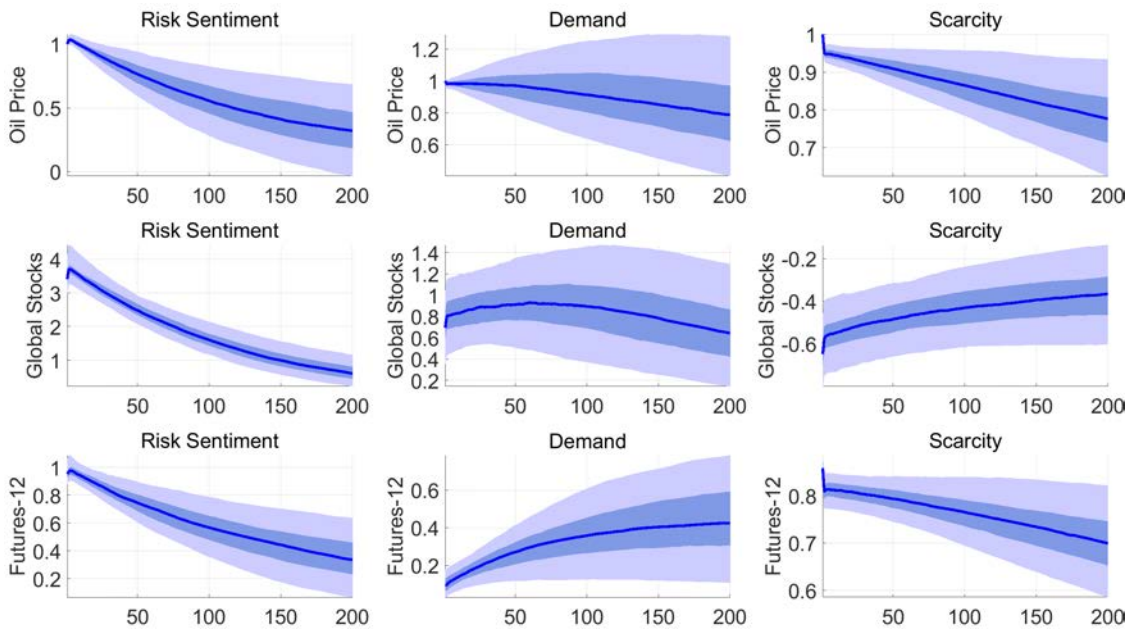

Figure E.23: Impulse Response Functions for the daily VAR

Note. 68 percent confidence bands. Both parameter and identification uncertainty is reflected in the confidence bands. Impulse response functions are standardized so as to lead to a 1 percent increase in the price of oil.

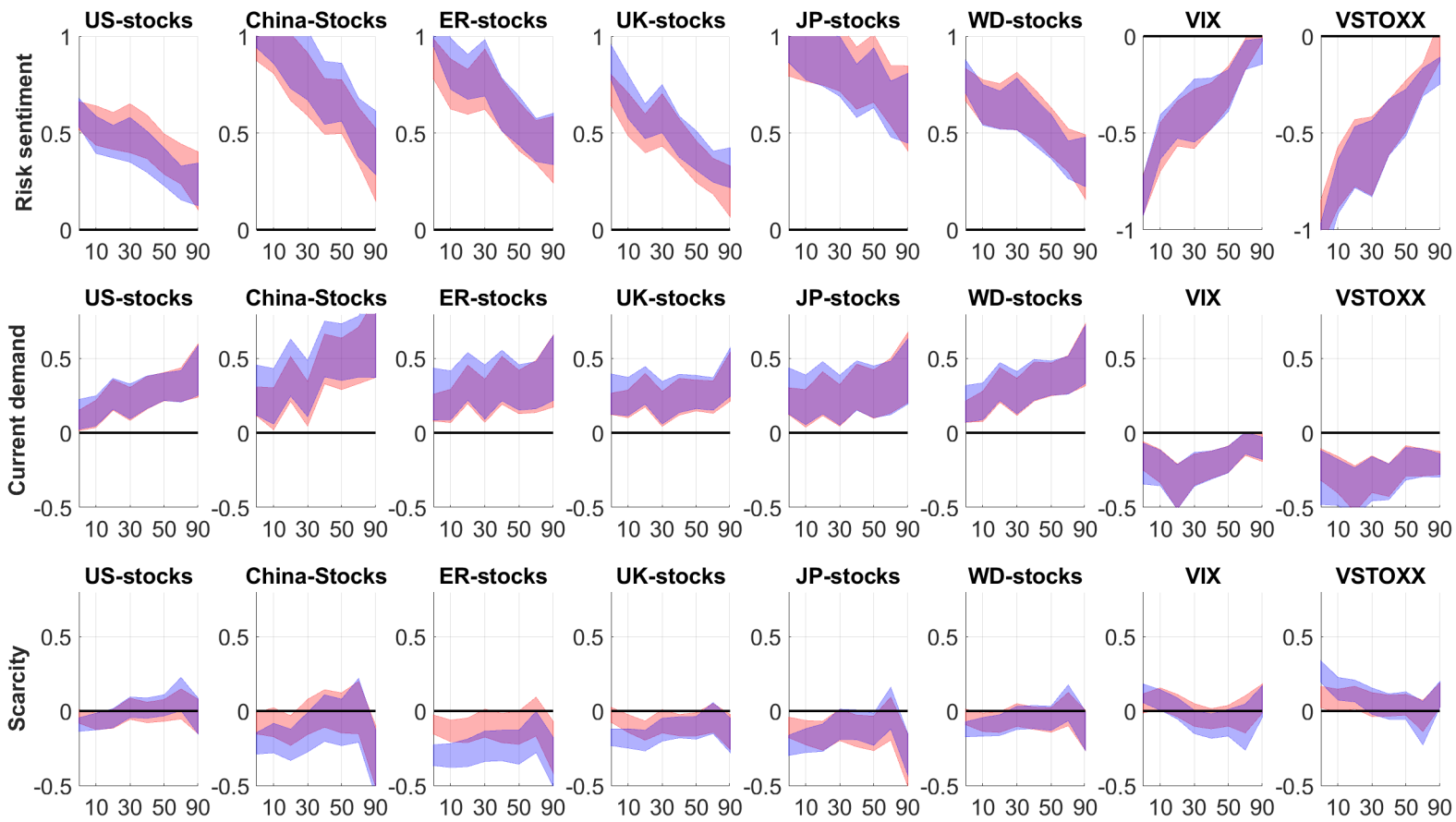

Figure E.24: Response of stock prices and equity volatility to structural shocks

Note. IRFs are estimated using local projections as in equation (4). Error bands are 90 percent confidence intervals obtained by simulation techniques taking into account both uncertainty on the estimation of the shock as well as uncertainty on the parameters of the local projections. They are adjusted to account for autocorrelation of the residuals via a Newey-West correction. The horizontal axis measures working days after the shock. In red we show the impulse response functions obtained with airline stock prices, in blue those obtained with the global stock market factor.

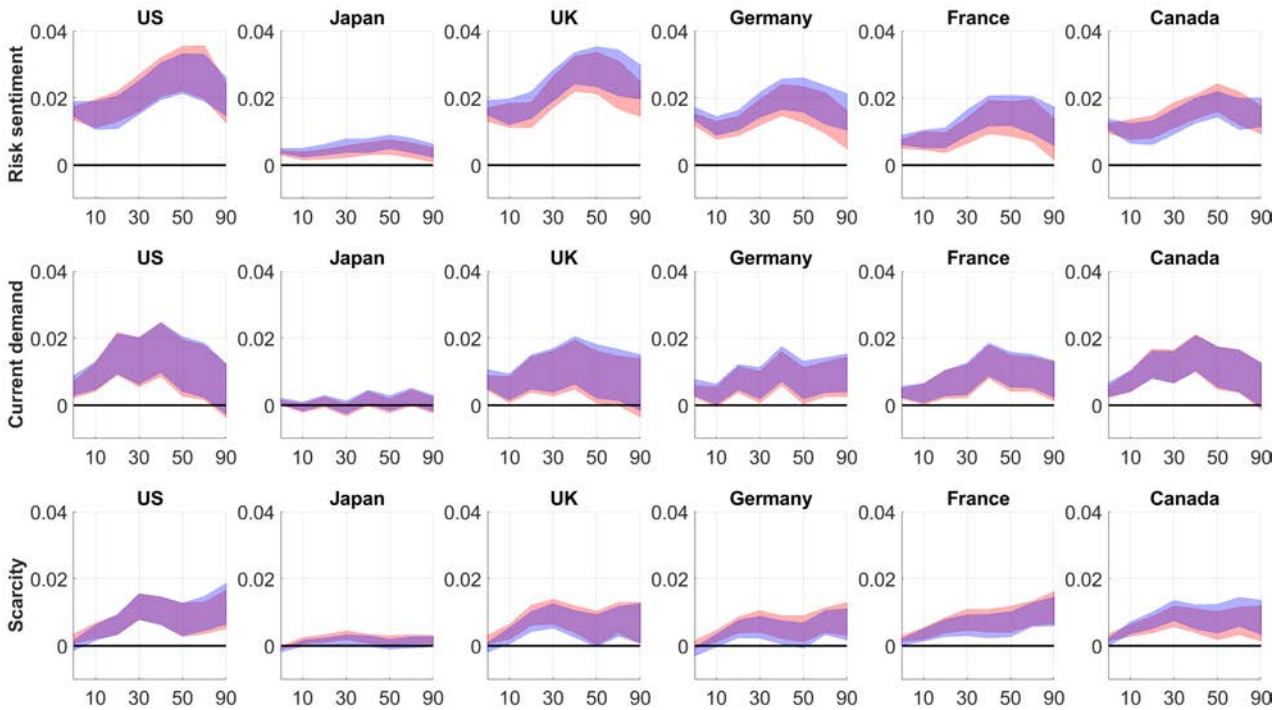

Figure E.25: Response of bond yields to structural shocks

Note. IRFs are estimated using local projections as in equation (4). Error bands are 90 percent confidence intervals obtained by simulation techniques taking into account both uncertainty on the estimation of the shock as well as uncertainty on the parameters of the local projections. They are adjusted to account for autocorrelation of the residuals via a Newey-West correction. The horizontal axis measures working days after the shock. In red we show the impulse response functions obtained with airline stock prices, in blue those obtained with the global stock market factor.

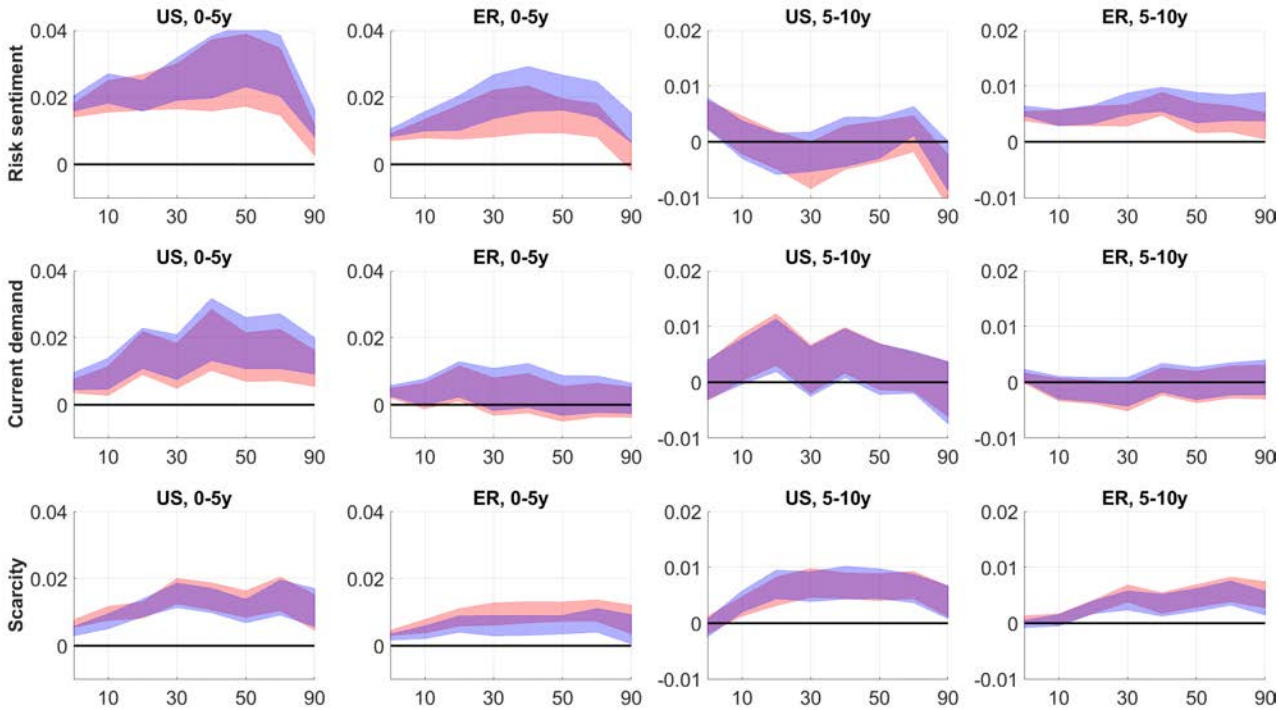

Figure E.26: Response of Market based inflation expectations to structural shocks

Note. The chart shows the IRFs to the identified structural shocks. IRFs are estimated using local projections. Error bands are obtained by simulation techniques taking into account both uncertainty on the estimation of the shock as well as uncertainty on the parameters of the local projections. They are adjusted to account for autocorrelation of the residuals via a Newey-West correction. The horizontal axis measures working days after the shock. In red we show the impulse response functions obtained with airline stock prices, in blue those obtained with the global stock market factor.

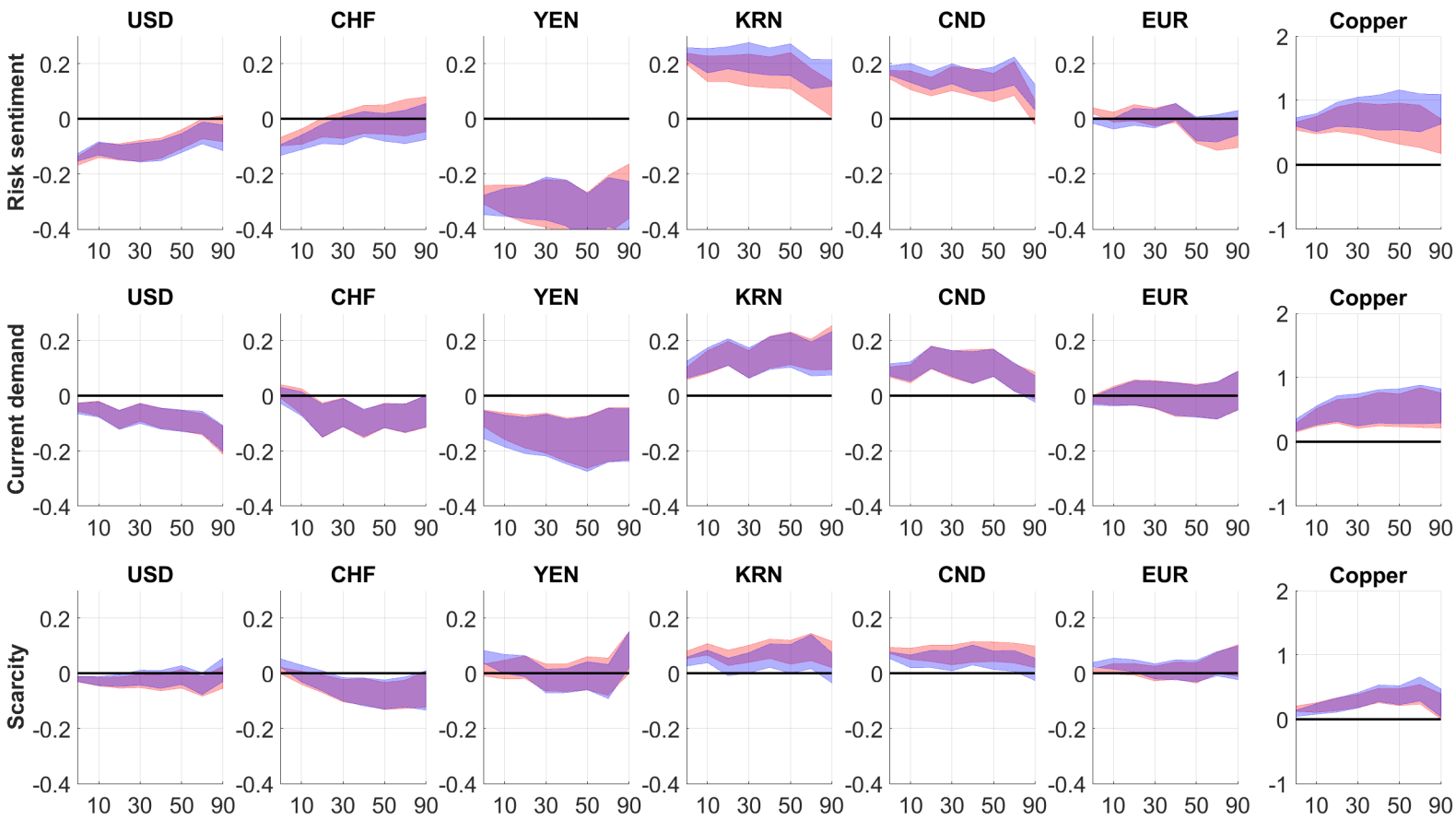

Figure E.27: Response of exchange rates, copper and Baltic index to structural shocks

Note. The chart shows the IRFs to the identified structural shocks. IRFs are estimated using local projections. Error bands are obtained by simulation techniques taking into account both uncertainty on the estimation of the shock as well as uncertainty on the parameters of the local projections. They are adjusted to account for autocorrelation of the residuals via a Newey-West correction. The horizontal axis measures working days after the shock. In red we show the impulse response functions obtained with airline stock prices, in blue those obtained with the global stock market factor.

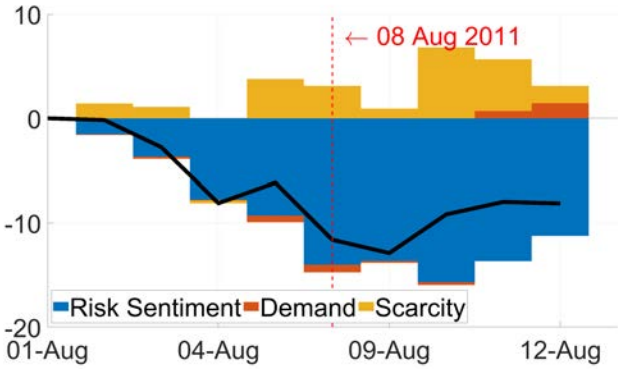

Figure E.28: August 2011, US downgrade

Note. The chart shows the contribution of the structural shocks to the cumulative percentage change of the price of oil in the days indicated.

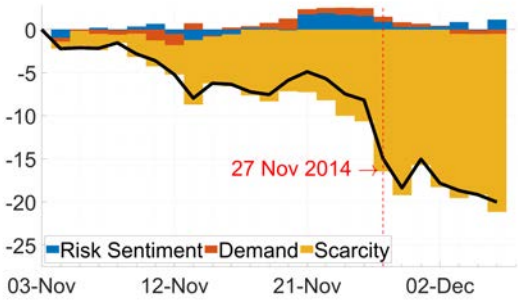

Figure E.29: November 2014: the oil glut

Note. The chart shows the contribution of the structural shocks to the cumulative percentage change of the price of oil in the days indicated.

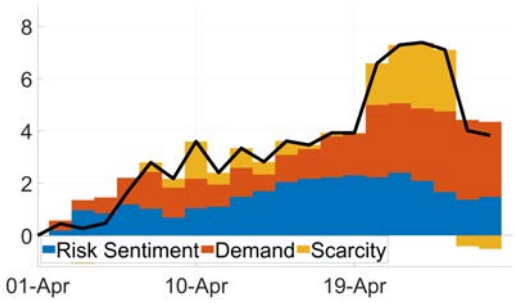

Figure E.30: April 2019: green shoots

Note. The chart shows the contribution of the structural shocks to the cumulative percentage change of the price of oil in the days indicated.

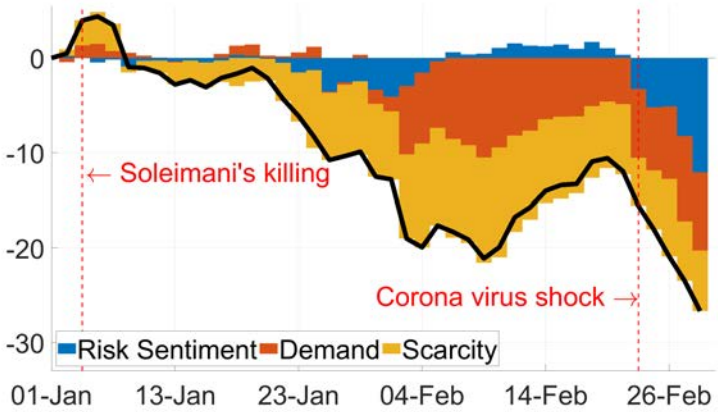

Figure E.31: Iran tensions and corona-virus fears

Note. The chart shows the contribution of the structural shocks to the cumulative percentage change of the price of oil in the days indicated.

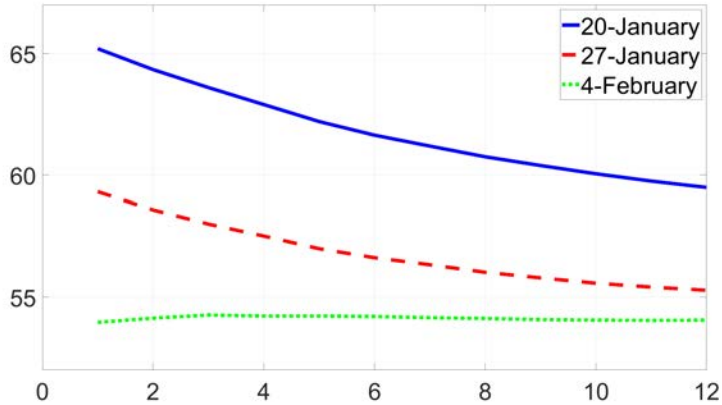

Figure E.32: Futures during the corona-virus outbreak

Note. The chart shows the term structure of oil price futures in the indicated days.

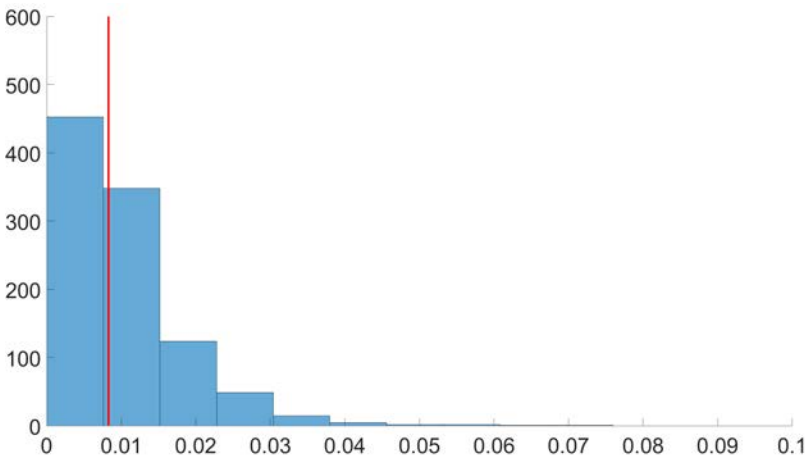

Figure E.33: Estimated Oil supply Elasticity

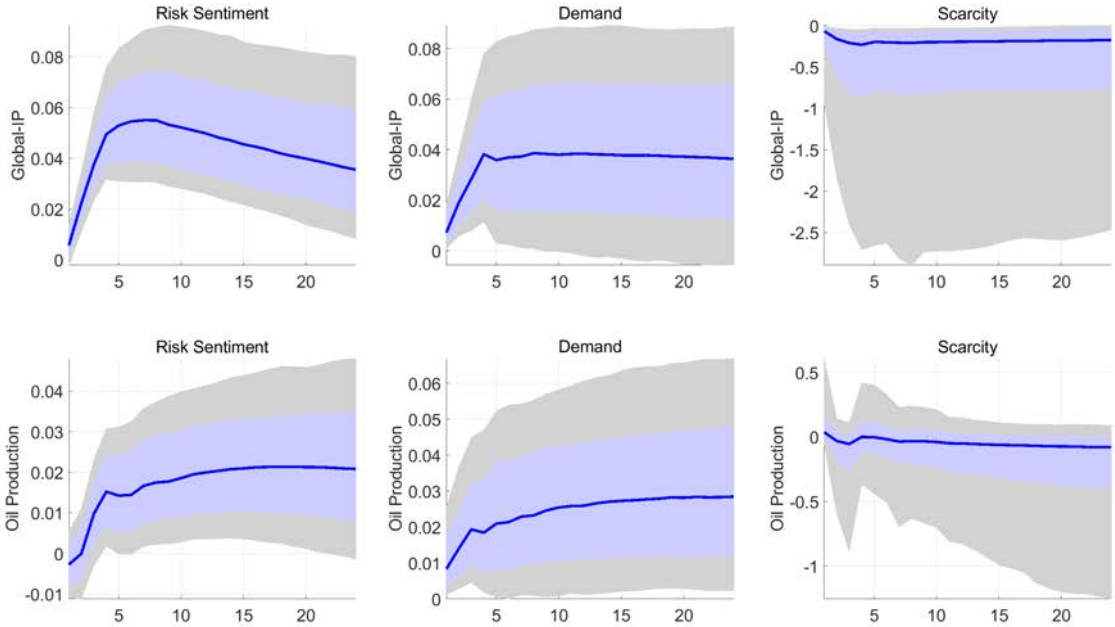

Figure E.34: Impulse Response Functions: monthly variables

Note. 68 percent confidence bands. Both parameter and identification uncertainty is reflected in the confidence bands. Impulse response functions are standardized so as to lead to a 1 percent increase in the price of oil.

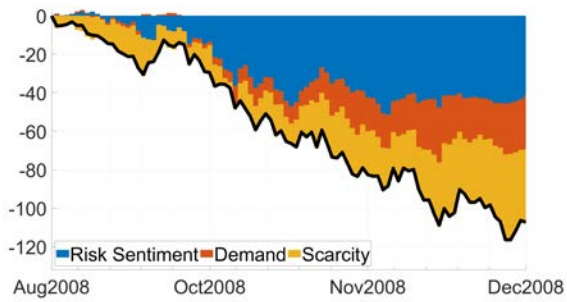

Figure E.35: The Global Financial Crisis oil price slump

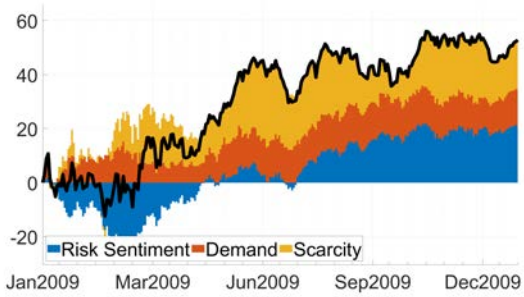

Figure E.36: the post Global Financial Crisis oil price recovery

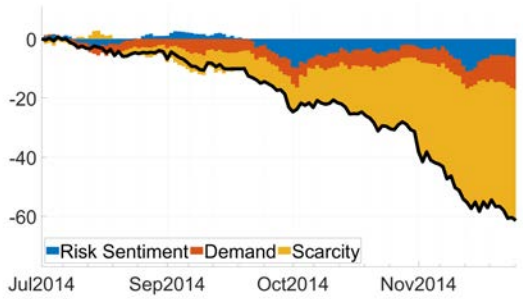

Figure E.37: The 2014 oil price slump

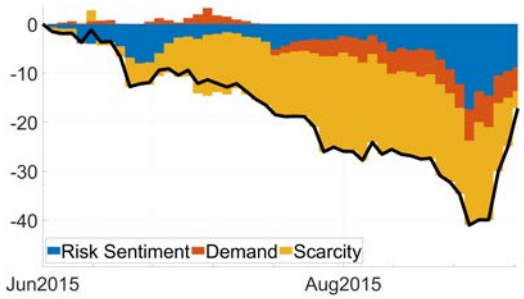

Figure E.38: The 2015 oil price slump

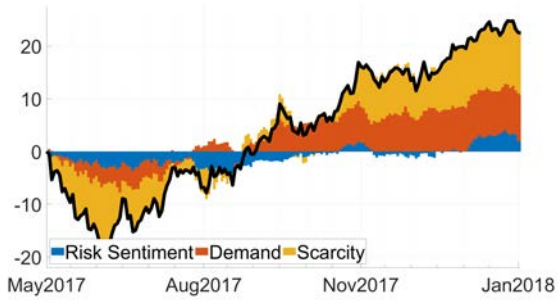

Figure E.39: The 2017 oil price recovery

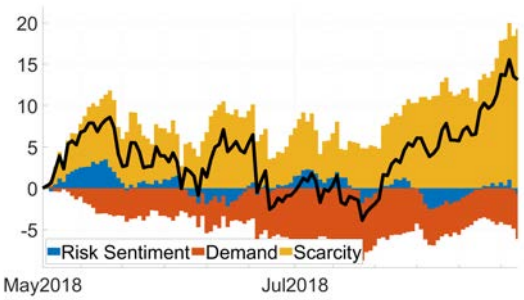

Figure E.40: 2018: contrasting forces

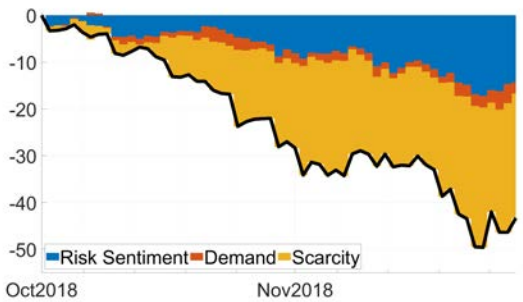

Figure E.41: The 2018 collapse

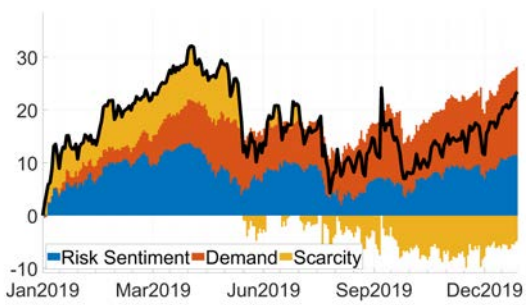

Figure E.42: The 2019 recovery

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