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Global Footprints of U.S. Energy Innovations

Energy Efficiency and the Shale Revolution

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Abstract

This paper studies the effects of U.S. energy shocks on international economic activity and the world oil market. The analysis uses a set of factor-augmented vector autoregressions to identify and compare the impact of unanticipated changes in U.S. energy efficiency and U.S. oil supply over 1980Q1–2019Q4. The identification strategy relies on the fact that positive shocks in both cases decrease the real price of oil and increase global gross domestic product (GDP), while generating opposite implications for world oil production and consumption. On average, U.S. energy efficiency shocks have a larger impact on the real price of oil and global GDP than U.S. oil supply shocks. Historical decompositions suggest that in 2010–19, U.S. oil supply shocks increased GDP by 2 percent, while (negative) energy efficiency shocks decreased global GDP by 1.3 percent. The latter effect dominated during the second shale boom in 2017–19. Considerable heterogeneity exists in cross-country responses, with favorable implications for GDP in advanced and emerging market oil importers and adverse implications for oil exporters. The empirical findings are interpreted through the lens of a dynamic general equilibrium multi-country model that features a global oil market and where key parameters are estimated using indirect inference.

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Global Footprints of U.S. Energy Innovations: Energy Efficiency and the Shale Revolution

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I. Introduction

The surge in U.S. shale oil production and its impact on world oil markets and the global economy have received considerable attention from scholars and policymakers. Spearheaded by productivity gains in the U.S. shale sector, the United States has become the world's leading oil producer, with U.S. oil production increasing from 4.9 million barrels per day (mbpd) in 2005 to 12.2 mbpd in 2019. The shale revolution expanded global oil supply, put downward pressure on world oil prices, and increased global GDP (see, for example, Nuño & Manescu, 2015; Mohaddes & Raissi, 2019). However, in recent decades, there has been another development in the U.S. energy sector that has not commanded as much notice—U.S. oil intensity, i.e., oil consumed per unit of GDP, has declined with improvements in U.S. energy efficiency (American Council for an Energy-Efficient Economy, 2015). In particular, the adoption of new energy efficiency standards and innovation in cleaner energy technologies have reduced U.S. oil intensity from 1.3 million British thermal units (BTUs) per dollar GDP to 0.5 million BTUs per dollar GDP during the period 1980–2019 (see Figure 1). The effects of this "silent revolution" on global output and the real price of oil are qualitatively similar to an increase in U.S. oil supply. Moreover, because the United States consumes 20 percent of the world's crude oil, the global economic implications of improvements in U.S. energy efficiency could be substantial.[1]

This paper studies both empirically and theoretically the impact of improvements in U.S. energy efficiency and the expansion in U.S. oil supply on international economic activity and the global oil market. It provides a first quantitative comparison of the macroeconomic effects of two U.S. energy market shocks that lower world oil prices while having different implications for global oil production and consumption. Improvements in U.S. energy efficiency reduce world oil use, an outcome that is in line with the world's transition to sustainable energy, whereas an increase in U.S. oil production has the opposite effect.[2] Thus, it is useful to compare the international economic consequences of these developments in U.S. energy markets. Moreover, despite oil's small share in global GDP, the economic effects of these shocks can be relatively large because oil is an essential factor input, characterized by low elasticities (on both the demand and the supply side), which generates complementarities with other economic activity (see Baqaee & Farhi, 2019). However, research on the quantitative comparison of the international economic effects of different U.S. energy market shocks is surprisingly limited. This study addresses this gap in the literature.

I proceed in two steps. First, the paper provides an empirical identification strategy to disentangle the causal effects of U.S. and non-U.S. energy market shocks on global and cross-country macroeconomic outcomes. The empirical framework uses a set of factor-augmented vector autoregression (FAVAR) models that exploit a combination of sign and elasticity restrictions to identify structural shocks. The identified shocks include, among other driving forces of global economic activity, a

[1] The U.S. oil consumption totaled 19.4 mbpd in 2019 (International Energy Association, 2019).

[2] The world energy transition refers to the shift in the global energy sector that replaces the consumption and production of fossil fuels with renewable energy sources and greater usage of energy efficient technologies. The aim of this transition is to achieve 2015 Paris Agreement goals in limiting carbon emissions (see Paris Agreement, 2015; IRENA, 2021).

U.S. oil supply shock and a U.S. energy efficiency shock.[3] Examples of positive U.S. oil supply shocks include the discovery of a new offshore oil field or an unexpected improvement in U.S. shale extraction technology, while damages to oil platforms and pipelines following a hurricane in the United States could be associated with corresponding negative shocks. An innovation in technology that allows firms to use less oil to produce the same level of output is an example of a positive shock to U.S. energy efficiency. Similarly, policy changes that disincentivize firms to implement energy efficiency measures such as repairing leaks and optimizing equipment start-up and power-down times are examples of negative energy efficiency shocks.

Second, I develop and calibrate a dynamic, stochastic, multi-country, business cycle model of the world economy that embeds a global oil market and where U.S. energy market shocks, among other forces, drive macroeconomic fluctuations. I estimate the key parameters of U.S. energy efficiency and U.S. oil sector productivity shocks via an indirect inference approach that minimizes the distance between empirical impulse responses and those generated from estimating an identical FAVAR on model simulated data. I use the model to provide an explicit interpretation of the channels and mechanisms through which improvements in U.S. energy efficiency and U.S. oil sector productivity drive international macroeconomic aggregates and oil market variables. For example, the empirical results indicate that the real price of oil decreases following a positive U.S. energy efficiency shock. The model reveals that this is because of a combined effect of low elasticity of substitution between oil and other factor inputs and positive correlation in energy efficiency improvements between U.S. and other oil importers that reduce global oil demand following an improvement in U.S. energy efficiency.

The empirical investigation covers the period 1980Q1–2019Q4, with a particular focus on the 2010Q1–2019Q4 window that witnessed a surge in U.S. shale oil production. Because the main objective of the empirical analysis is to assess the impact of U.S. energy market shocks on global output, I construct an index of the world business cycle. Studies have shown that business cycles across countries have become increasingly synchronized over the past few decades (see Kose et al., 2003; de Soyres & Gaillard, 2019). This interdependence of business cycles across countries could be a result of correlated shocks or propagation mechanisms such as trade and financial linkages (see Frankel & Rose, 1998; Imbs, 2004; Huo, Levchenko, & Pandalai-Nayar, 2019). I use a Bayesian dynamic factor model (DFM) in line with Kose, Otrok, & Whiteman (2003) and Crucini, Kose, & Otrok (2011) to empirically model business cycle fluctuations (quarterly GDP growth rates) across 20 advanced economies and 13 emerging market and developing economies (EMDEs) as an unobserved common factor and an idiosyncratic term.[4] The unobserved dynamic factor summarizes underlying information common to business cycle fluctuations of these 33 countries and captures both simultaneous shocks and shocks that propagate across countries. To assess the usefulness of the estimated measure in representing the global business cycle, I compute a variance decomposi-

[3]The remaining shocks include a non-U.S. oil supply shock, an aggregate (non-oil) economic activity shock, and a precautionary oil demand shock. These three shocks are similar to those identified in Kilian (2009), Peersman & van Robays (2009), and Kilian & Murphy (2012).

[4]These 33 countries together represent more than 90 percent of the world's GDP and include both net oil importers and net oil exporters.

tion that explains how much of the variation in each country's GDP growth rate is a result of the constructed measure.

I include the estimated global GDP factor in a structural factor-augmented VAR (FAVAR) model with data on the real price of oil, U.S. oil consumption, and U.S. and non-U.S. oil production. The FAVAR models the dynamic relationships between these endogenous variables and links them to exogenous shocks, including U.S. energy efficiency and U.S. oil supply shocks. This framework allows me to examine the impact of exogenous changes in, for example, U.S. oil production and U.S. oil consumption on the global business cycle—a difficult task as movements in other endogenous variables tend to confound these effects in the data. The identification of shocks is based on a combination of sign and elasticity restrictions in line with Kilian & Murphy (2012). For example, I impose the restriction that a positive U.S. oil supply shock increases U.S. oil production and decreases real price of oil on impact. The decline in the oil price, in turn, increases U.S. oil consumption and decreases non-U.S. oil production. At the same time, global economic activity—as represented by the global GDP factor—increases because the cost of production falls. Similarly, a positive U.S. energy efficiency shock decreases U.S. oil consumption on impact as firms require less oil to produce a given level of output. This decline in oil consumption leads to a decrease in the real price of oil, and, consequently, increases the global GDP factor and decreases U.S and non-U.S. oil production.

The sign restrictions are sufficiently flexible to capture a wide spectrum of effects. For example, some studies argue that improvements in energy efficiency may not translate to a one-to-one reduction in energy use or may even increase energy consumption as the real price of oil falls—a phenomenon known as the "rebound effect" (see Gillingham et al., 2013; Bruns et al., 2021). Because the maintained sign restrictions do not restrict the magnitude of responses to structural shocks and are only imposed on the impact period, the framework is agnostic about these general equilibrium effects that may result in a sign reversal in later periods.

My main empirical findings can be summarized as follows. First, the results from the dynamic factor model estimation indicate the presence of a world business cycle that has increased in importance in the last two decades. The estimated common factor (henceforth, the global GDP factor) captures key global economic and financial events of the past four decades. The global GDP factor also tracks the changes in world industrial production but it is relatively moderated in amplitude. Moreover, I find that it accounts for an average of 21.6 percent of the variation in GDP growth rates across countries for the period 1980–2019, while its average contribution to output variability has increased to 39.1 percent since early 2000s.

Second, impulse responses from the FAVAR indicate that U.S. energy efficiency shocks have a larger impact on global output and real price of oil than U.S. oil supply shocks. Moreover, I reaffirm the key insight from Kilian (2009) that it is important to disentangle the underlying drivers of oil price fluctuations. In particular, the impulse responses show that both positive U.S. energy efficiency and U.S. oil supply shocks decrease the real price of oil and increase global GDP, while their effects on total oil production and consumption have opposite implications for global oil use.

Third, the historical decompositions indicate that the importance of U.S. energy efficiency and U.S. oil supply shocks varies over time. In particular, the positive effects of improvements in U.S. energy efficiency on global economic activity are most prominent during the early 1980s. This period followed the 1970s oil crisis and featured the 1980 Energy Security Act, the purpose of which was to spur innovation in energy efficiency and renewable energy technologies. The positive effects of U.S. oil supply shocks are limited to the post-2010 period when the U.S. shale revolution resulted in a surge in domestic oil production. More precisely, the overall productivity gains in the U.S. shale sector increased global GDP by approximately 2 percent over the period 2010–2019. The effects are most pronounced starting in 2014—a period when exemptions were heavily used to circumvent the U.S. crude oil export ban, which contributed to a decline in global oil prices. Focusing exclusively on the 2010–2019 period, I find that a series of predominantly negative U.S. energy efficiency shocks had an adverse impact on global economic activity; in the absence of these shocks, global GDP would have been higher by about 1.3 percent over this period. The results are most prominent during the period 2017–2019, which overlaps with the second shale boom. In particular, the positive impact of the second shale boom on global GDP during the period 2017–2019 is eclipsed by the effect of negative U.S. energy efficiency shocks.

I then demonstrate that a multi-country international business cycle model that incorporates a global oil market is capable of explaining most of the empirical results. The model builds on Backus & Crucini (2000) and is similar to Bodenstein & Guerrieri (2011) and Gars & Olovsson (2017). The key difference is that, in order to capture U.S. oil supply shocks and U.S. energy efficiency shocks, I model the United States as an economy that produces oil and either exports or imports it. Specifically, the model includes three countries: a net oil importer, a net oil exporter, and the United States. Intermediate-good producing firms in each oil-importing country choose capital, labor, and oil (as an energy source) to produce a distinct tradable intermediate good, where firms' demand for oil is affected by energy efficiency shocks. The intermediate good is traded across countries to produce a final good, which is used for consumption and investment. Additionally, the model features oil supply shocks. The U.S. oil sector uses labor as an input to produce oil, which is affected by unexpected changes in productivity, while the net oil exporting country is endowed with a stochastic supply of oil that is affected by exogenous shocks. The U.S. energy efficiency and oil supply shocks are modeled as persistent but transitory processes and they are estimated using an indirect inference approach. The indirect inference method estimates these parameters by matching empirical impulse responses obtained from the FAVAR with impulse responses from an identical FAVAR estimated on data simulated from the theoretical model. The model abstracts from a number of features such as nominal frictions, the strategic behavior of oil producers, long-run growth, and different types of crude oil to focus on features that serve to demonstrate the main mechanisms underlying the empirical results.

My model-simulated impulse responses closely match the empirical impulse responses and provide a framework for interpreting the empirical findings. In particular, the results provide an interpretation for the mechanisms by which changes in U.S. oil production and consumption affect the global oil market and GDP across countries. A key parameter restriction that generates a larger impact on the global output of U.S. energy efficiency shocks, relative to U.S. oil supply shocks, is the positive spillover of U.S. energy efficiency improvements to other countries, which is estimated using indirect inference. This restriction follows the rationale that the replicability of productivity gains in the U.S. shale sector across other countries is constrained by the availability of recoverable oil reserves, whereas U.S. energy efficiency improvements are more transferable to other countries. I use the model to discuss the role of U.S. energy efficiency improvements in decreasing (increasing) the real price of oil (global output) if there is a cutback in U.S. oil production. My results show that the correlation of U.S. energy efficiency improvements across countries and the strong complementarity of other factors of production (i.e., capital and labor) with an energy input are key features in generating these results.

The remainder of the paper is organized as follows. Section II provides an overview of the related literature. Section III discusses developments in the U.S. shale oil sector and energy efficiency. Section IV details the data and the empirical methodology that I use to assess the impact of U.S. oil supply and energy efficiency shocks on international economic activity and the global oil market. Section V presents the theoretical model. Section VI concludes.

II. Literature Review

The paper broadly relates to the significant body of research that has investigated the effects of energy and, in particular, oil price shocks on U.S. and international economic activity. Geopolitical tensions in the Middle East, the rapid growth and industrialization of emerging market economies, and concerns about climate change have provided a large impetus to examine linkages between oil price fluctuations and economic activity. Prominent contributions include Kim & Loungani (1992), Backus & Crucini (2000), Blanchard & Gali (2007), Kilian (2008, 2009), Peersman & van Robays (2009), Crucini, Kose, & Otrok (2011), Kilian & Murphy (2012, 2014), Melek, Plante, & Yücel (2020). Recent research has also illustrated how shocks to the oil sector, characterized by a small GDP share but strong complementarity with other factors of production, can have relatively large aggregate effects (see Baqaee & Farhi, 2019).

A key insight from recent literature is that the response of economic activity to oil price fluctuations depends on the underlying driver of the oil price shift. Kilian (2009) employs a structural VAR methodology to show that U.S. real GDP and CPI respond differently to oil price changes depending on whether the oil price shifts are linked to oil supply, oil market-specific demand, or aggregate demand shocks. Other papers have used quantitative models to disentangle the implications of oil demand versus oil supply shocks for macroeconomic activity and related policy responses. For example, Plante (2009) uses a New Keynesian model that distinguishes between oil supply and productivity-driven oil demand shocks to assess the response of U.S. monetary policy to the two shocks. Bodenstein & Guerrieri (2011) develop a two-country business cycle model to examine the impact of foreign oil efficiency and oil supply shocks on global oil price and U.S. activity. Similarly, Gars & Olovsson (2017) use a three-country model to study the impact of oil supply, energy efficiency, and total factor productivity shocks on international business cycle comovement. A common finding of these papers is that not all oil price changes have the same macroeconomic consequences. Thus, it is crucial to distinguish between different types of oil shocks when evaluating the impact of oil price fluctuations on macroeconomic aggregates.

Specifically, the paper links two strands of this literature that have largely evolved independently: the literature on energy efficiency and environmental policies and the literature on oil supply shocks and the shale boom. The impact of oil supply shocks on business cycles has been studied extensively in the literature. In particular, oil price spikes due to geopolitical flare ups have long been regarded as a driver of business cycles (see, for example, Blanchard & Gali, 2007; Hamilton, 2009; Ramey & Vine, 2010).

More recently, studies have examined the economic effects of the boom in U.S. shale oil production. Using a two-country general equilibrium model with three types of oil (light, medium, and heavy), Melek, Plante, & Yücel (2020) assess the impact of the boom in U.S. shale (light) oil production on U.S. economy, trade balances, and the global oil market. They find that the shale boom increased U.S. real GDP by more than 1 percent from 2010 to 2015, an increase equivalent to almost one tenth of the GDP growth during this period—thus, suggesting its contribution to the recovery after the 2007-09 global financial crisis. Their findings also indicate that the U.S. crude oil export ban led to distortions in the relative price of light crude to other types of crude oil, with important consequences for the U.S. and world oil market. Other papers have focused on the international effects of U.S. shale revolution. For example, Hunt, Muir, & Sommer (2015) use the International Monetary Fund's (IMF) Global Economy Model (GEM) and the Global Integrated Monetary and Fiscal Model (GIMF) to estimate the medium-term potential impact of the shale revolution on U.S. and global growth. Similarly, Nuño & Manescu (2015) develop a three-region general equilibrium model with two oil exporters and one oil importer. The oil exporting regions include a dominant producer and a competitive "fringe" that captures shale oil production. Both papers suggest a modestly positive increase in oil importers' real GDP (ranging from 0.2 to 0.25 percent during the period 2010–2018) as a result off the shale boom, with an adverse impact on energy exporters.

A few empirical studies have employed vector autoregression (VAR) models to examine the impact of U.S. oil supply shocks and the boom in shale production on the global oil market, U.S. economy, and cross-country macroeconomic aggregates. For example, Gundersen (2018) augments the 3-variable structural VAR model in Kilian (2009) to examine the effects of U.S. and OPEC oil supply shocks on the real price of oil, where the shocks are identified using a lower triangular ordering of the variables. Results indicate that U.S. oil supply shocks explain 13 percent of the variation in oil prices over the period 2003–2015.[5] Mohaddes & Raissi (2019) examine the global macroeconomic consequences of the shale revolution using a global VAR model with 38 countries. US supply-driven oil price movements are identified using dynamic and cross-country sign restrictions. In particular, the U.S. oil revolution is identified by a simultaneous decrease in oil prices, an increase in U.S. oil production, a constant OPEC oil production, and an increase in the total real GDP across major oil importers. Using an impulse response analysis, they find that, as a result of the US supply-driven

[5] See also Bjørnland & Zhulanova (2019), who employ a time-varying structural VAR model, identified using a recursive ordering, to study U.S. state and country level consequences of U.S. shale oil boom.

fall in oil prices, global growth increases by 0.16–0.37 percentage points in the medium term, where the global growth effects are computed by aggregating individual country responses.

The relationship between energy efficiency and economic activity has also been of considerable interest to scholars and policymakers, especially after the two oil price shocks of the 1970s. However, most macroeconomic research has focused on the relationship between energy efficiency and long-term economic growth. The impact of environmental policies such as investments in energy efficiency programs on short-term economic fluctuations has been less studied. More recently, researchers have stressed the effects of environmental policies on business cycle fluctuations and vice versa. A few studies use a real business cycle (RBC) model to compare how different environmental policies interact with short-run fluctuations (see, amongst others, Angelopoulos et al., 2010; Fischer & Springborn, 2011; Heutel, 2012). For example, Angelopoulos et al. (2010) incorporate pollution emissions as a by-product of production and compare the performance of three different environmental policies (namely, a tax, a cap, and Kyoto-like rules) in the presence of productivity shocks.[6] Annicchiarico & Di Dio (2015) do a similar comparison but expand the analysis by adding nominal frictions and monetary policy shocks using a New Keynesian (NK) model. Xiao, Fan, & Guo (2018) extend the framework of Annicchiarico & Di Dio (2015) by embedding energy efficiency shocks, which are assumed to follow an AR(1) process. An improvement in energy efficiency would imply an increase in the marginal product of the energy input. Their results indicate that a positive energy efficiency shock would lead to an increase in output, consumption, investment, real wage, and the capital stock. Moreover, an energy efficiency enhancement also results in an increase in energy use, which is known as the "rebound effect".

A few empirical studies have investigated the macroeconomic effects of changes in energy efficiency.[7] Two notable exceptions are Rajbhandari & Zhang (2018) and Bruns, Moneta, & Stern (2021). Rajbhandari & Zhang (2018) use a panel VAR model to examine the relationship between energy efficiency and economic growth for 56 high- and middle-income economies. A particular advantage of analyzing energy efficiency in this framework is that it allows for an economy-wide assessment of the impact of energy efficiency improvements. However, Rajbhandari & Zhang (2018) confine the interpretation of causality to Granger's sense. Bruns et al. (2021), on the other hand, estimate a three-variable structural VAR model for the United States with energy consumption, energy price, and GDP data to evaluate the impact of energy efficiency shocks on U.S. macroeconomic aggregates and energy price. The identification of energy efficiency shocks is based on a lower triangular ordering of the variables (Cholesky factorization).

[6] In Angelopoulos et al. (2010), "Kyoto-like rules" are defined as how fast pollution decreases from one period to the next.

[7] The macroeconomic linkages between total energy consumption and economic growth have been studied extensively using vector autoregression (VAR) models in the empirical literature.

III. Developments in U.S. Energy Markets

The 1973 oil crisis accelerated efforts by the U.S. government to find alternative sources of energy.[8] The U.S. federal government responded with initiatives to increase domestic shale oil production by, for example, leasing large tracts of land in Colorado and Utah for shale oil projects through its Synthetic Fuels Corporation (SFC) (Riva, Atwater, & Boak, 2020). Legislations such as the 1978 National Energy Act and the 1980 Energy Security Act were also introduced to conserve energy and improve energy efficiency in the United States (American Council for an Energy-Efficient Economy, 2015).

U.S. Shale Revolution. Following a decline in oil prices in the 1980s, interest in shale oil extraction diminished in the United States. However, as shown in Figure 1 (top), U.S. oil production started increasing around late 2008, reversing a long period of production declines. The boom that followed in U.S. shale production—also called the shale revolution—was simulated by productivity improvements in drilling activities (namely, horizontal drilling and refined hydraulic fracturing or slick water fracturing) that made extraction cost competitive. U.S. oil production surged from of 4.9 mbpd in late 2008 to 9.5 mbpd in 2015, catapulting the United States to the status of the world's top oil producer, passing Saudi Arabia and Russia. Consequently, U.S. oil imports decreased with the expansion in domestic shale oil production and in 2015, as the U.S. crude oil export ban was lifted, the United States became a net oil exporter.

The collapse in the world oil price in mid-2014 led to a temporary decline in U.S. oil production that ended the first shale boom, 2012–2014, as U.S. shale producers competed with OPEC and other low-cost producers. However, by focusing on the most productive acreage and improving extraction technologies, new-well oil production per rig increased between 2017 and 2019, and overall U.S. shale oil output expanded to record levels, as seen in Figure 1 (top)—an episode known as the second shale boom.

U.S. Energy Efficiency. The United States is the world's largest oil consumer; since the 1980s, U.S. oil consumption averages about 20 mbpd and represents roughly 20 percent of the world's consumption. Over these years, U.S. oil consumption has oscillated rather than grown. Figure 1 (bottom) shows that U.S. oil intensity (U.S. oil consumption/U.S. GDP) has declined over time. This finding implies that the United States is producing more output with a given amount of oil. Improvements in energy efficiency have significantly contributed to this decline in U.S. oil intensity, while a structural shift of the U.S. economy to less energy-intensive sectors has also played a role (American Council for an Energy-Efficient Economy, 2015).

Overall improvements in U.S. energy efficiency are a consequence of a number of small and large

[8] In October 1973, Arab members of the Organization of Petroleum Exporting Countries (OPEC) announced an oil embargo targeted at countries supporting Israel during the 1973 Arab-Israeli War. The embargo banned petroleum exports to targeted countries and also introduced OPEC oil production cuts. As a result, global oil price increased 300 percent over the period from October 1973 to March 1974. This event is known as the "first oil crisis" or the "1973 oil crisis".

productivity gains achieved via a combination of policies and technological improvements. In particular, policies to boost energy efficiency have played a key role. These policies include the introduction of equipment, vehicle, and appliance efficiency standards, utility management programs, and building codes. The steep decline in U.S. oil intensity during the 1980s is typically attributed to energy conservation policies introduced from the mid-1970s onwards, following the 1970s oil price shocks. Moreover, the development of more energy efficient products and services has also contributed to a decline in oil use. However, improvements in energy efficiency have slowed down in recent years. In particular, the International Energy Agency (IEA) reports a decline in energy efficiency gains since 2015 and attributes it to a stagnation in the passing of new energy efficiency policies (see International Energy Association, 2017, 2019).

IV. Empirical Analysis

IV.1 Data

I use quarterly data covering the period 1980:Q1 to 2019:Q4. The database consists of real GDP growth rates, the real price of oil, U.S. and non-U.S. crude oil production, and U.S. per capita oil consumption. The data on real GDP growth rates are from the Global VAR (GVAR) dataset, 2019 Vintage (Mohaddes & Raissi, 2018). The GVAR dataset is based on Haver Analytics, the International Monetary Fund's International Financial Statistics (IFS) database, and Bloomberg. The dataset consists of 33 countries, which include oil-importing advanced economies, oil-importing emerging markets and developing countries, and oil exporters. The oil market data consist of monthly series on U.S. and non-U.S. crude oil production, the real price of oil based on the U.S. refiner acquisition cost of imported crude oil, and U.S. per capita oil consumption. The oil market data is obtained from the U.S. Energy Information Administration (EIA). The U.S. oil consumption data is based on EIA's data on petroleum consumption measured in BTUs.[9] The oil production and consumption data is transformed by taking first differences of logs. The monthly data are converted to a quarterly frequency using simple averages.

IV.2 Methodology

This section lays out the empirical framework. First, I present the dynamic factor model, which allows for the extraction of an underlying common factor (henceforth, global GDP factor) using GDP growth rates for 33 countries. Furthermore, I do a variance decomposition to compute the fraction of variation in country GDP growth rates accounted by the global GDP factor to evaluate its performance as a metric of fluctuations in global economic activity. Second, I specify and estimate a structural FAVAR model to assess the effects of U.S. energy market shocks on global economic activity. I discuss an identification strategy based on sign and elasticity restrictions to disentangle U.S. oil supply and energy efficiency shocks.

[9] A robustness check in Section IV.4 uses fossil fuel consumption data (aggregate of coal, natural gas, and petroleum consumption), which is also obtained from EIA.

IV.2.1 Dynamic Factor Model

I estimate a dynamic factor model (henceforth, DFM) that contains: (i) a factor common to all series, F_t^{global} and (ii) an idiosyncratic component for each series i, $\epsilon_{i,t}$.[10] Let $Y_{i,t}$ denote the GDP growth rate for country i at time t. The model can then be written as follows:

$$Y_{i,t} = \alpha_i + \beta_i F_t^{global} + \epsilon_{i,t}, \tag{1}$$

$$F_t^{global} = \phi(L) F_{t-1}^{global} + \nu_t, \tag{2}$$

$$\epsilon_{i,t} = \psi_i(L)\epsilon_{i,t-1} + u_{i,t}, \tag{3}$$

where $i = 1, \ldots, N$, $t = 1, \ldots, T$, and $\phi(L)$ and $\psi_i(L)$ are lag polynomial operators. The disturbances ν_t and $u_{i,t}$ are distributed as $N(0, \sigma^2_{F^{global}})$ and $N(0, \sigma_i^2)$, respectively. Also, it is assumed that ν_t and $u_{i,t}$ are mutually orthogonal and all $u_{i,t}$, $i = 1, ..., N$, contemporaneously uncorrelated. Thus, all comovement in GDP growth rates across countries is due to the common factor, F_t^{global}.[11] The β parameters are known as factor loadings and determine the extent to which the variation in the observed GDP data, $Y_{i,t}$, is explained by the global GDP factor, F_t^{global}. The factor loadings can vary across countries but are assumed to be constant over time for each country.

The DFM (1) – (3) has two identification issues. Because both the factor and the factor loadings are unobserved, first, the signs, and second, the scales of the factor and the factor loadings are not separately identified. To overcome these problems, I follow Kose et al. (2003), first by normalizing the factor loading for the global GDP factor to be positive for U.S. GDP and second by assuming that $\sigma^2_{F^{global}}$ is 1.

Variance Decomposition. To find the relative contribution of the global GDP factor to fluctuations in GDP across countries, the variance of GDP growth rate of each country can be decomposed as follows:

$$\text{var}\left(Y_{US,t}\right) = \left(\beta_i\right)^2 \text{var}\left(F_t^{global}\right) + \text{var}\left(\epsilon_{i,t}\right). \tag{4}$$

Thus, the share of variation in, for example, the U.S. GDP growth rate due to the global GDP factor is given as $\frac{(\beta_{US})^2 \text{var}\left(F_t^{global}\right)}{\text{var}\left(Y_{US,t}\right)}$.

Estimation. Equations (1) – (3) comprise a state-space system where equation (1) corresponds to an observation equation and equations (2) and (3) correspond to the transition equation. The estimation of this system follows a Bayesian state-space approach (see C. Kim & Nelson, 1998). The objective of here is to estimate both the parameters of the observation and transition equations, $\varphi =$

[10] Note that I also estimated a multi-level dynamic factor model by including common factors specific to different groups of countries (oil importing advanced economies, oil importing emerging markets and developing countries, and oil exporters). However, other than oil importing advanced economies, I did not find sizeable common variation in GDP growth rates across countries.

[11] Note that this comovement captures both common shocks affecting economic activity in all countries simultaneously and spillovers from one country affecting other countries.

$(\alpha_i, \beta_i, \phi(L), \psi_i(L), \sigma_i, \sigma_{F^{global}})$, and the common factor, $f = F_t^{global}$.[12] The Bayesian estimation is based on Gibbs sampling. The idea behind Gibbs sampling is that it allows samples from the joint distribution $p(\varphi, f)$ to be generated by sampling only from the conditional distributions $p(\varphi|f)$ and $p(f|\varphi)$. It can be shown that starting from any initial values, sampling iteratively from $p(\varphi|f)$ and $p(f|\varphi)$ for a sufficiently large number of times, we obtain a draw from the joint distribution $p(\varphi, f)$. Thus, for estimating DFM (1) – (3), starting from an initial value, f^0, the Gibbs sampler proceeds by repeating the following two steps:

1. Given the global GDP factor and the data, sample the parameters of the observation and transition equations from their posterior distributions, $p(\varphi|f)$.

2. Given the parameters, sample the global GDP factor from its posterior distribution, $p(f|\varphi)$.

If regularity assumptions (see Chib & Greenberg, 1994) are satisfied, the sequence of draws obtained from the above steps produces a Markov chain that converges to its invariant distribution, which is also the joint distribution, $p(\varphi, f)$, of the entire system. The details of the estimation are presented in Appendix VII.1.

IV.2.2 Factor-Augmented Vector Autoregression Model

I estimate the following general form of the factor-augmented vector autoregression (FAVAR) model

$$\mathbf{B_0 y_t} = \sum_{i=1}^{p} \mathbf{B_i y_{t-i}} + \mathbf{w_t}, \tag{5}$$

where $\mathbf{y_t}$ is a $K \times 1$ vector of endogenous variables, $p = 3$ is the lag length, $\mathbf{B_0}$ is the structural impact multiplier matrix, $\mathbf{B_i}$ is a $K \times K$ matrix of coefficients, and $\mathbf{w_t}$ denotes the $K \times 1$ vector of mutually uncorrelated structural innovations.

The vector of endogenous variables $\mathbf{y_t}$ is based on quarterly data. I estimate two sets of VAR models to assess the response of the global GDP factor and country-level output fluctuations to U.S. oil supply and energy efficiency shocks. First, I estimate a VAR model that contains five variables: $\mathbf{y_t^{(1)}} = (\Delta nonUSprod_t, F_t^{global}, rpo_t, \Delta USprod_t, \Delta UScons_t)'$, where $\Delta nonUSprod_t$ and $\Delta USprod_t$ is the percent change in non-U.S. and U.S. oil production, respectively, F_t^{global} is the global GDP factor, rpo_t is real price of oil, and $\Delta UScons_t$ is the percent change in per-capita U.S. oil consumption. Second, I estimate a set of VAR models that contain six variables for each country: $\mathbf{y_t^{(2)}} = (\mathbf{y_t^{(1)'}}, \Delta countryGDP_t)'$, where $\mathbf{y_t^{(1)}}$ are the variables included in the first model and $\Delta countryGDP_t$ is the respective country GDP growth rate for each country. The sample period is 1980:Q1–2019:Q4.

[12] The estimation can be performed with the classical approach to state space modeling, which is based on maximizing the likelihood function with respect to all parameters. However, this approach can be computationally inefficient in large scale models with many countries. The Bayesian approach based on Gibbs sampling splits the estimation into smaller components of the model and deals with these one at a time by drawing from conditional distributions of the parameters (see, Blake & Mumtaz, 2012). Another approach is the non-parametric principal component analysis (PCA), which is computationally faster and commonly used. However, the parametric state space approach to estimating factor models gives more accurate variance decomposition estimates compared to PCA-based methods. For a comparison of different estimation methods, see Jackson, Kose, Otrok, & Owyang (2015).

Table 1: Sign Restrictions on Impulse Response Functions

	Non-US Oil Supply	**Economic Activity**	**Precautionary Oil Demand**	**US Oil Supply**	**US Energy Efficiency**
Non-US Oil Production	+	+	+	-	-
Global GDP Factor	+	+	-	+	+
Real Price of Oil	-	+	+	-	-
US Oil Production	-	+	+	+	-
US Oil Consumption	+	+	-	+	-

The reduced-form representation of (5) is given by

$$\mathbf{y_t} = \sum_{i=1}^{p} \mathbf{A_i y_{t-i}} + \mathbf{u_t}, \tag{6}$$

where $\mathbf{A_i} = \mathbf{B_0^{-1} B_i}$ and $\mathbf{u_t} = \mathbf{B_0^{-1} w_t}$ are the mutually correlated reduced-form innovations with $K \times K$ variance-covariance matrix $E(u_t u_t') = \Sigma_u$.

Identification of Structural Shocks

The structural FAVAR model is set-identified based on a combination of sign and elasticity restrictions. In particular, sign restrictions are imposed on the impact response of endogenous variables to identify five structural shocks: (i) a non-U.S. oil supply shock, (ii) an aggregate economic activity shock, (iii) a precautionary oil demand shock, (iv) a U.S. oil supply shock, and (v) a U.S. energy efficiency shock. The baseline sign restrictions provide a set of candidate impulse responses that are further narrowed down using elasticity restrictions as discussed below.

Impact Sign Restrictions. Table 1 provides the baseline sign restrictions, where signs are imposed on elements of the structural impact multiplier matrix, $\mathbf{B_0}$, and all shocks are positive by construction.[13] The sign restrictions are in line with the existing empirical literature.[14] For example, a positive oil supply shock, both U.S. and non-U.S., increases respective oil production, decreases the real price of oil, increases the global GDP factor, and increases U.S. oil consumption. Moreover, in response to a positive non-U.S. oil supply shock, U.S. oil production decreases (and vice versa) as real price of oil falls. Examples of positive oil supply shocks include discovery of a new offshore oil field or an unexpected improvement in U.S. shale extraction technology. However, disruptions in OPEC oil supply arising from a conflict in the Middle East or damage to oil platforms and pipelines following a hurricane in the United States are associated with negative non-U.S. and U.S. oil supply shocks, respectively.

[13] Note that since the sign restrictions are only imposed on the structural impact multiplier matrix, all responses following the impact period are unrestricted.

[14] The sign-restricted VAR model builds on the three-variable oil market model of Kilian & Murphy (2012). The signs imposed on oil production, global output, and the real price of oil are, therefore, consistent with Kilian & Murphy (2012), Peersman & Van Robays (2012), and the vast literature that has employed these identifying assumptions (see, amongst others, Kilian & Murphy, 2014; Kilian & Zhou, 2020). The sign-based identifying strategy to disentangle U.S. oil supply and U.S. energy efficiency shocks is a contribution to the literature. The reasoning behind the imposed signs is in line with the empirical evidence, as discussed in this section.

The remaining three shocks all affect oil demand. A positive aggregate economic activity shock is characterized by positive comovement in all five endogenous variables. Economic activity shocks include, for example, a loosening of monetary policy or reforms that increase economy-wide productivity. In particular, an increase in total factor productivity would increase the marginal product of all inputs including oil and, consequently, increase oil demand. A positive precautionary oil demand shock, on other hand, increases the real oil price, decreases global output, decreases U.S. oil consumption, and increases U.S. and non-U.S. oil production. These shocks are designed to account for oil price movements that are associated with uncertainty about expected oil supply relative to expected oil demand. Precautionary demand for oil relates to holding oil inventories that provide a convenience yield driven by supply concerns, which can occur over potential unanticipated expansion in oil demand, unanticipated contraction in oil supply, or both (see Kilian, 2009; Kilian & Murphy, 2012).

A positive U.S. energy efficiency shock decreases U.S. oil consumption, decreases the real price of oil, increases the global GDP factor, and decreases U.S and non-U.S. oil production. Since the sign restrictions are only imposed on the impact period, the framework is agnostic about general equilibrium effects that may result in a sign reversal. For example, I postulate that U.S. oil consumption will decrease in response to a positive U.S. energy efficiency shock as firms require less oil to produce a given level of output. However, improvements in energy efficiency may not necessarily translate into energy-use reduction owing to a rebound effect. This implies that following a positive energy efficiency shock, a decrease in oil consumption would be less than expected as a result of a "rebound" in oil use as real price of oil decreases. The magnitude of the rebound effect can vary from "backfire" (also known as the Jevons paradox), where energy use increases following an improvement in energy efficiency, to super-conservation, where energy consumption declines more than the improvement in energy efficiency (Bruns et al., 2021). Thus, the sign restrictions imposed here are sufficiently flexible to capture the full spectrum of effects in the period following impact. However, at impact, a backfire effect is ruled out by assumption, which is not problematic given that overall existing evidence provides little support for the backfire hypothesis (see Gillingham, Kotchen, Rapson, & Wagner, 2013; Gillingham, Rapson, & Wagner, 2015).

Table 2 provides the sign restrictions imposed on the set of VAR models augmented with country GDP data. The sign restrictions only differ in terms of how country output responds to oil demand and oil supply shocks across oil exporting and importing countries. In particular, in response to a positive oil supply shock, oil exporters' GDP declines and oil importers' GDP increases as the real price of oil falls. Similarly, in response to an unanticipated improvement in U.S. energy efficiency, oil demand decreases and, consequently, the real price oil falls. This results in a decrease (increase) in oil exporter's (importer's) GDP, whereas, in response to a positive precautionary oil demand shock, oil exporters' GDP declines and oil importers' GDP increases as the real price of oil increases. A positive aggregate economic activity shock increases GDP across all countries.

Elasticity Bound on Impact Price Elasticity of Oil Supply. A fundamental drawback of the VAR model identified based on sign restrictions is that it does not provide point estimates

Table 2: Sign Restrictions on Impulse Response Functions

	Non-US Oil Supply	**Economic Activity**	**Precautionary Oil Demand**	**US Oil Supply**	**US Energy Efficiency**
Non-US Oil Production	+	+	+	-	-
Global GDP Factor	+	+	-	+	+
Real Price of Oil	-	+	+	-	-
US Oil Production	-	+	+	+	-
US Oil Consumption	+	+	-	+	-
Oil Importer/Exporter GDP	+/-	+	-/+	+/-	+/-

of structural impulse responses—the estimated impulse response functions (IRFs) are only set-identified because sign restrictions represent inequality constraints. In other words, instead of a unique structural impact multiplier matrix, $\mathbf{B_0}$, a set of models (i.e., a set of matrices $\mathscr{B} = \{\mathbf{B_0}|\mathbf{B_0}\mathbf{B_0}' = \mathbf{\Sigma_u}\}$) satisfy the maintained sign restrictions, where some of the admissible models may be empirically implausible. In particular, in the context of oil markets, the empirical evidence indicates that the short-run price elasticity of oil supply is close to zero (see Kilian, 2020, for a survey). Thus, retaining all admissible models may imply magnitudes for the impact price elasticity of oil supply that contradict the existing evidence in the literature.[15]

To mitigate this problem, I follow Kilian & Murphy (2012) to narrow down the set of admissible impulse responses by constructing an upper bound on the one-quarter price elasticity of oil supply. Kilian & Murphy (2012) define the impact price elasticity of oil supply as the ratio of the impact responses of oil production and the real price of oil to an oil demand shock. They compute a value of 0.0258 as an upper bound for this ratio. The rationale behind this computation is as follows: the Iraqi invasion of Kuwait in August 1990 was an exogenous event that partially disrupted oil supply from these two countries and increased demand for oil produced outside Iraq and Kuwait. Moreover, a positive precautionary oil demand shock based on the expectation that Iraq would attack Saudi Arabia next, further raised oil demand. Consequently, the real price of oil increased by 45.3 percent. However, even with the large increase in the oil price, oil production outside Iraq and Kuwait only increased by 1.17 percent. Thus, the ratio of the percent change in oil production outside Iraq and Kuwait to the percent change in the oil price in August 1990 (i.e., $1.17/45.3 = 0.0258$) can be considered as an estimate of the one-month price elasticity of oil supply (Kilian & Murphy, 2012; Kilian, 2020).[16]

The above approach, therefore, motivates the imposition of an upper bound on the ratios of elements of the structural impact multiplier matrix, $\mathbf{B_0}$. In particular, I restrict the ratios of the impact response of oil production (U.S and non-U.S.) and of the real price of oil to an unexpected increase in aggregate economic activity, precautionary oil demand, and U.S. energy efficiency. This restriction corresponds to selecting admissible models where the ratios a_{12}/a_{32}, a_{42}/a_{32}, a_{13}/a_{33}, a_{43}/a_{33},

[15] Kilian & Lütkepohl (2017) argue that for sign-identified SVAR models, the burden of proof is on the researcher to use all available information to pin down the magnitudes of interest.

[16] This is regarded as an upper bound on oil supply elasticity during normal times by Kilian & Murphy (2012) because of excess capacity in 1990 and because "there was rare unanimity among oil producers in 1990 that it was essential to offset market fears about a wider war in the Middle East."

a_{15}/a_{35}, and a_{45}/a_{35} are less than the upper bound. Since the analysis is at quarterly frequency, I choose 0.077 as an upper bound for the one-quarter oil supply elasticity. This value is a conservative estimate of the upper bound given that it is three times the one-month oil supply elasticity estimate used in Kilian & Murphy (2012). Moreover, in comparison to a small one-month price elasticity of oil supply, evidence from other studies suggest a small price elasticity of oil supply at quarterly frequency as well. For example, Newell & Prest (2019) use microeconomic data to estimate a one-quarter oil supply elasticity of 0.017 for conventional crude oil.

However, it can be argued that short-run price elasticity of oil supply would be higher when incorporating shale oil production. Empirical findings suggest a one-quarter supply elasticity that is close to zero even for shale oil production (see Newell & Prest, 2019; Kilian, 2020). This result does not invalidate the common view that, relative to conventional producers, shale oil producers are more agile in responding to movements in oil prices. It only implies that it takes more than three months for both conventional and shale oil producers to respond to changes in oil market conditions (Kilian, 2020). Moreover, based on survey evidence from U.S. shale firms, Golding (2019) states that "the average horizontal well pad in the Permian Basin takes four to six months from the commencement of drilling to production coming online," and for wells that are drilled but not hydraulically fractured "it may take one to three months to go into production."

Estimation. The sign restrictions are imposed using the procedure developed by Rubio-Ramirez, Waggoner, & Zha (2010). The procedure involves generating a random orthonormal matrix Q such that $QQ' = I$ by obtaining the QR decomposition of a $K \times K$ matrix X of independent $N(0,1)$ values. I then let B be a lower triangular matrix corresponding to the Cholesky decomposition of the variance-covariance matrix of the reduced-form residuals, $\Sigma_u = PP'$, obtained from estimating the model (6). Thus, the following equality holds: $\Sigma_u = PP' = PQQ'P = (PQ)(PQ)'$, where $PQ = B$.[17] The matrix B is a candidate structural impact multiplier matrix, and we can verify whether its elements satisfy the maintained sign restrictions discussed in Section IV.2.2.

The procedure can, thus, be summarized by the following steps:

1. Draw an independent standard normal $K \times K$ matrix X. Obtain the QR decomposition of X such that $X = QR$ and $QQ' = I$.

2. Compute the the candidate solutions B such that $B = PQ$ and P is the Choleksy decomposition of the reduced form residuals Σ_u.

3. Use the candidate solutions to compute the impact effects of structural shocks.

4. Repeat step 1-2 until the desired number of iterations. Record each candidate solution and the corresponding impulse response that satisfies the restrictions.

[17] Note that unlike P, the matrix $B = PQ$ is not a lower triangular matrix and, thus, does not depend on the ordering of the endogenous variables in the model (5).

IV.3 Empirical Results

This section presents the main empirical results. First, I present the estimates of the global GDP factor that measures global economic activity and discuss its importance for fluctuations in output across countries based on the methodology in Section IV.2.1. Then, I report the results obtained from the FAVAR framework in Section IV.2.2 that show the impact of U.S. energy shocks on global economic activity. In particular, I present impulse responses of the global GDP factor to changes in U.S. oil supply and energy efficiency. Moreover, I investigate two specific historical episodes to evaluate the contribution of unanticipated improvements in U.S. shale technology and energy efficiency on global economic activity. Finally, I present results that illustrate how the impact of U.S. energy shocks differs across countries that are advanced economy net oil importers, emerging market net oil importers, and net oil exporters.

IV.3.1 Common Factors of Global and Regional Economic Activity

Figure 2 plots the median, alongside the 16- and 84-percent quantiles, for the posterior distribution of the estimated global GDP factor over the period 1980:Q4-2019:Q4. The tightness of the 16- and 84-percent quantile bands indicates that the factor is estimated precisely. Because the factor is latent and we simply observe an estimate based on its hypothesized relationships with the observed data, its interpretation requires special attention. In particular, a closer look at Figure 2 indicates that the factor peaks and declines around key historical world economic and financial events, suggesting its suitability as a measure of global economic activity. For example, the factor declines during the three global recessions experienced by the world economy over the past four decades: in 1982, 1991, and 2009. Also, the decline is largest during the 2007-09 global financial crisis, followed by the global recessions of 1982 and 1991, respectively. In this way, it accurately captures the relative severity of the three recessions, with the 2007-09 global financial crisis being the deepest and the 1991 global recession being the mildest. Moreover, it also captures periods of global expansions such as post-1991 and post-2009.[18]

The factor registers a decline in 2001 when the U.S. economy went through a recession, while global economic activity experienced slow growth. Because the U.S. economy has a relatively large influence on global economy activity, it is no surprise that the global GDP factor picks up changes in U.S. GDP. However, is the estimated factor merely a stand in for fluctuations in U.S. economic activity? Figure 3 (top) plots the global GDP factor alongside a common factor estimated using GDP growth rates for 32 countries that exclude U.S. GDP data. The plot shows that the two common factors, estimated with and without U.S. data, move closely together; the correlation is 0.94. Moreover, the respective median factor loading for the Unites States is 0.46, indicating that the U.S. contribution to the global GDP factor is sizeable but not dominant.[19] Moreover, in

[18]See Kose, Sugawara, & Terrones (2020) for identification of global economic recessions and expansions since early 1950s.

[19]Note that the common factor estimated without U.S. GDP data may still pick up changes in U.S. economic activity that spillover to other countries. A more detailed assessment of whether the fluctuations in the global GDP factor capture broad-based changes in economic activity across countries can be seen in Figure 13, Appendix VII.1. Factor loadings are in Figure 12, Appendix VII.1.

order to compare the global GDP factor with other measures of global economic activity, Figure 3 (bottom) plots the global GDP factor alongside an index of world industrial production and the Kilian's index (see Kilian, 2009; Hamilton, 2019). The global GDP factor and the world industrial production are highly correlated, with correlation 0.85, whereas the correlation between the global GDP factor and the Kilian index is 0.14.[20]

The histogram in Figure 13, Appendix VII.1, provides a closer look at the importance of the global GDP factor in accounting for fluctuations in economic activity across countries. The figure shows the distribution of the amount of variance in country GDP growth rates accounted for by the global GDP factor. The results indicate that in the majority of countries, the global GDP factor explains a significant fraction of GDP growth volatility; it accounts for 21.6 percent of output variability across countries on average.[21] The contribution of the global GDP factor to country GDP growth rates is highest for oil importing advanced economies (32.9 percent) followed by oil exporters (21.8 percent), and its contribution to the fluctuations in output growth rates of oil importing emerging markets and developing countries is 12.4 percent.

IV.3.2 Global Economic Activity and U.S. Energy Market Shocks

This section provides the results from the FAVAR Model 5 described in Section IV.2.2. I first discuss the impulse responses of the endogenous variables to U.S. energy efficiency and U.S. oil supply shocks. These results compare the average effects of the two shocks over the period 1980–2019. I then present the historical decompositions to assess the impact of U.S. energy efficiency and oil supply shocks in the evolution of global economic activity during 2010–2019, a period that overlaps with the shale revolution.

Impulse Responses. Figure 4 presents the IRFs of endogenous variables to U.S. energy market shocks. The left and right columns plot impulse responses for non-U.S. oil production, the global GDP factor, the real price of oil, U.S. oil production, and U.S. oil consumption to a one standard deviation increase in U.S. oil supply and U.S. energy efficiency, respectively.[22] The results are based on the combined restrictions discussed in Section IV.2.2. The results for the global GDP factor, oil

[20]The Kilian index is a popular measure of worldwide economic activity and it is used in many studies (see, for example, Baumeister & Kilian, 2012; Kilian & Murphy, 2014; Lütkepohl & Netšunajev, 2014; Anzuini, Pagano, & Pisani, 2015; Antolín-Díaz & Rubio-Ramírez, 2018). The Kilian's index is constructed using cost of international shipping in commodity markets. The shipbuilding cycle moves more slowly relative to the business cycle due to the time involved in scrapping and launching ships (see Kilian & Zhou, 2018). Thus, the Kilian index captures longer swings in economic activity, which are important for accounting for cycles in commodity prices. However, because the objective of the analysis is to assess the impact of U.S. energy shocks on short-run fluctuations, I use the estimated global GDP factor in the structural VAR model instead of the Kilian index. Moreover, I multiply the estimated global GDP factor with the average factor loading in the subsequent analysis. The resulting measure is a moderated world business cycle relative to the world industrial production index. Consequently, the estimates of the impact of U.S. energy shocks on global economic activity will be more conservative.

[21]The variation in each observed variable can be decomposed as $var(y_{i,t}) = (\beta_i^{Global})^2 var(f_t^{Global}) + var(\epsilon_{i,t})$. Thus, the share of variance due to the global factor is given as $\frac{(\beta_i^{Global})^2 var(f_t^{Global})}{var(y_{i,t})}$.

[22]Note that IRFs are reported without parameter estimation uncertainty. The median, 16^{th}, and 84^{th} percentiles impulse responses are reported from the admissible models. The results, thus, summarize the set of admissible models and focus on identification uncertainty (i.e., value of $\mathbf{B_0}$), which is due to inequality restrictions.

production (U.S. and non-U.S.), and U.S. oil consumption are shown in levels (measured in percent deviations from the baseline) by accumulating the estimated responses.[23]

A positive U.S. oil supply shock increases U.S. oil production and decreases the real price of oil on impact that gradually returns to baseline over time, while the global GDP factor increases persistently in response over the 12-quarter horizon. Non-U.S. oil production decreases on impact with the response becoming insignificant after 1 quarter. The shock also triggers a positive response of U.S. oil consumption over the 12-quarter horizon. An unexpected increase in U.S. energy efficiency, on the other hand, decreases U.S. oil consumption. This results in a decline in the real price of oil and raises global economic activity (as indicated by an increase in the global GDP factor). At the same time, this shock causes a decrease in both U.S. and non-U.S. oil production, with the response of non-U.S. oil production turning insignificant after 2 quarters.

Note that the increase in the global GDP factor is slightly larger in response to a positive U.S. energy efficiency shock compared to a positive U.S. oil supply shock. This is true for the response of the global GDP factor at impact and over the 12-quarter horizon to the two shocks of interest. A closer look suggests that this is partly a result of a larger decrease in the real price of oil in response to an improvement in U.S. energy efficiency in comparison to its response to an expansion in U.S. oil supply.[24] Moreover, the two shocks trigger dissimilar responses in U.S. oil production and consumption. In particular, an unanticipated expansion in U.S. oil supply increases both U.S. oil production and consumption, while an unanticipated improvement in U.S. energy efficiency decreases both U.S. oil production and consumption. Thus, total oil used in equilibrium declines in response to a positive U.S. energy efficiency shock, while having a similar positive impact on global economic activity.

Historical Decomposition. The impulse responses presented above are useful in studying average movements in the data. However, to assess the importance of U.S. energy market shocks in accounting for fluctuations in global economic activity during particular historical episodes, it is more useful to look at the cumulative effect of each shock on the global GDP factor. This is especially crucial for examining the effects of unanticipated improvements in U.S. shale technology since significant advances in U.S. shale sector productivity only occurred starting in the early 2000s. Figure 5 shows the contribution of U.S. energy efficiency and U.S. oil supply shocks to fluctuations in the global GDP factor during the period 2010-2019.[25]

The top panel of Figure 5 corresponds to the period that includes the first and the second shale

[23]For the full set of the estimated impulse response functions, see Appendix A, Figure 15.

[24]This result is consistent with broader findings in the oil market literature that oil demand shocks have a bigger role in driving the real price of oil than oil supply shocks (see, for example, Kilian, 2009; Kilian & Murphy, 2012). Kilian (2009) interprets an oil market-specific demand shock as a speculative or precautionary demand shock for oil. Kilian & Zhou (2020) state that this shock can also be interpreted as a preference shock: for example, "an increased preference of smaller, more fuel-efficient automobiles would result in lower demand for oil, given the same level of global real activity." Note that in this study, I differentiate between precautionary oil demand shocks and shocks to U.S. energy efficiency.

[25]Note that I multiply the global GDP factor with the average factor loading to represent it in units of GDP growth rates.

boom. The plot shows the evolution of the global GDP factor with and without the contribution of U.S. oil supply shocks, where U.S. oil supply shocks are interpreted as unanticipated improvements in U.S. shale sector productivity. The results indicate that expansion in U.S. oil supply due to innovations in shale technology had an overall positive impact on global activity during this period. The results are especially pronounced starting in 2014—a period when exemptions were heavily used to circumvent the U.S. crude oil export ban, which contributed to a decline in global oil prices (see Melek, Plante, & Yücel, 2020). In particular, during the period 2014–2016 oil markets experienced one of the largest oil price declines since the 1970s. Stocker et al. (2018) attribute this decline primarily to supply factors with the "booming U.S. shale production [playing] a significant role in the oil price plunge from mid-2014 to early 2016." Similarly, Nuño & Manescu (2015) conclude that the decline in oil prices in the second half of 2014 was mainly due to an unexpected increase in oil supply. The global oil price decline led to a temporary reduction in shale oil production as teh U.S. fracking industry competed with OPEC and other low-cost oil producers. However, further innovations in productivity allowed shale producers to mitigate production costs, which resulted in the second shale boom, which saw U.S. shale oil output expanding to record levels in 2019 (Rystad, 2019). These unexpected cost-reducing productivity gains had a relatively large positive impact on global output over the period 2017–2019 as seen in Figure 5. Overall, in the absence of the first and the second U.S. shale boom, global GDP growth would have been lower by approximately 0.27 percentage points during the period 2010–2019.[26] This translates to an increase of approximately 2.03 percent in global GDP as a result of the two shale booms, which represents approximately 7.5 percent of the total growth in global GDP that occurred over the period 2010–2019.

During the same period, a series of predominantly negative U.S. energy efficiency shocks had an adverse impact on global economic activity. The bottom panel in Figure 5 shows the evolution of the global GDP factor with and without U.S. energy efficiency shocks. The results indicate that in absence of U.S. energy efficiency shocks, global GDP growth would have been higher by approximately 0.19–0.23 percentage points over the period 2010-2019, which maps to an increase of 1.33 percent in the level of global GDP. The results are most pronounced during the period 2017–2019—a period that overlaps with the second shale boom—when negative energy efficiency shocks eclipse the positive impact on global growth of the expansion in U.S. oil supply. These results are in line with other empirical findings. For example, the International Energy Agency (IEA) reports a decline in energy efficiency improvements since 2015 (see International Energy Association, 2017, 2018, 2019).[27]

[26] See also Mohaddes & Raissi (2019) who find that a U.S. supply-driven oil price shock increases global growth by 0.16–0.37 percentage points in the medium term. Their results are based on a Global VAR model, where they obtain a weighted average of country impulse responses to a U.S. oil supply shock. The use of historical decompositions to assess the impact on global GDP of U.S. shale revolution is crucial because the actual variation in GDP is driven by shocks of different magnitudes and signs (see Kilian & Lütkepohl, 2017).

[27] In particular, International Energy Association (2017) states that, "progress [in energy efficiency] has become dependent on yesterday's policies, with the implementation of new policies slowing. If the world is to transition to a clean energy future, a pipeline of new efficiency policies needs to be coming into force. Instead, the current low rate of implementation risks a backward step." Similarly, International Energy Association (2019) states that, "this decline [in energy efficiency improvements] partly reflects stagnation in the passing of new energy efficiency policies in recent years. Also, Acemoglu et al. (2019) study the impact of the shale revolution on CO_2 emissions. They find that in the long run, a shale gas boom increases CO_2 emissions and induces firms to direct innovation away from

I find that a comparison between the effects of U.S energy efficiency and U.S. oil supply shocks during the period 2010–2019 suggests that U.S. energy efficiency shocks had an equally sizeable, but negative, impact on global GDP. In particular, as seen in Figure 5, the positive impact on global activity of the second shale boom over 2017–2019 is wiped out by the effect of negative U.S. energy efficiency shocks during this period. Moreover, in comparison to technological improvements in shale oil production that are constrained by the availability of recoverable reserves, improvements in U.S. energy efficiency are more transferable to other countries. Therefore, U.S. energy efficiency improvements may have, on average, a larger impact on global economic activity as indicated earlier by the impulse response functions in Figure 4. Furthermore, the historical counterfactuals over the full sample period, 1980–2019, indicate that the positive impact of U.S. oil supply shocks on global output are limited to the post-2010 period, whereas energy efficiency improvements have had a largely positive effect on global GDP from 1980 to the early 2000s.[28]

IV.3.3 Cross-country Economic Activity and U.S. Energy Market Shocks

Figures 6 and 7 plot the response of the level of the real GDP of selected net oil-importing and oil-exporting countries to a positive U.S. oil supply and a positive U.S. energy efficiency shock, respectively.[29] Figure 6 shows that in response to an unanticipated increase in U.S. oil supply, the real GDP of advanced oil importing countries, namely, Japan, Germany, and France, increases gradually for about two quarters and remains persistently positive thereafter. On the other hand, the GDP response of emerging economies, namely, China, India, and the Rebulic of Korea, is relatively large on impact, but the effect dies out much faster.

For oil-exporting countries in the sample, the GDP response to a U.S. oil supply shock is more varied. For example, an unexpected increase in U.S. oil supply results in a relatively large negative impact on Saudi Arabia's real GDP. The negative response peaks after two quarters and then diminishes back to zero after six quarters. Because Saudi Arabia's oil and gas sector accounts for more than 40 percent of its GDP, a U.S. oil supply shock that results in a decline in the real price of oil would also negatively affect Saudi Arabia's oil production and revenue. A positive U.S. oil supply shock, however, results in a relatively small negative response of Canada's real GDP on impact, which returns to zero after two quarters. The corresponding response for Norway is largely flat and close to zero at all horizons. Canada and Norway are net oil-exporting countries but their respective oil sector's share of GDP is roughly between 10 and 15 percent, which is about one third of that of Saudi Arabia's GDP share of oil. Moreover, these two countries also have other, relatively large and energy-intensive, manufacturing and commodity sectors that benefit from a decline in the real price of oil.

Figure 7 shows that GDP responses to a positive U.S. energy efficiency shock are broadly similar to a U.S. oil supply shock. As discussed previously, an improvement in U.S. energy efficiency mimics

cleaner alternatives. In this paper, I do not account for a substitution between technological innovations in shale oil production and energy efficiency."

[28]The historical counterfactual for the full sample period is provided in Figure 16 in Appendix A.

[29]Note that here I present results for the top net oil-importing advanced and emerging economies and the top net oil exporters in the sample.

an increase in U.S. oil supply in terms of its effect on the real price of oil. Thus, as the oil price decreases in response to a positive energy efficiency shock, net oil-importing countries experience a boost in economic activity. Moreover, the GDP response of net oil importing advanced economies is typically larger and more persistent than the response of emerging economies. For oil exporting countries, as in the case of a U.S. oil supply shock, the impulse responses are more diverse. For example, Saudi Arabia experiences a large negative impact in response to an improvement in U.S. energy efficiency, which follows a pattern similar to the response to an increase in U.S. oil supply. The real GDP of Canada, however, increases in response to an improvement in U.S. energy efficiency, and the response of Norway's GDP is close to zero.

A key takeaway from the results in Figures 6 and 7 is that there exist differences in GDP responses across countries to U.S. oil supply and energy efficiency shocks. In particular, responses vary both within and across net oil-importing and oil-exporting countries. These heterogeneities are masked by the response of the global GDP factor to the corresponding shocks (shown in Figure 4). However, the results in all three figures combined show that overall positive shocks to U.S. oil supply and energy efficiency result in a net positive impact on global economic activity but large oil exporters such as Saudi Arabia are worse off because of a decline in the world oil price. Moreover, a comparison of the country impulse responses across the two types of U.S. energy market shocks, indicates that a positive U.S. energy efficiency shock typically has a larger effect on real GDP across countries. This result is consistent with the finding in Figure 4 that a U.S. energy efficiency shock results in a larger decline in the world oil price in comparison to its response to a U.S. oil supply shock. Strikingly, the response of Canada—a net oil exporter—also has a largely positive response to a positive U.S. energy efficiency shock.[30] Because improvements in energy efficiency should be more correlated across countries than innovations in oil production (for example, because of geographical limitations), Canada is likely to experience direct positive spillovers in domestic energy efficiency in sectors such as manufacturing, following a U.S. energy efficiency shock.

IV.4 Robustness

This section provides a sensitivity analysis of the main findings discussed in Section IV.3.

Elasticity Restrictions. First, I check the sensitivity of the empirical results to relaxing the upper bound imposed on the short-run price elasticity of oil supply. Recall that I restricted the ratio of the impact response of oil production to the impact response of the oil price triggered by an exogenous shift in oil demand. I imposed a value of 0.07 as an upper bound for the ratios a_{12}/a_{32}, a_{42}/a_{32}, a_{13}/a_{33}, a_{43}/a_{33}, a_{15}/a_{35}, and a_{45}/a_{35}, where a_{ij} are elements of the structural impact matrix $\mathbf{B_0}$. The upper bound I select is three times larger than the one-month elasticity estimate imposed in Kilian & Murphy (2012) and is chosen as a conservative estimate for the model at a quarterly frequency. In the robustness analysis, I further relax the upper bound by choosing values that are two and three times larger (0.14 and 0.21, respectively) than the baseline.

[30] Note that period 0 response is still negative, which is by construction based on the maintained sign restriction in Table 2.

These values are less realistic based on evidence from other empirical studies (see Kilian, 2020, for a survey). However, I pick these values to demonstrate how the results vary as the oil supply elasticity restriction becomes less binding.

Figure 17 in the Appendix VII.1 presents the impulse responses of the global GDP factor and the real price of oil to U.S. oil supply and U.S. energy efficiency shocks with different upper bounds on the short-run price elasticity of oil supply. The results indicate that as we relax the elasticity constraint, the impact of a U.S. oil supply shock on the real price of oil and the global GDP factor becomes larger, while the impact of a U.S. energy efficiency shock on the same variables decreases. When the upper bound is 0.14, the effect on the global GDP factor of U.S. oil supply and U.S. energy efficiency shocks is almost identical after four quarters. However, the response at impact and during the first two quarters is always larger when triggered by a U.S. energy efficiency shock.

Fossil Fuel Data. Next, I also check the robustness of the empirical results by using fossil fuel consumption data to identify U.S. energy efficiency shocks. Note that the historical decomposition results presented in Section IV.3 are obtained based on an identification of the U.S. energy efficiency shock using U.S. oil consumption data. However, it can be argued, for example, that a positive shock that satisfies the restrictions in Table 1, column 5, does not capture U.S. energy efficiency shocks because the decrease in U.S. oil consumption might be accompanied by an increasing the consumption of other fossil fuels such as coal and natural gas. Examples of such shocks include the increase in coal mining in the United States after the 1970s oil crisis and similarly a surge in natural gas production following the application of hydraulic fracturing and horizontal drilling to the development of shale gas in the 2000s. Thus, I use the following identification as a robustness test to identify U.S. energy efficiency shocks

$$\begin{pmatrix} u_t^{\text{Non-US Oil Production}} \\ u_t^{\text{Global GDP Factor}} \\ u_t^{\text{Oil Price}} \\ u_t^{\text{US Oil Production}} \\ u_t^{\text{US Fossil Fuel Consumption}} \end{pmatrix} = \begin{bmatrix} + & + & + & - & - \\ + & + & - & + & + \\ - & + & + & - & - \\ - & + & + & + & - \\ + & + & - & + & - \end{bmatrix} \begin{pmatrix} (+)w_t^{\text{Non-US Oil Supply}} \\ (+)w_t^{\text{Economic Activity}} \\ (+)w_t^{\text{Precautionary Oil Demand}} \\ (+)w_t^{\text{US Oil Supply}} \\ (+)w_t^{\text{US Energy Efficiency}} \end{pmatrix},$$

where the reduced-form residuals, u_t, are obtained using data on U.S. fossil fuel consumption instead of U.S. oil consumption.[31] The sign restrictions imposed on the structural impact multiplier matrix, $\mathbf{B_0}$, to map u_t to the structural shocks, w_t, remain unchanged.

The results in Figure 18 indicate that the overall findings for the period 2010–2019 are similar to those obtained with U.S. oil consumption data (if we compare the red and orange dashed lines in the Figure 18). The historical counterfactual shows that in the absence of negative U.S. energy efficiency shocks, global GDP would have been higher during the periods that overlap with the first and the second shale oil booms (2012–2014 and 2017–2019, respectively).

[31] Note that the other variables are the same as those used in Table 1.

V. Model

In this section, I construct a quantitative model of the world economy to provide a structural interpretation of the mechanisms transmitting U.S. oil supply and energy efficiency shocks. The model extends the three-country framework of Backus & Crucini (2000) and is similar to Bodenstein & Guerrieri (2011) and Gars & Olovsson (2017). The key difference is that I model the United States as an economy that produces oil and either exports and imports it, where oil production is endogenous in order to capture innovations in oil sector productivity such as shale technology shocks. The model abstracts from a number of features such as nominal frictions, the strategic behavior of oil producers, long-run growth, and different types of crude oil to focus on specific features that demonstrate the main mechanisms underlying the empirical results.[32]

The world economy consists of three countries: the United States, an oil importer, and an oil exporter. I refer to the United States, the rest of the world (ROW) oil importer, and the oil exporter as countries 1, 2, and 3, respectively. Each oil importing country specializes in producing country-specific intermediate good using capital, labor, and oil, where oil is the only energy source available. Factor-specific technology shocks affect the production of intermediate goods. In particular, positive shocks to energy efficiency allow firms to produce the same level of output using less oil. The intermediate goods are traded and combined to produce a final good that is used for consumption and investment in each of the three countries.

Oil is produced by both the United States and the oil exporter. The United States produces oil by employing domestic labor, where oil supply is affected by stochastic movements in oil sector productivity. The oil exporter's supply of oil consists of both a stochastic endowment of oil and an endogenous component requiring labor for oil production, which captures the heterogeneity in oil production across oil-exporting countries.

V.1 The economic environment

Households. In each country, representative agents maximize the following utility function

$$E_0\left(\sum_{t=0}^{\infty}\beta^t \frac{\left[c_{it}^{\mu}(1-n_{it}-n_{it}^{o})^{1-\mu}\right]^{1-\gamma}}{1-\gamma}\right), \quad 0<\mu<1; \quad 0<\beta<1; \quad 0<\gamma; \quad i=1,2,3 \tag{7}$$

where c_{it}, n_{it}, and n_{it}^{o} are consumption, non-oil sector and oil sector labor supply, respectively, in country i at time t.[33] μ is the share of consumption in utility and $1/\gamma$ is the intertemporal elasticity of substitution. The budget constraint for country 1 is given as follows

$$c_{1t}+x_{1t}+q_{1t}^{a}Q_{1t}B_{1t} \;=\; q_{1t}^{a}\left(r_{1t}k_{1t}+w_{1t}n_{1t}+w_{1t}^{o}n_{1t}^{o}\right)+q_{1t}^{a}B_{1t-1} \tag{8}$$

[32] For related literature, see, amongst others, Lippi & Nobili (2009), Nakov & Nuño (2013), Bodenstein, Guerrieri, & Kilian (2012), Melek, Plante, & Yücel (2020).

[33] Note $n_{it}^{o}=0$ and $n_{it}=0$ for countries 2 and 3, respectively.

where x_{1t} is investment, Q_{1t} is the price of a state contingent bond that pays one unit of good a if a particular state occurs, and B_{1t} is the quantity of such bonds. The households also earn wages, w_{1t}, from supplying labor and income, r_{1t}, from renting out capital. The household budget constraint in country 2 is analogous. Capital is accumulated based on the following law of motion

$$k_{it+1} = (1-\delta)k_{it} + x_{it} \tag{9}$$

where δ is the rate of depreciation, and x_{it} is investment.

The intermediate goods sector. Each oil-importing economy consists of perfectly competitive firms that produce an intermediate good, y, by combining a domestic value-added with oil using a CES technology, where the former is a Cobb-Douglas production function of labor, l, and capital, k. The production technology is given by the following function

$$y_{it} = \left[(1-\alpha_o)\left(z_{it}^n n_{it}^{\theta} k_{it}^{1-\theta}\right)^{1-\nu} + \alpha_o \left(z_{it}^e o_{it}\right)^{1-\nu}\right]^{\frac{1}{1-\nu}}, \quad 0<\theta<1,\ \nu>0,\ \alpha_o>0; \quad i=1,2,3 \tag{10}$$

where θ is the cost-share of labor in producing the domestic value-added, $1/\nu$ is elasticity of substitution between the domestic value-added and oil, and α_o is the share of oil in production. z^n and z^e are productivity and energy efficiency shocks, respectively. Since oil is the only energy source in the model, the oil efficiency shock, z^e, can be interpreted as an energy efficiency shock.

The shocks are described by the following stochastic processes

$$\begin{bmatrix} z_{1t}^j \\ z_{2t}^j \end{bmatrix} = \begin{bmatrix} \rho_j & \chi_j \\ \chi_j & \rho_j \end{bmatrix} \begin{bmatrix} z_{1t-1}^j \\ z_{2t-1}^j \end{bmatrix} + \begin{bmatrix} \epsilon_{1t}^j \\ \epsilon_{2t}^j \end{bmatrix}, \qquad \begin{bmatrix} \epsilon_{1t}^j \\ \epsilon_{2t}^j \end{bmatrix} \sim N(0,\Sigma) \tag{11}$$

where $j \in \{n, e\}$. The off-diagonal elements in the coefficient matrix capture the spillovers of productivity and energy efficiency shocks between countries 1 and 2. For example, a positive energy efficiency shock in country 1 in period t would result in an improvement in energy efficiency in country 2 in period $t+1$.[34]

Energy efficiency shocks are modeled as persistent and transitory shocks.[35] One example of this shock would be a major improvement in energy efficiency that allows firms to use less oil to produce the same level of output. However, it would also capture other shocks such as a public awareness program that raises energy efficiency by encouraging firms to implement low-cost measures (for example, optimizing equipment start-up time, power-down time, and repairing leaks).

[34] Note that the correlation between ϵ_1^j and ϵ_2^j is 0 for $j = \{n, e\}$.

[35] Note that since the main purpose of the model is to discuss the mechanisms driving the empirical results, I abstract from long-run growth and consider a stationary model. Thus, energy efficiency can decrease from one period to another. A positive trend can be added to the productivity process to overcome this issue and make productivity less likely to decrease (see, Gars & Olovsson, 2017; Hassler, Krusell, & Olovsson, 2019).

The oil sector. The U.S. oil sector produces oil, y^o_{1t}, using the following production technology

$$y^o_{1t} \;=\; z^o_{1t}(n^o_{1t})^{\alpha} \tag{12}$$

where n^o_{1t} is labor employed by the U.S. oil sector, and the productivity shock, z^o_{1t}, is given by the following stochastic process

$$z^o_{1t} \;=\; \rho^o_1 z^o_{1t-1} \;+\; \epsilon^o_{1t} \tag{13}$$

where ρ^o_1 is the persistence parameter, and the disturbance $\epsilon^o_{1t} \sim iidN(0, \sigma^o_1)$.

The oil exporter's production of oil consists of two components: (1) an endogenous component, $(n^o_{3t})^{\alpha}$, and (2) an exogenous component, z^o_{3t}. In particular, total oil produced by the oil exporter at time t is given as following

$$y^o_{3t} \;=\; (n^o_{3t})^{\alpha} \;+\; z^o_{3t}, \tag{14}$$

where the endogenous component can be considered as oil supplied by non-OPEC oil producers that requires a labor input, n^o_{3t}, for production. Whereas, the exogenous component can be considered as OPEC's oil supply that reflects a stochastic endowment of oil (see Backus & Crucini, 2000). The exogenous component follows an $AR(1)$ process as following

$$z^o_{3t} \;=\; \rho^o_3 z^o_{3t-1} \;+\; \epsilon^o_{3t}, \tag{15}$$

where ρ^o_3 is the persistence parameter, and the disturbance, ϵ^o_{3t}, is independent and normally distributed with mean 0 and standard deviation σ^o_3.

The final goods sector. All countries produce final goods that are used for consumption and investment by combining the tradable intermediates using a CES (or Armington) aggregator. More specifically, the final goods production function is as following

$$G_i\left(a,b\right) = \left[\omega_{ai} a_i^{\frac{\sigma-1}{\sigma}} + \omega_{bi} b_i^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \quad i = 1,2,3 \tag{16}$$

where σ is the elasticity of substitution between the two intermediates (or Armington elasticity), ω_{ji} is the weight on the intermediate good j imported by country i, where $j = \{a, b, c\}$.

Equilibrium. **Definition 1.** An equilibrium is a sequence of allocations, $(\{c_{it}, k_{it}, o_{it}, B_{it}, x_{it}, y_{it}\}^{\infty}_{t=0}$ for $i = \{1, 2\}$, $\{n^o_{it}, y^o_{it}\}^{\infty}_{t=0}$ for $i = \{1, 3\}$, and $\{n_{it}, a_{it}, b_{it}, G_{it}\}^{\infty}_{t=0}$ for $i = \{1, 2, 3\})$, and prices, $\{w_{it}, r_{it}, Q_{it}, w^o_{it}, q^a_{it}, q^b_{it}, p^o_t\}^{\infty}_{t=0}$, such that

1. Households

   - In the U.S., the representative household maximizes utility by choosing consumption, capital, bonds, non-oil and oil-sector labor by solving the following problem

$$v(k_1) \;=\; \max_{c_1,n_1,n_1^o,k_1',B_1'} \; u(c_1,n_1,n_1^o) + \beta E\left[v(k_1')\right] \tag{17}$$

such that

$$c_1 + k_1' + q_1^a Q_1 B_1' \;=\; q_1^a\left(r_1k_1 + w_1n_1 + w_1^o n_1^o\right) + (1-\delta)k_1 + q_1^a B_1 \tag{18}$$

- In the ROW oil importing country, the representative household maximizes utility by choosing consumption, capital, bonds, and labor by solving the following problem

$$v(k_2) \;=\; \max_{c_2,n_2,k_2',B_2'} \; u(c_2,n_2) + \beta E\left[v(k_2')\right] \tag{19}$$

such that

$$c_2 + k_2' + q_2^b Q_2 B_2' \;=\; q_2^b\left(r_2k_2 + w_2n_2\right) + (1-\delta)k_2 + q_2^b B_2 \tag{20}$$

- In the oil exporting country, the representative household consumes the final good given its respective budget constraint maximizes

$$v(k_3) \;=\; \max_{c_3,k_3',B_3'} \; u(c_3) + \beta E\left[v(k_3')\right] \tag{21}$$

such that

$$c_3 + k_3' + q_3^a Q_3 B_3' \;=\; q_3^a p^o y_3^o + (1-\delta)k_3 + q_3^a B_3 \tag{22}$$

2. Firms

- Intermediate goods-producing firms in each country $i \in \{1,2\}$ choose factor inputs to maximize profits

$$\max_{n_{it},k_{it},o_{it}} \left[(1-\alpha_o)\left(z_{it}^n n_{it}^\theta k_{it}^{1-\theta}\right)^{1-\nu} + \alpha_o\left(z_{it}^e o_{it}\right)^{1-\nu}\right]^{\frac{1}{1-\nu}} - r_{it}k_{it} - w_{it}n_{it} - p_t^o o_{it} \tag{23}$$

- Final goods-producing firms in each country $i \in \{1,2,3\}$ solve the following profit maximization problem

$$\max_{a_{it},b_{it}} \; G_{it}(a,b) - a_{it} - b_{it} \tag{24}$$

- U.S. oil producing firm chooses factor inputs to maximize profits

$$\max_{n_{1t}^o} \; p_t^o z_{1t}^o (n_{1t}^o)^\alpha \;-\; w_{1t}^o n_{1t}^o \tag{25}$$

3. Market Clearing

- Intermediate-good market clears

$$a_{1t} + a_{2t} + a_{3t} = y_{1t} \tag{26}$$
$$b_{1t} + b_{2t} + b_{3t} = y_{2t} \tag{27}$$

- Final-good market clears in each country $i \in \{1, 2\}$

$$c_{it} + x_{it} = G_{it}(a, b) \tag{28}$$

and country $i = 3$ as

$$c_{it} = G_{it}(a, b) \tag{29}$$

- Oil market clears

$$y^o_{1t} + y^o_{3t} = o_{1t} + o_{2t} \tag{30}$$

- Bond market clears

$$B_{1t} + B_{2t} + B_{3t} = 0 \quad \forall t \tag{31}$$

- Law of one price holds (i.e., the relative price of intermediates is same in all countries)

$$\frac{q^a_{1t}}{q^b_{1t}} = \frac{q^a_{2t}}{q^b_{2t}} = \frac{q^a_{3t}}{q^b_{3t}} \tag{32}$$

V.2 Calibration and Estimation

The model is calibrated and estimated at quarterly frequency to match the empirical estimation in the previous section. Country 1 is identified as the United States and country 2 as the rest of the world (ROW). Moreover, ROW only includes oil importing countries in line with Section IV.. Following Backus & Crucini (2000), country 3 is an oil exporter that represents OPEC and non-OPEC oil producers, excluding the United States. The parameters are divided into two groups. For the first group, I follow Backus & Crucini (2000), Heathcote & Perri (2002), and Gars & Olovsson (2017). The second group of parameters are estimated using an indirect inference strategy. In particular, the estimation is done by minimizing the distance between impulse responses obtained from actual data (presented in Figure 4) and impulse responses generated from the same factor-augmented VAR estimated on model simulated data (see Kehoe, 2006).

The first group primarily contains parameters that have uncontroversial values in the literature, where similar parameters across the three countries take on the same values, unless otherwise stated. The discount factor (β) is set to 0.99, which equals an annual rate of approximately 4%. The consumption share (μ) in the utility function is 0.34, which implies that 30% of the fraction of time is spent working. The intertemporal elasticity of substitution ($1/\gamma$) is 0.5. These three parameters determine the curvature properties of the utility function. Armington weights (ω_i) are calibrated to 0.9 to ensure each oil importing country's home bias. The oil exporter is indifferent towards importing intermediate goods from each manufacturing country and, thus, the respective armington weight (ω_o) is set to 0.5. The Armington elasticity (i.e., the elasticity of substitution between home and foreign goods ($1/\sigma$)) is 1.5.

Technology parameters are set as follows: the cost-share of labor in intermediate-goods production (θ) is 0.64 and depreciation rate of capital (δ) is 0.025. The share of oil in the production of the intermediate good (α_o) is 0.05, which is calibrated to be close to the GDP-share of oil on average across countries. A key parameter is the elasticity of substitution between oil and capital-labor aggregate ($1/\nu$) in the production of intermediate goods. It is set to 0.09.

The world economy is driven by six disturbances: home productivity shocks, foreign productivity shocks, home energy efficiency shocks, foreign energy efficiency shocks, U.S. oil supply shocks, and non-U.S. oil supply shocks. Following Heathcote & Perri (2002), the process of technology shocks is given as following

$$\begin{pmatrix} z_t^a \\ z_t^b \end{pmatrix} = \begin{pmatrix} 0.97 & 0.025 \\ 0.025 & 0.97 \end{pmatrix} \begin{pmatrix} z_{t-1}^a \\ z_{t-1}^b \end{pmatrix} + \begin{pmatrix} \epsilon_t^a \\ \epsilon_t^b \end{pmatrix},$$

where the shock process is symmetric across the United States and the ROW.

The persistence parameter for non-U.S. oil supply shocks is 0.98 and standard deviation of innovations is 0.01, following Backus & Crucini (2000).

Indirect Inference. A key objective is to estimate the parameters of U.S. energy efficiency and U.S. oil supply shocks. As discussed above, I employ an indirect inference strategy to estimate these parameters as they are not readily available in the literature. In particular, I use the Sims-Cogley-Nason (SCN) impulse response matching approach as outlined in Kehoe (2006). The main idea behind this approach is to estimate parameters of interest by comparing empirical impulse responses to impulse responses from identical structural VARs estimated on data simulated from the theoretical model. This approach addresses the Chari, Kehoe, & McGrattan (2008) critique, which argues that a direct comparison of model generated and structural VAR impulse responses is inappropriate as it matches different objects in the model and the actual data.

I use the SCN impulse response matching approach to estimate the persistence of U.S. energy efficiency shock, correlation of U.S. energy efficiency shock with the ROW oil importer's energy efficiency shock process, and persistence of U.S. oil supply shock. The parameters are collected in the vector ζ. Let $\Omega(\zeta)$ be the mapping from ζ to the impulse responses obtained from the model simulated data and let Ω be the empirical counterparts. I match the empirical and model impulse responses to a U.S. energy efficiency shock and a U.S. oil supply shock, where the first 6 quarters of each response function are included. The estimator of Ω is the solution to

$$J \; = \; \min_{\Omega} \left[\hat{\boldsymbol{\Omega}} - \boldsymbol{\Omega}(\zeta)\right] \mathbf{V^{-1}} \left[\hat{\boldsymbol{\Omega}} - \boldsymbol{\Omega}(\zeta)\right],$$

TABLE 3: Benchmark Calibration

	Description	Parameter	Value	Source
Preferences	Discount factor	β	0.99	BC, HP, GO
	Consumption share	μ	0.34	HP
	Intertemporal Substitution	$1/\gamma$	0.5	BC, HP, GO
Trade	Armington elasticity	$1/\sigma$	1.5	HP, GO
	Armington aggregator weights	$\omega_{i=\{1,2\}}$, ω_3	0.9, 0.5	HP, GO
Technology	Cost-share of labor in intermediate-goods production	θ	0.64	BC, HP
	Depreciation rate of capital	δ	0.025	BC, HP
	Cost of adjustment parameter	η	0.99	BC, GO
Oil sector	Oil share	α_o	0.10	BC, GO
	Elasticity of substitution kl, o	$1/\nu$	0.09	BC, GO
	Oil exporter's share of oil output	ϕ^o	0.5	BC, GO
	Labor parameter	α	0.6	BC, GO
Shocks	Persistence of productivity shock	ρ_n	0.97	HP, GO
	Correlation of productivity shocks across $i = \{1, 2\}$	χ_n	0.025	HP
	Persistence of energy efficiency shock	ρ_e	0.70	II
	Correlation of energy efficiency shocks across $i = \{1, 2\}$	χ_e	0.11	II
	Persistence of non-U.S. oil supply shock	ρ_3^o	0.98	BC
	Persistence of U.S. oil supply shock	ρ_1^o	0.91	II

Note: BC: Backus & Crucini (2000), HP: Heathcote & Perri (2002), GO: Gars & Olovsson (2017), II: indirect inference.

where $\mathbf{V}$ is a diagonal matrix with diagonal elements as the variances of Ω.

Figure 8 displays the empirical impulse responses, along with the response functions estimated using model simulated data. The persistence of U.S. oil supply shock is estimated as 0.91 and innovation standard deviation is 0.012. The persistence and correlation for U.S. energy efficiency is estimated as 0.7 and 0.11, respectively. I follow the standard assumption in the literature that the shock process is symmetric across countries. Thus, the estimated energy efficiency shock process is given as following

$$\begin{pmatrix} z_t^a \\ z_t^b \end{pmatrix} = \begin{pmatrix} 0.70 & 0.11 \\ 0.11 & 0.70 \end{pmatrix} \begin{pmatrix} z_{t-1}^a \\ z_{t-1}^b \end{pmatrix} + \begin{pmatrix} \epsilon_t^a \\ \epsilon_t^b \end{pmatrix},$$

where the standard deviation of innovations is 0.02.

V.3 Baseline Results

In this section, I discuss the impulse responses to U.S. energy efficiency and U.S. oil supply shocks. In particular, I focus on understanding the mechanisms by which changes in U.S. oil production and consumption can affect the GDP of oil importing and oil exporting countries. Each shock has direct implications for either U.S. oil demand or U.S. oil supply and, thus, results in changes in oil price and, consequently, U.S. and international macroeconomic aggregates. Figure 9 shows the effects of a one-standard deviation improvement in U.S. energy efficiency. A positive shock to U.S.

energy efficiency decreases U.S. oil demand on impact as the marginal product of oil decreases. This result depends especially on the elasticity of substitution between oil and other factor inputs, ν, and the cost-share of oil in production, α_e. In particular, the decline in U.S. oil demand following an improvement in U.S. energy efficiency is due to the complementarity between oil and the value added from capital and labor.[36] As oil price decreases, the firm's cost of production declines and this raises the marginal product of other inputs. Thus, demand for capital and labor increases and leads to an increase in U.S. GDP.

Following the positive U.S. energy efficiency shock, oil demand in the foreign oil importing country increases as the world oil price declines. From the optimality conditions, we know that oil consumption in the ROW country would increase untill the marginal product of oil across the two oil importing regions (i.e., the U.S. and the foreign oil importer) is equalized.[37] However, after two quarters, ROW oil demand becomes negative as the innovation in U.S. energy efficiency spills over to the ROW. Moreover, since oil is an input into production, a decrease in oil price reduces the intermediate-good producing firm's cost and increases the marginal product of capital and labor. Thus, GDP, investment, and consumption increase in the foreign oil importing country as well.

The U.S. oil sector production declines in response to an improvement in U.S. energy efficiency. In particular, with a decline in oil price, the demand for labor in the U.S. oil sector falls as the return on labor decreases. The oil exporting country also experiences a fall in employment as oil price decreases. Consequently, the oil exporter's oil production, GDP, and consumption decline. The overall increase in GDP across U.S. and the ROW oil importing region is greater than the decline in the oil exporter's GDP. Thus, in comparison to the empirical results in Figure 4, this indicates that the increase in global economic activity in response to a positive U.S. energy efficiency shock is primarily due to the cost reduction experienced by firms' in U.S. and oil importing countries. Overall the results are heterogeneous across oil and non-oil sectors and oil importers and oil exporters.

Figure 10 presents the impulse responses to a one-standard deviation increase in U.S. oil sector productivity. This results in an increase in U.S. oil sector labor and, consequently, U.S. oil production. With an increase in U.S. oil production, the world oil price falls. A decline in world oil price, reduces the oil exporter's revenue. Thus, demand for factor inputs to produce oil decreases as the respective marginal product effectively declines. Consequently, the oil exporter's oil production, GDP, and consumption fall. For the oil exporter, a U.S. energy efficiency shock or a U.S. oil supply shock results in qualitatively similar responses. In both cases, oil exporter's GDP declines as world price of oil decreases. However, as expected, the U.S. oil sector booms in response to a U.S. oil productivity shock, while U.S. oil sector's employment and output decline after an improvement in

[36]Note that from the first order conditions we have that the intermediate-good producing firm's marginal product of oil must equal the price of oil, i.e., $\left[(1-\alpha_o)\left(z_{it}^{n} n_{it}^{\theta} k_{it}^{1-\theta}\right)^{1-\nu} + \alpha_e \left(z_{it}^{e} o_{it}\right)^{1-\nu}\right]^{\frac{\nu}{1-\nu}} \alpha_e (z_{it}^{e})^{1-\nu} o_{it}^{-\nu} = p_t^{o}$. Thus, the response of U.S. oil demand to a domestic energy efficiency shock depends especially on the elasticity of substitution, ν, between oil and the value-added. As discussed in Section V.2, I choose ν such that oil and the capital-labor aggregate are complements.

[37]See optimality conditions in Appendix B.

U.S. energy efficiency.

Moreover, a decrease in the oil price following a U.S. oil supply shock, reduces production cost for U.S. intermediate-good producing firms and, thus, demand for factor inputs, including oil, increases as this raises marginal product of factor inputs. A U.S. oil supply shock, therefore, increases U.S. GDP alongside domestic consumption and investment. The ROW oil importing country also experiences an increase in output, consumption, investment, and employment in response to the U.S. oil supply shock as the oil price decreases. Thus, for the ROW oil importing region a positive oil supply shock and an increase in U.S. energy efficiency invokes similar responses in GDP, consumption, and investment. However, the magnitude of the responses with U.S. energy efficiency and U.S. oil supply shocks differ. In particular, in contrast to the U.S. oil supply shock, following a U.S. energy efficiency shock, ROW's GDP increases both due to a decrease in oil price and also because of a direct spillover of the innovation in energy-efficiency technology.

Figure 11 shows the impulse responses to a one standard deviation home productivity shock with the benchmark calibration. In response to a positive home productivity shock, U.S. output increases. Higher productivity implies higher marginal product of all inputs, including oil. This raises demand for oil and increases oil price. An increase in oil price, raises oil production and oil exporter's GDP. However, ROW oil importer experiences an initial decline in output due to an increase in the cost of production as oil price increases. Moreover, there is a transfer of resources from ROW to U.S. as productivity in U.S. is higher and resources seek the highest return. This concentration of labor and capital in U.S. further decreases ROW's output. However, technological spillover eventually raises output in ROW.

Figure 11 also shows the response of the U.S. trade balance. U.S. trade balance worsens due to investment inflows and an increase in consumption. The ROW trade balance (not shown) improves but it is dampened by a larger oil import bill. Moreover, following a positive productivity shock, the price of consumption in the United States decreases relative to foreign consumption. Thus, the U.S. terms of trade (i.e., price of U.S. imports relative to U.S. exports) depreciates. The exchange rate (i.e., price of the consumption basket in ROW oil importer relative to the price of consumption basket in the United States) increases as well or U.S. exchange rate worsens. The production technology in the model implies that there is a linear relationship in the real exchange rate and terms of trade (Heathcote & Perri, 2002). These results depend on the Armington aggregator weights, ω, and the Armington elasticity, $1/\sigma$. In particular the Armington aggregator weight, ω, determines the relative demand of home and foreign intermediates in producing the final good.

V.4 Sensitivity

Zero Correlation between U.S. and ROW Energy Efficiency Shocks. The baseline results in Figure 9 indicate that because the shocks to energy efficiency are correlated (with a lag of one quarter) across oil importing countries, ROW oil demand increases on impact but turns negative after two quarters following a positive U.S. energy efficiency shock; the correlation parameter is estimated using indirect inference as discussed in Section V.2. Therefore, due to the spillover of U.S. energy efficiency improvements to rest of the world, there is negligible rebound in oil demand from the foreign oil importer even as the oil price falls. However, the magnitude of the rebound-effect is highly debated in the literature, with the magnitude varying from "backfire" to "super-conservation" (see Section 5). In an international framework, this issue is even more evident as other oil importing countries may increase oil consumption as world oil price declines. To test the sensitivity of the baseline results, I assume that there is no spillover of U.S. energy efficiency improvements to other countries.

Figure 20 in Appendix VIII. presents impulse responses when the correlation of energy efficiency shock, ρ, is set to 0. Because shocks are correlated with a lag in the benchmark calibration, impulse responses in Figure 20 indicate that ROW oil demand increases by the same magnitude on impact following a U.S. energy efficiency shock in both cases when correlation, ρ, is 0 and 0.11. Thus, global oil demand decreases on impact with a positive U.S. energy efficiency shock in both scenarios. However, following the impact period, ROW oil demand decreases more gradually and returns to zero after four quarters, versus turning negative after two quarters as seen in the baseline case. Moreover, because there is an overall smaller decline in global oil demand, the decrease in oil price is smaller in magnitude and less persistent as well. Consequently, global oil production falls by a lesser magnitude and the deviation below the steady state is more transitory. Additionally, the increase in U.S. and ROW output is not as large and returns to zero after roughly five quarters (compared to seven quarters in the case with baseline calibration). The different impact on output occurs mainly via two channels. First, the decline in oil price is smaller and, therefore, the decrease in cost of production is not as large as in the baseline scenario. Second, the smaller decline in cost of production is transmitted through the trade channel as well—with a smaller increase in demand of intermediate inputs across countries—which puts additional downward pressure on output.

Elasticity of Substitution between Oil and Capital-Labor Aggregate. The benchmark elasticity of substitution between oil and capital is 0.09. Figure 21 plots the impulse responses to a positive U.S. energy efficiency shocks when the elasticity of substitution between oil and capital-labor aggregate increases to 0.4. The results indicate that as oil and other inputs become less complementary, U.S. oil demand decreases by a smaller magnitude following a positive U.S. energy efficiency shock compared to the baseline case. Consequently, there is a relatively small decline in oil price, while ROW oil importer's oil demand increases by a lower magnitude on impact. The increase (decrease) in the United States' and ROW's (oil exporter's) GDP is also less amplified relative to the low elasticity case.

VI. Conclusion

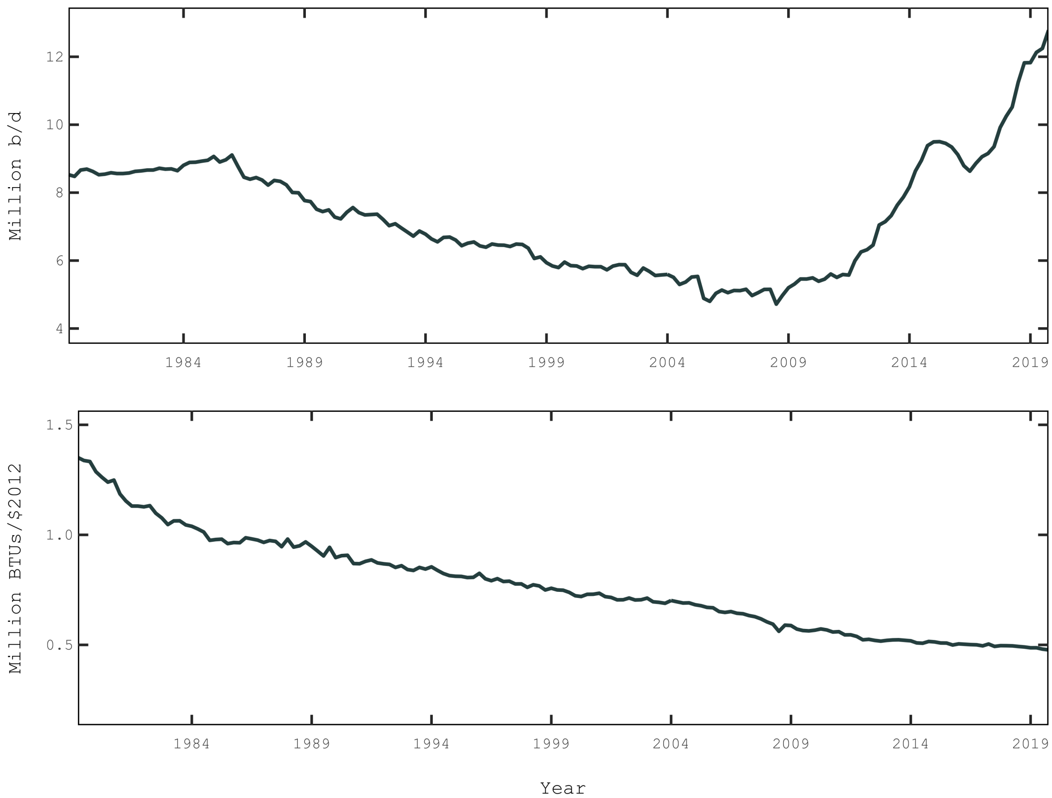
In this paper, I have examined both empirically and theoretically the global economic consequences of U.S. energy shocks. The empirical strategy combines dynamic factor modeling with a structural VAR framework to quantify the effects of unexpected changes in U.S. energy efficiency and U.S. oil supply on global and cross-country output and the world oil market. I use a dynamic factor model to extract a common factor in GDP growth rates across a large number of countries. The common factor captures fluctuations in global economic activity and represents the world business cycle. I include the estimated common factor and oil market variables (the real price of oil, U.S. oil consumption, and U.S and non-U.S. oil production) in a factor-augmented VAR model. Exploiting a set of sign and elasticity restrictions, I identify structural shocks, including U.S. energy efficiency and U.S. oil supply shocks.

My empirical results support previous findings in the oil market literature and provide additional evidence of the effects of U.S. energy efficiency and U.S. oil supply shocks. For example, I find that U.S. energy efficiency shocks have a larger impact on global output and the real price of oil than U.S. oil supply shocks. I reaffirm the key result from Kilian (2009) that it is important to disentangle the underlying drivers of oil price movements. The impulse responses indicate that both shocks decrease real price of oil and generate a favorable effect on global output. However, U.S. energy efficiency shocks decrease total world oil production and consumption, whereas U.S. oil supply shocks have the opposite effect. Moreover, results from a set of FAVAR models augmented with country GDP data indicate that the GDP implications of U.S. energy shocks are heterogenous across net oil-importing and net-oil exporting countries.

Historical decompositions indicate that the importance of U.S. energy efficiency and U.S. oil supply shocks has varied over time. For the period 2010–2019, positive U.S. oil supply shocks, led by productivity gains in the U.S. shale sector, resulted in an increase of 0.27 percentage points in global GDP growth. During the same period, a series of negative energy efficiency shocks decreased global GDP growth by 0.19 percentage points. The latter results are most prominent during the second shale boom, 2017–2019, when negative energy efficiency shocks cancelled out the positive impact on the global growth of U.S. oil supply expansion.

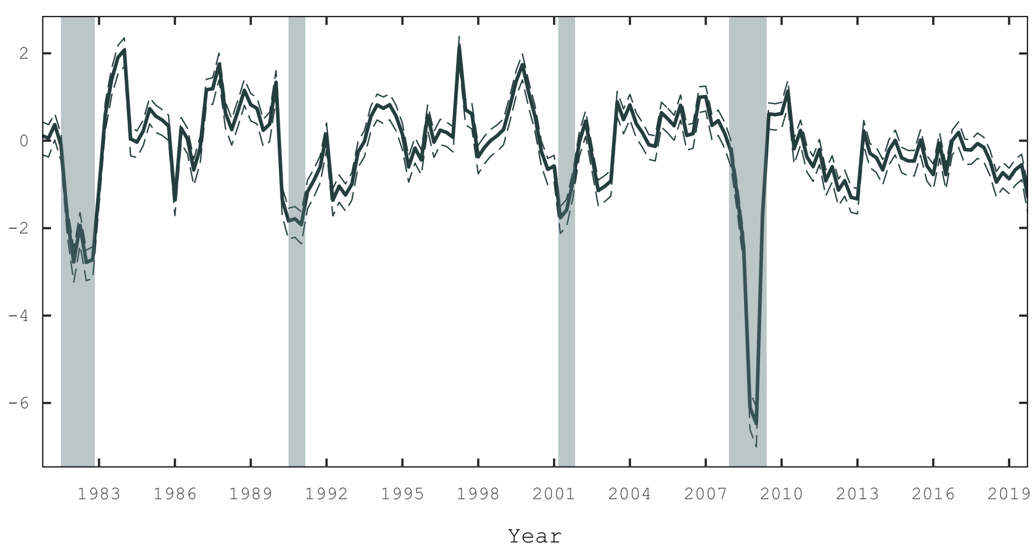
Using indirect inference, I estimate key parameters of U.S. energy efficiency and U.S. oil supply shocks in a general equilibrium multi-country model that incorporates a global market. The model provides an explicit interpretation of the empirical results and highlights channels and mechanisms via which U.S. energy efficiency and U.S. oil supply shocks impact international macroeconomic aggregates and the global oil market. For example, the model reveals that a decrease in the real price of oil following a positive U.S. energy efficiency shock is a result of a combination of the low elasticity of substitution of oil with other factors of production and a positive correlation of energy efficiency improvements across countries. I also use the model to discuss the role of U.S. energy efficiency improvements in decreasing the real price of oil and increasing global output as the world transits away from fossil fuels, such as crude oil. My results show that increasing the transferability of U.S. energy efficiency improvements to other countries can be used as a policy instrument in mitigating the negative global economic implications of a cutback in U.S. oil production.

Figure 1: U.S. Oil Production and Oil Intensity



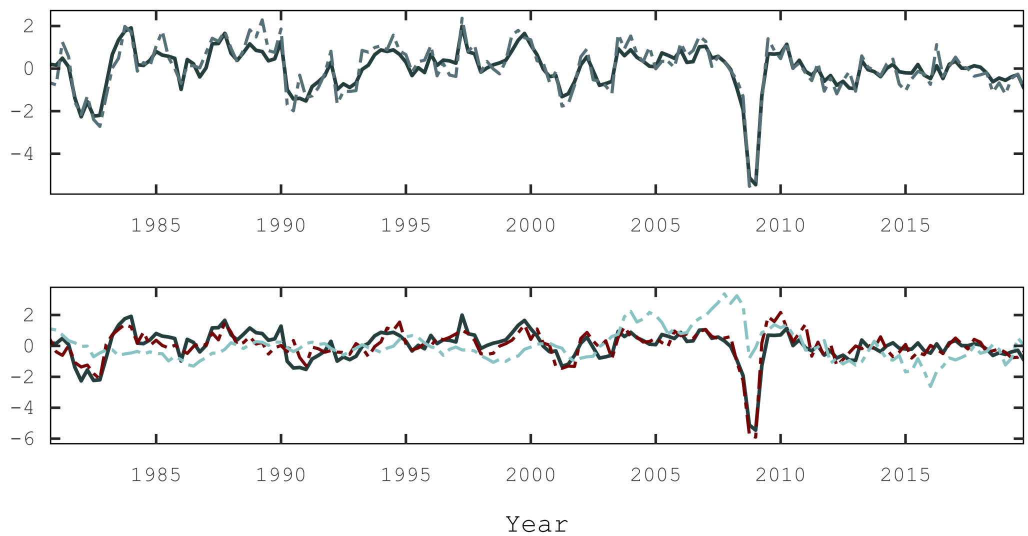
Note: Top: U.S. oil (crude oil and noncrude petroleum liquids and refined petroleum products) production in millions of barrels per day (mbpd). Bottom: Quarterly U.S. oil (petroleum, excluding biofuels) intensity in million BTUs per \$2012, where oil intensity is U.S. oil consumption/U.S. GDP.

Figure 2: Global GDP Factor: 1980:Q4 - 2019:Q4



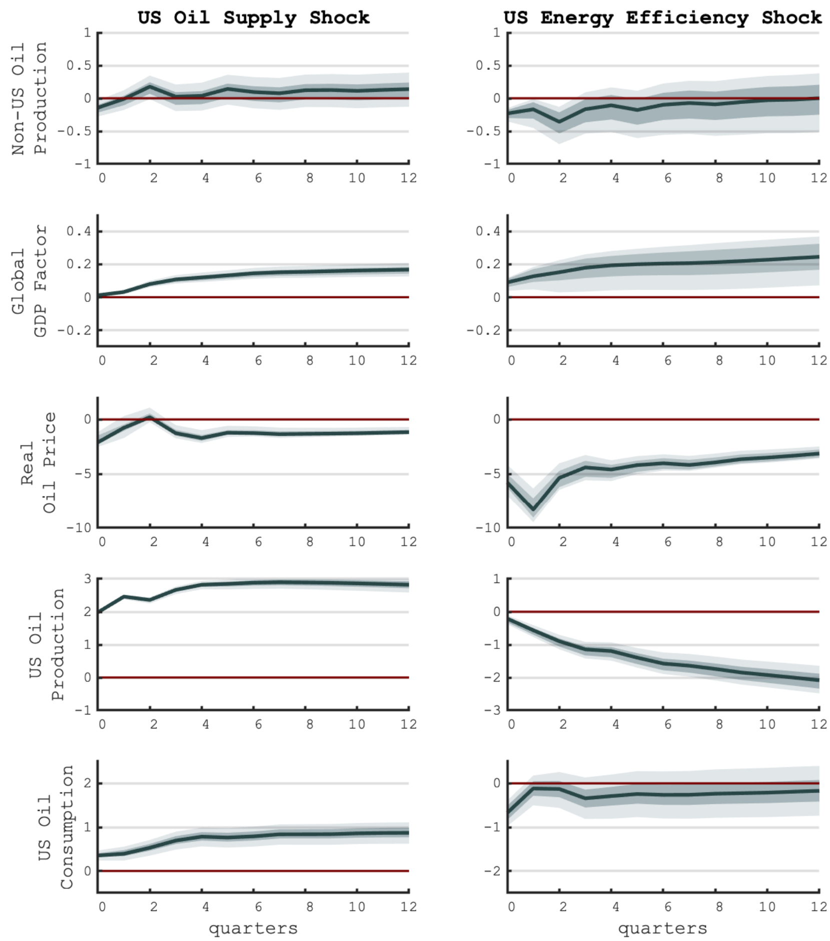
Note: Solid line: Global factor in GDP growth rates of 33 countries estimated using DFM (1) - (3). Dashed lines: 32^{nd} and 68^{th}-percentile bands. Grey bars show U.S. recession periods, from NBER.

Figure 3: Global GDP Factor: 1980:Q4 - 2019:Q4



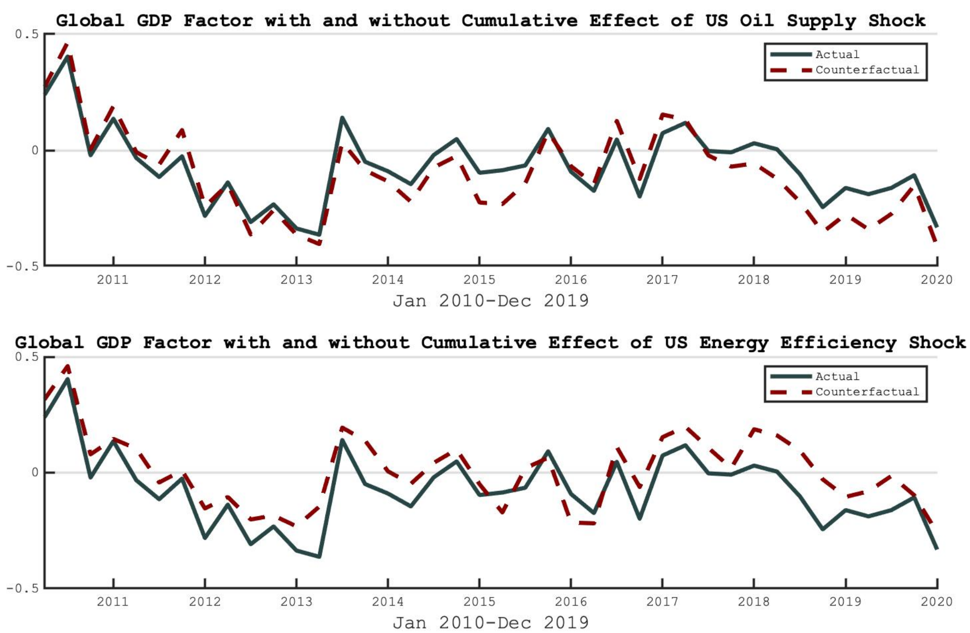
Note: Top: Global GDP factor estimated with and without U.S. GDP data (solid and dashed lines, respectively). Bottom: Global GDP factor, world industrial production, and the Kilian index (solid, dashed red, and dashed blue lines, respectively).

Figure 4: Impulse Responses to US Energy Market Shocks



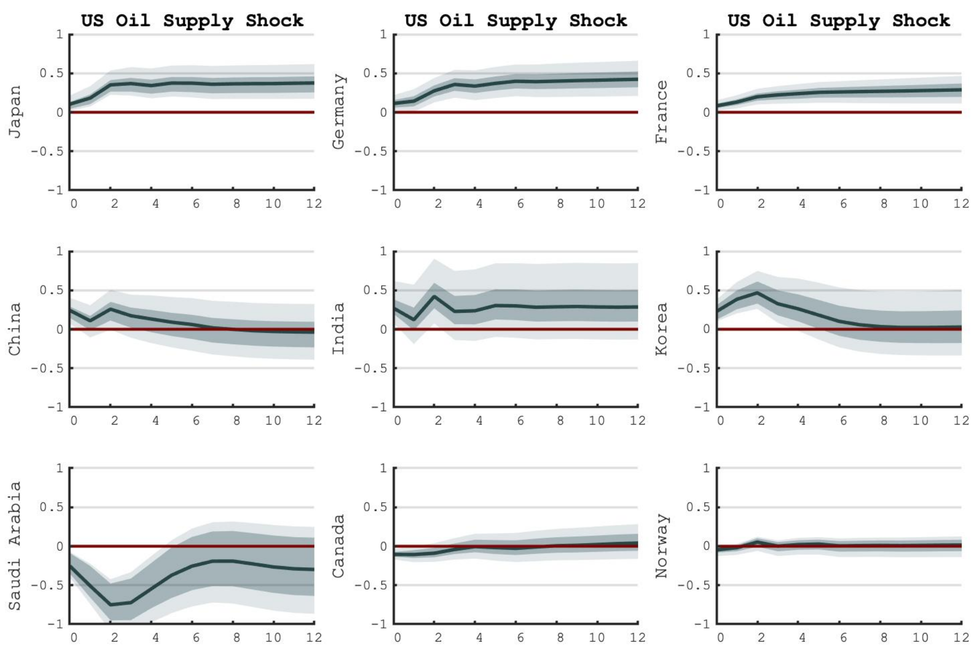
Note: Solid line represents median impulse response of all admissible models, with corresponding 32^{nd}–68^{th} and 16^{th}–84^{th} percentile bands. The estimation period is 1980:Q2–2019:Q4.

Figure 5: Historical Counterfactuals Global GDP Factor: 2010Q1–2019Q4



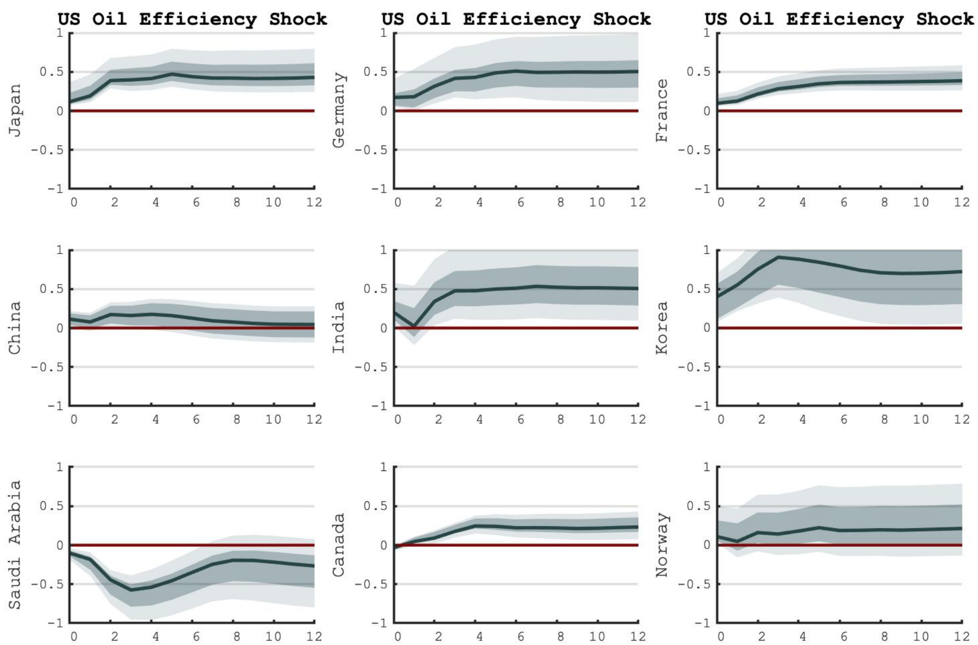
Note: Historical decompositions for global GDP Factor with and without U.S. oil supply shocks (top) and energy efficiency shocks (bottom). The reported historical decomposition results are based on the median of all admissible models. The global GDP factor is multiplied with the average factor loading to represent it in units of GDP growth rates.

Figure 6: Responses of Country Real GDP to a positive U.S. Oil Supply Shock



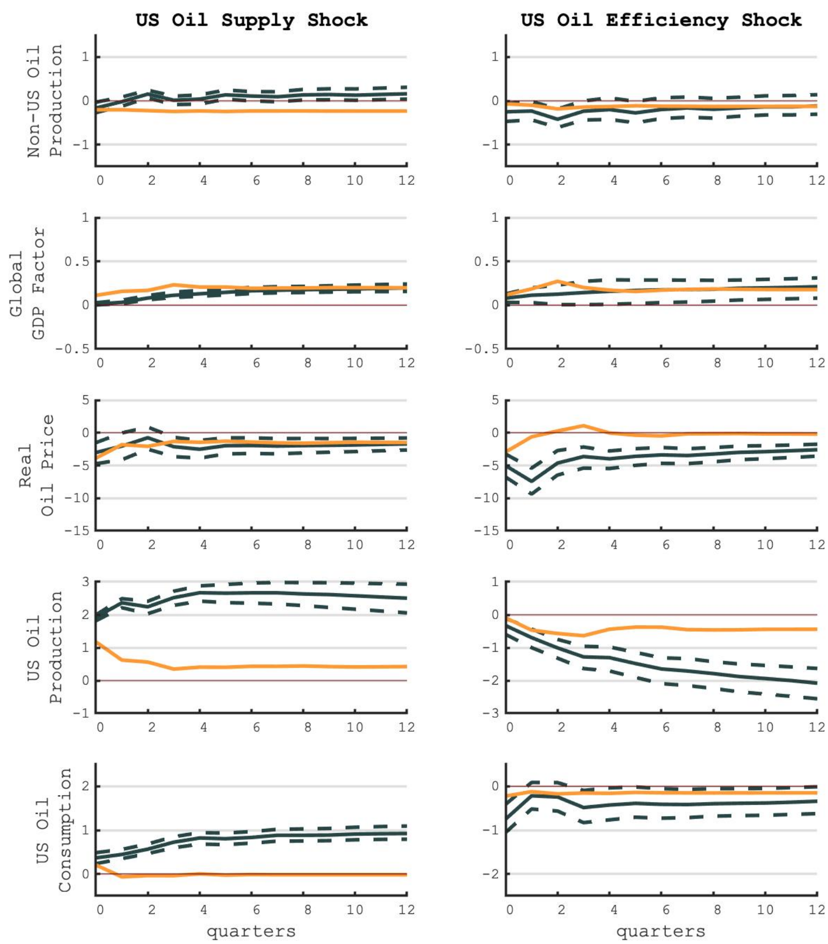
Note: Impulse responses of country real GDP to a positive U.S. oil supply shock. The estimation period is 1980:Q2–2019:Q4. Solid line represents median impulse response of all admissible models, with corresponding 32^{nd}–68^{th} and 16^{th}–84^{th} percentile bands.

Figure 7: Responses of Country Real GDP to a positive U.S. Energy Efficiency Shock



Note: Impulse responses of country real GDP to a positive U.S. energy efficiency shock. The estimation period is 1980:Q2–2019:Q4. Solid line represents median impulse response of all admissible models, with corresponding 32^{nd}–68^{th} and 16^{th}–84^{th} percentile bands.

Figure 8: Model Simulated and Empirical Impulse Responses to US Energy Market Shocks



Note: Impulse response functions (IRFs) from FAVAR estimated on model-simulated and actual data. Orange: Median IRFs of endogenous variables to structural shocks from FAVAR estimated on model-simulated data. Green: Median IRFs of endogenous variables to structural shocks estimated using FAVAR model (5) with 16^{th}–84^{th} percentile bands for the period 1980:Q2–2019:Q4.

Figure 9: Model Impulse Responses to a Positive U.S. Energy Efficiency Shock

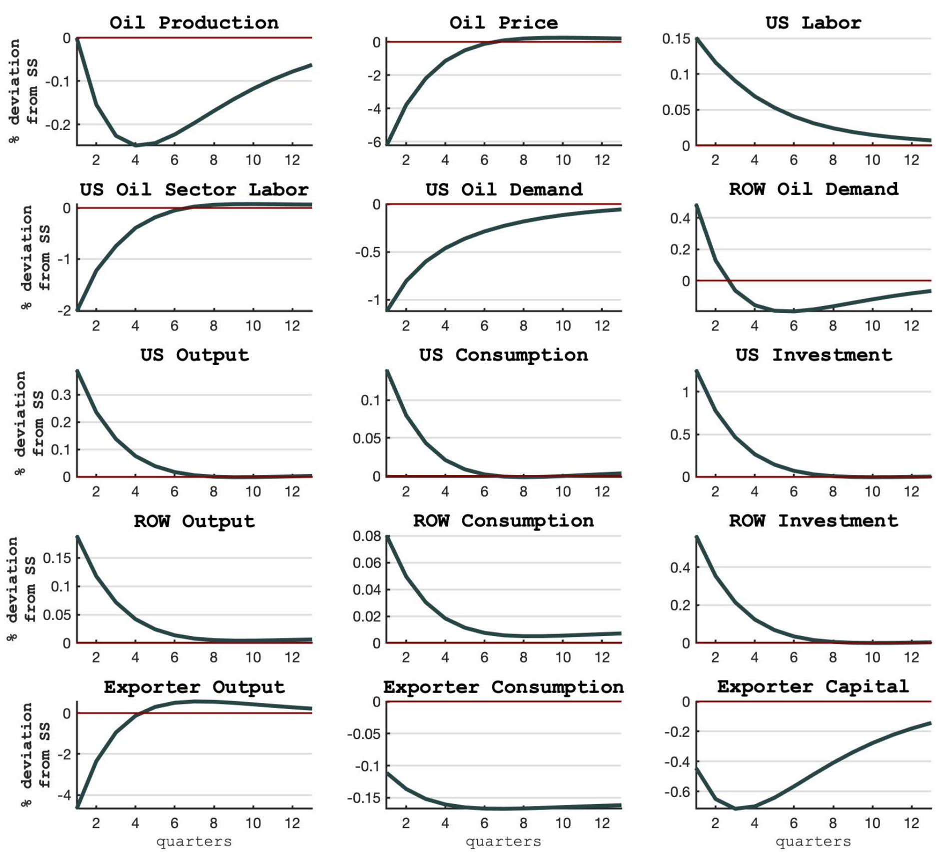


Figure 10: Model Impulse Responses to a Positive U.S. Oil Supply Shock

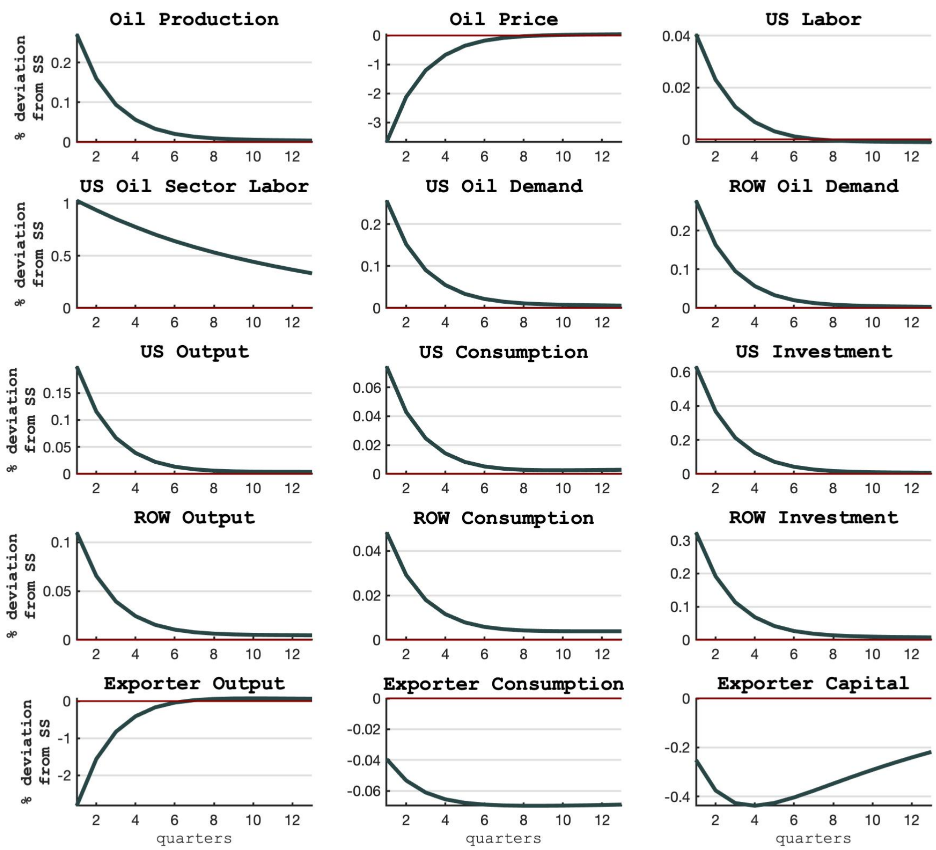
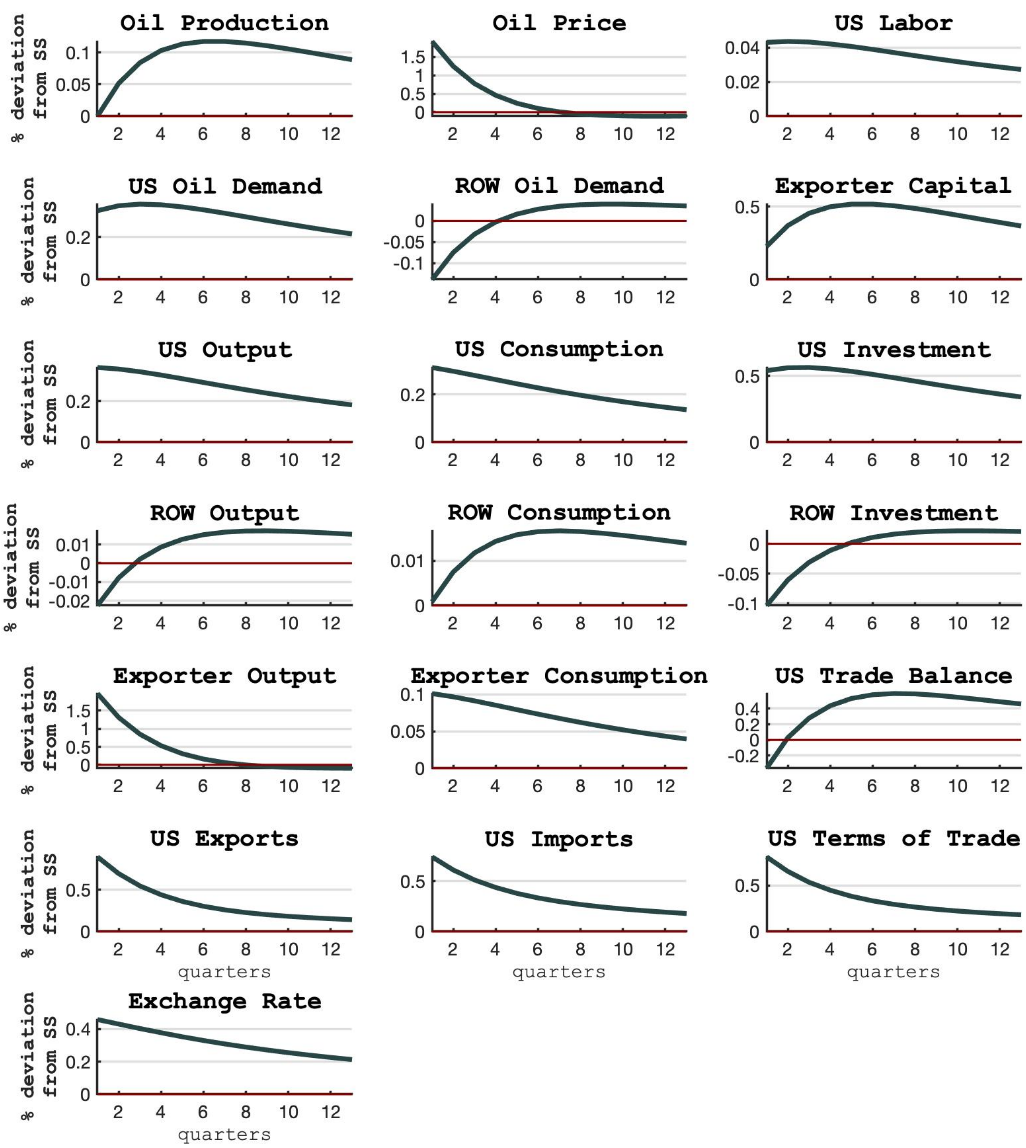


Figure 11: Model Impulse Responses to a Positive U.S. TFP Shock



VII. Appendix A

VII.1 Estimation of Dynamic Factor Model

The estimation objective is to infer from the observed data: (1) the path of common factors F_t and (2) all unknown parameters of the model.[38] The Bayesian approach views these as two vectors of random variables. Inference in the Bayesian framework is based on obtaining the joint and marginal distribution of these given the historical data on GDP growth rates i.e. obtaining the joint and marginal posterior distributions of all factors and model parameters. However, since the joint posterior distribution of these vectors is not analytically obtainable, therefore, Gibbs sampling is used to sample from the posterior.

The Gibbs sampling proceeds by taking a drawing from the conditional distribution of the model parameters given the data $\mathbf{Y_t}$ and the factor $\mathbf{F_t}$ and then drawing from the conditional distribution of the factor $\mathbf{F_t}$ given data $\mathbf{Y_t}$ and the prior drawing of the model parameters. The estimation of the model parameters given the factors, $\mathbf{F_t}$, is straightforward. Notice that by treating $\mathbf{F_t}$ as a set of data, generating the unknown parameters of the observation and state transition equations ($\mathbf{B}$, Ω, $\Phi(L)$, I_K) is a standard application of Bayesian linear regression. The latter step involving the generation of the vector, $\mathbf{F_t}$, is based on the multimove Gibbs-sampling (or the forward-backward) algorithm as described by Carter & Kohn (1994). The procedure allows us to generate the whole vector $\mathbf{F_t}$ from the joint distribution $p(F_1, F_2, \ldots, F_T|\mathbf{Y_t})$.[39] Using the Markov property of the state equation, the joint posterior of $\mathbf{F_t}$ can be factorized into $p(F_T|\mathbf{Y_t})$ and $p(F_s|F_{s+1}, \mathbf{Y_t})$ for all $s = 1, \ldots, T-1$. Since these two components are normally distributed given that error terms in the observation and state transition equations are normaly distributed, we can draw from distributions by computing their mean and variance. The Kalman filter is used to compute the mean and variance of $p(F_T|\mathbf{Y_t})$ and a backward recursion provides the mean and variance of $p(F_t|F_{t+1}, \mathbf{Y_t})$. Thus, the Carter & Kohn (1994) forward-backward algorithm delivers a draw of $\mathbf{F_t}$.[40] The estimation procedure can be summarized in the following four steps:

1. Conditional on $\mathbf{F_t}$, sample $\mathbf{B}$ and Ω from their posterior distributions.
2. Conditional on $\mathbf{F_t}$, sample $\Phi(L)$ and I_K from their posterior distributions.
3. Conditional on the parameters of the state space, $\mathbf{B}$, Ω, $\Phi(L)$ and I_K, sample F_t from its posterior distribution as discussed above.
4. Repeat steps 1 to 3 until convergence.

[38] This section draws heavily from Kabundi & Zahid (2021).

[39] Note that singlemove Gibbs sampling generates elements of $\mathbf{F_t}$ one at a time from the conditional distribution $p(F_t|\mathbf{F_{\neq t}}, \mathbf{Y_t})$. The multimove Gibbs sampling procedure is computationally faster and more efficient (C. Kim & Nelson (1999)).

[40] For a detailed exposition, see C. Kim & Nelson (1999), Blake & Mumtaz (2012) and Jackson et al. (2015).

VII.2 Results

Table 4: Variance Decomposition

	1980–1999			**2000–2019**			**1980–2019**		
	Global	*Group*	*Idiosync*	*Global*	*Group*	*Idiosync*	*Global*	*Group*	*Idiosync*
Australia	58.7	5.4	35.9	12.0	2.6	85.4	30.4	23.7	45.9
Austria	2.6	33.1	64.3	41.7	5.2	53.1	18.4	15.8	65.8
Belgium	22.6	36.4	41.0	63.6	8.7	27.7	42.3	12.0	45.7
Finland	15.4	2.4	82.2	52.9	9.7	37.4	29.9	2.7	67.5
France	14.9	38.6	46.6	57.9	16.9	25.3	44.3	21.9	33.8
Germany	6.2	46.2	47.6	63.5	17.6	18.9	33.4	22.1	44.5
Italy	32.7	24.7	42.6	52.2	30.8	17.0	52.6	13.3	34.1
Japan	2.8	3.7	93.5	56.4	1.8	41.7	19.9	7.0	73.2
Netherlands	20.0	12.8	67.2	36.0	27.2	36.8	32.8	6.3	60.9
Spain	3.5	2.2	94.3	11.9	45.4	42.6	10.6	7.8	81.6
Sweden	19.0	4.6	76.4	44.8	8.2	47.0	27.4	1.9	70.6
Switzerland	45.3	12.8	41.9	43.4	2.6	54.0	40.3	1.3	58.4
United States	50.4	1.6	48.0	50.5	2.1	47.3	45.2	4.3	50.5
China	3.5	3.7	92.7	44.0	4.1	51.9	9.3	1.8	88.9
Chile	24.2	2.9	72.9	45.9	18.9	35.2	18.6	2.2	79.1
India	6.4	1.4	92.2	20.3	10.0	69.8	6.6	0.9	92.5
South Korea	2.3	37.3	60.3	45.9	9.9	44.2	11.9	46.2	41.8
Philippines	3.8	6.3	89.9	31.0	3.8	65.3	1.7	6.9	91.4
South Africa	25.2	3.8	71.0	41.4	10.1	48.5	17.8	1.4	80.7
Singapore	4.9	12.9	82.2	51.4	10.6	38.0	22.9	14.7	62.4
Thailand	2.2	82.4	15.4	18.9	5.4	75.6	8.9	30.0	61.1
Turkey	5.7	2.1	92.2	41.1	12.7	46.2	13.5	1.9	84.6
Canada	55.9	1.5	42.6	52.9	13.3	33.8	43.6	2.3	54.1
Mexico	18.3	8.5	73.2	71.6	7.8	20.6	25.7	8.0	66.3
Norway	9.0	2.2	88.8	8.5	7.4	84.1	6.8	2.9	90.2
Saudi Arabia	2.5	44.1	53.4	8.1	6.6	85.3	1.0	48.3	50.7
United Kingdom	19.7	3.7	76.6	25.4	5.8	68.8	31.9	1.9	66.2
Argentina	5.3	1.9	92.8	10.7	20.5	68.8	3.1	0.6	96.2
Brazil	15.7	3.5	80.7	51.9	3.5	44.6	19.6	2.2	78.2
Indonesia	2.6	34.2	63.2	13.6	24.0	62.3	2.7	25.4	71.9
Malaysia	3.7	82.3	14.0	76.5	2.0	21.5	19.9	71.3	8.8
New Zealand	35.7	9.2	55.1	10.7	8.2	81.1	15.5	3.0	81.4
Peru	5.2	1.6	93.3	33.8	25.7	40.5	2.8	0.8	96.4
Average	16.5	17.3	66.2	39.1	11.8	49.1	21.6	12.5	65.9

Note: Results from variance decompositions obtained from a hierarchical dynamic factor (HDFM) model. The HDFM estimates 1 global factor common to all countries, and 4 group-specific factors. Group-specific factors are based on groups: (1) advance economy oil importers, (2) emerging market oil importers, (3) oil exporters, and (4) other countries. The 'other countries' group includes large commodity exporters or countries that changed status from net oil exporter to importer (or vice versa). Each cell reports variance share attributable to the relevant factor as indicated. The results are reported for the full sample period 1980–2019 and two subsample periods 1980–1999 and 2000-2019.

Figure 12: Histogram Of Factor Loading

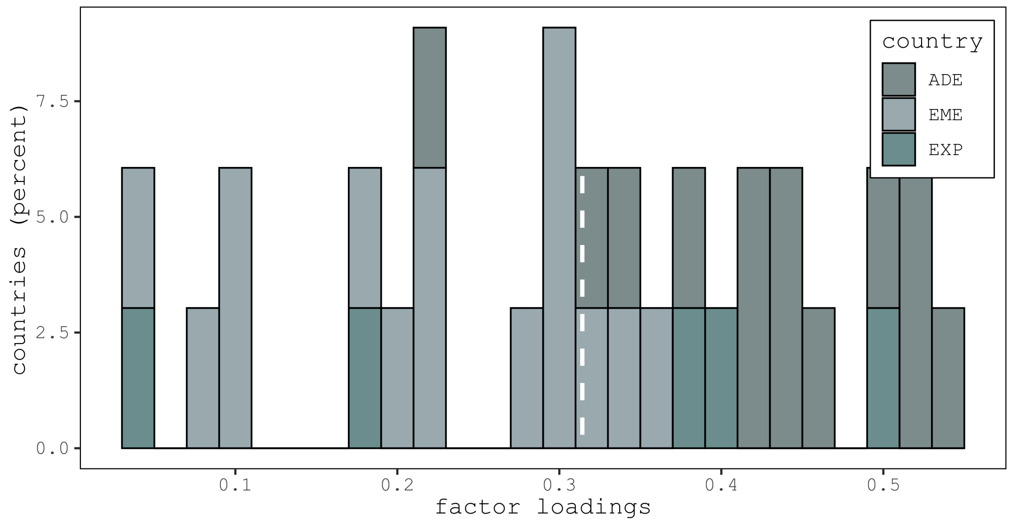


Figure 13: Histogram Of GDP Variance Due To Global GDP Factor

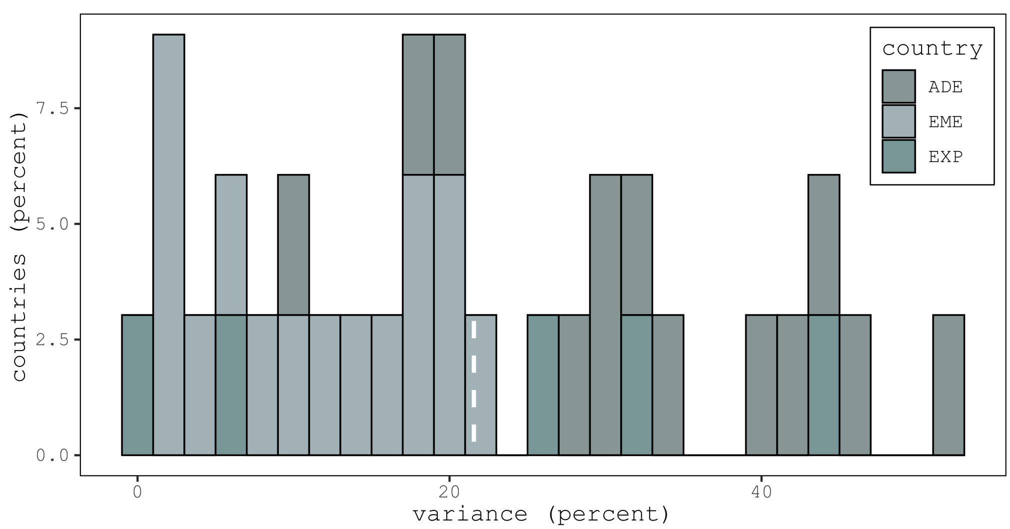
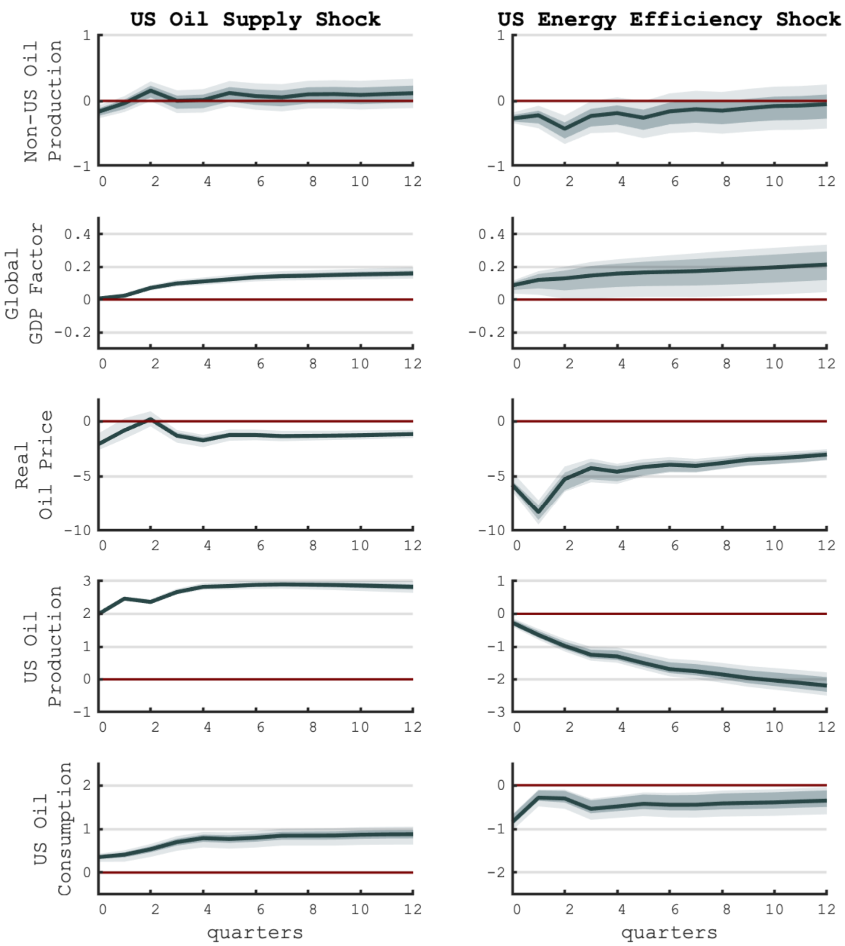
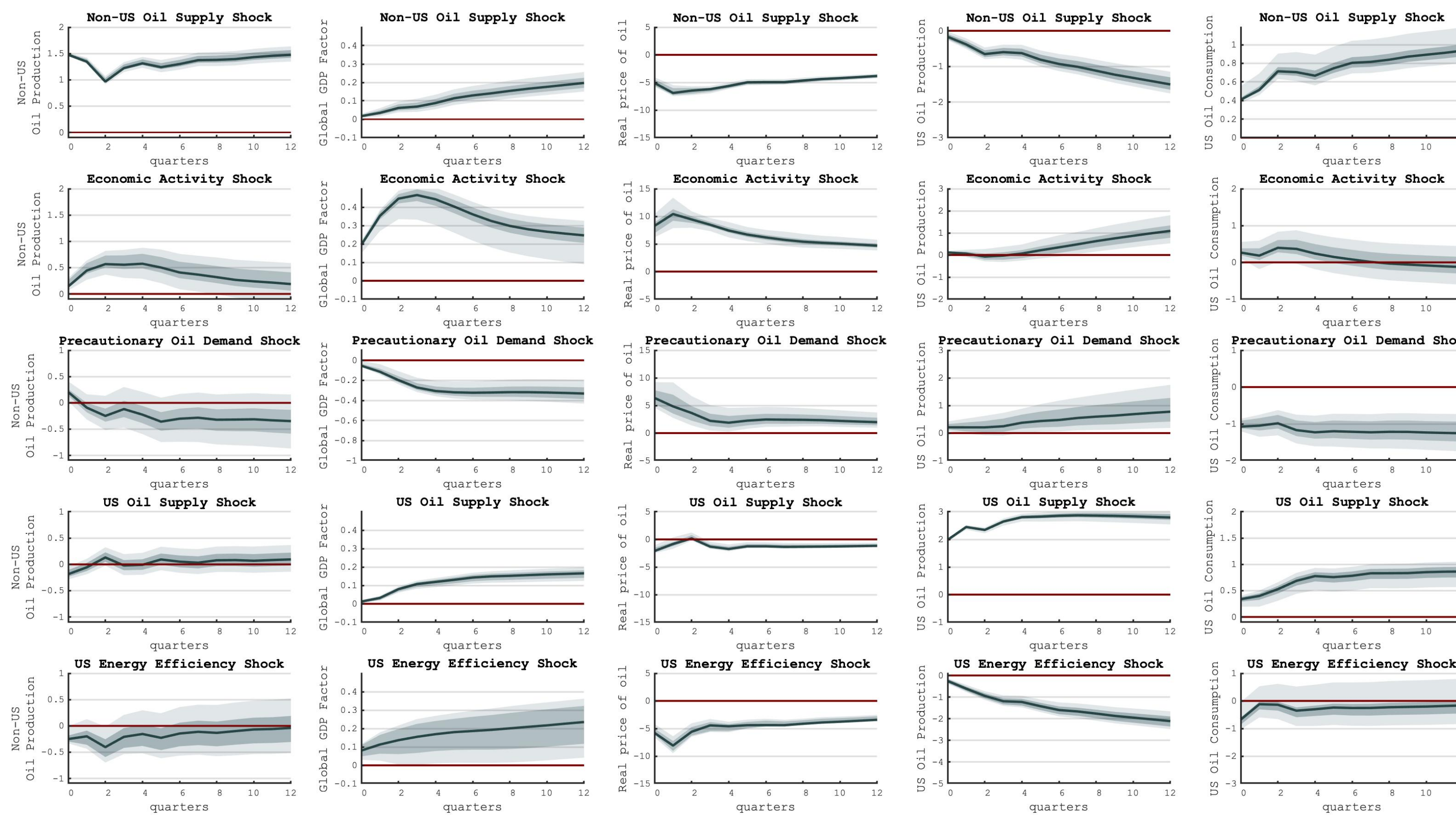


Figure 14: Robustness: Identification with dynamic restrictions on U.S. oil consumption to a US Energy Efficiency Shock



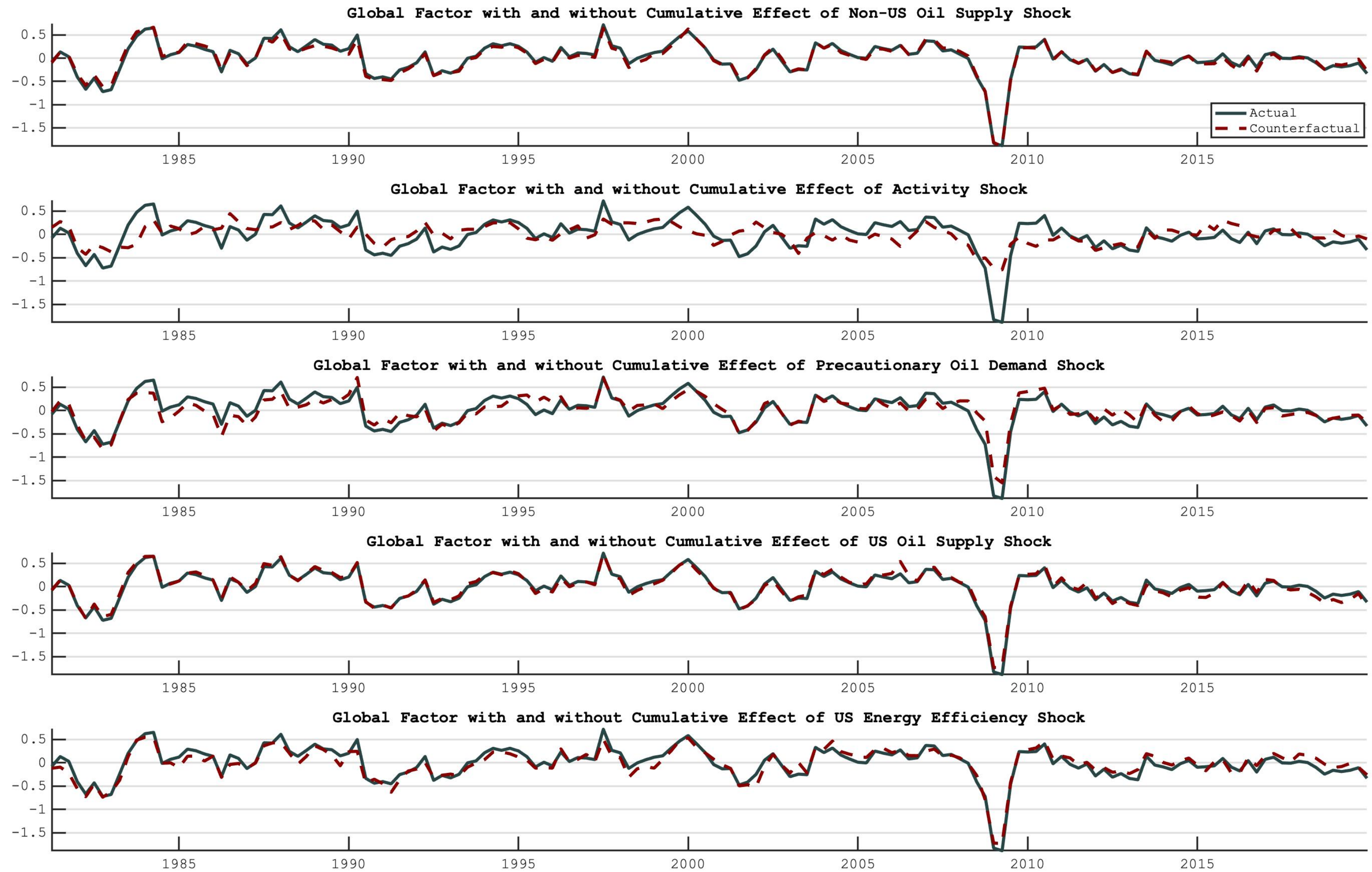
Note: Median impulse response functions of endogenous variables to structural shocks estimated using FAVAR model (5) with 32^{nd}–68^{th} and 16^{th}–84^{th} percentile bands of the admissible set for the period 1980:Q2–2019:Q4.

Figure 15: Impulse Responses



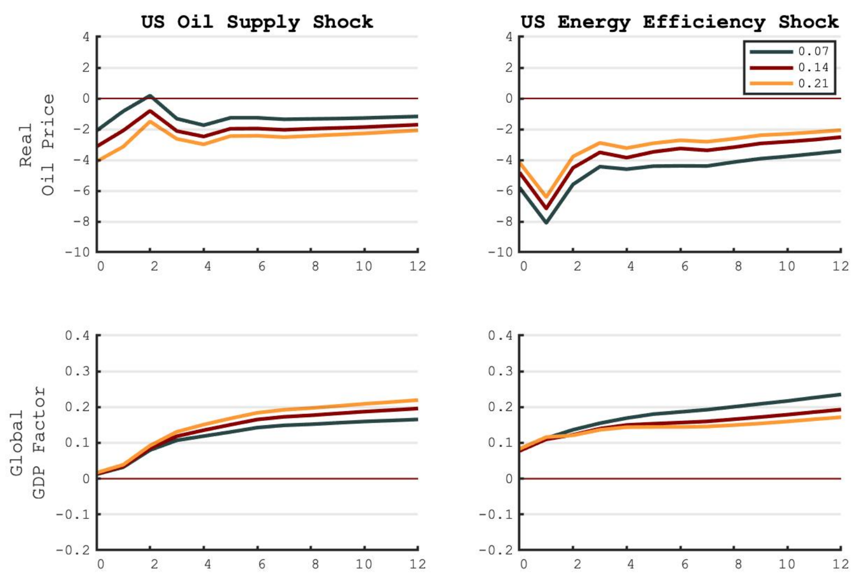
Note: Median impulse response functions of endogenous variables to structural shocks estimated using FAVAR model (5) with 32^{nd}–68^{th} and 16^{th}–84^{th} percentile bands for the period 1980:Q2–2019:Q4.

FIGURE 16: Historical Decomposition: Global GDP Factor, 1980:Q1 - 2019:Q4



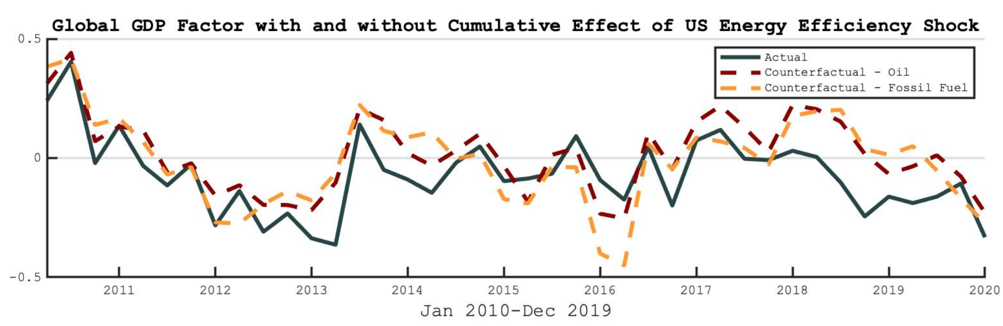
Note: Historical decompositions for Global GDP Factor with and without structural shocks.

Figure 17: Robustness: Impulse Responses to US Energy Market Shocks



Note: Median impulse response functions of real GDP to a positive U.S. oil supply and U.S. energy efficiency shock.

Figure 18: Robustness: Historical Counterfactuals Global GDP Factor



Note: Historical decompositions for Global GDP Factor with and without U.S. energy efficiency shocks. Counterfactuals based on U.S. oil consumption and U.S. fossil fuel consumption data.

VIII. Appendix B

VIII.1 First Order Conditions

I reformulate the problem as a social planning problem, where the social planner maximizes the weighted average of the utility of the representative households in each country. Let ω^i be the relative weights placed on the utility of each country i. Then, the planner's problem is as following

$$\sum_{t=0}^{\infty} \beta^t \left\{ \omega^a U\left(c_t^a, L_t^a\right) + \omega^b U\left(c_t^b, L_t^b\right) + \omega^o U\left(c_t^o L_t^o\right) \right\}$$

subject to the constraints given by equations (3) - (7).

First Order Conditions

c_t: $\theta \left(c_t^{\theta}(1-n_t)^{1-\theta}\right)^{-\gamma} c_t^{\theta-1}\left(1-n_t\right)^{1-\theta} \;=\; \lambda_t$

c_t^*: $\theta \left(c_t^{\theta}(1-n_t)^{1-\theta}\right)^{-\gamma} c_t^{\theta-1}\left(1-n_t\right)^{1-\theta} \;=\; \lambda_t$

c_t^o: $c_t^{-\gamma} \;=\; \lambda_t$

n_t: $-(1-\theta)\left(c_t^{\theta}(1-n_t)^{1-\theta}\right)^{-\gamma} c_t^{\theta}(1-n_t)^{-\theta} \;+\; \lambda_t \alpha \frac{y_t}{n_t} \;=\; 0$

n_t^*: $-(1-\theta)\left(c_t^{\theta}(1-n_t)^{1-\theta}\right)^{-\gamma} c_t^{\theta}(1-n_t)^{-\theta} \;+\; \lambda_t \alpha \frac{y_t}{n_t} \;=\; 0$

n_t^o: $-\theta_L\left(1-n_t^o\right)^{-\xi_L} + \lambda_t \alpha \frac{y^o,t}{n^o,t} = 0$

k_{t+1}: $\lambda_t = \beta E\left[\lambda_{t+1}\frac{(1-\alpha)y_{t+1}\eta k_{t+1}^{-v}}{\eta k_{t+1}^{1-v}+(1-\eta)o_{t+1}^{1-v}} + \lambda_{t+1}\left(1-\delta+(1-\varphi)\left(\frac{i_{t+1}}{k_{t+1}}\right)^{\varphi}\right)\right]$

k_{t+1}^*: $\lambda_t = \beta E\left[\lambda_{t+1}\frac{(1-\alpha)y_{t+1}\eta k_{t+1}^{-v}}{\eta k_{t+1}^{1-v}+(1-\eta)o_{t+1}^{1-v}} + \lambda_{t+1}\left(1-\delta+(1-\varphi)\left(\frac{i_{t+1}}{k_{t+1}}\right)^{\varphi}\right)\right]$

$a_{c,t}$: $\lambda_t \psi \left(\frac{c_t}{a_{c,t}}\right)^{\mu} - \lambda_t = 0$

$a_{c,t}^*$: $\lambda_t \left(c_t^*\right)^{\mu}(1-\psi)\left(a_{c,t}^*\right)^{-\mu} - \lambda_t = 0$

$a_{c,t}^o$: $\lambda_t \psi_o \left(\frac{c_t^o}{a_{c,t}^o}\right)^{\mu} - \lambda_t = 0$

$a_{i,t}$: $\lambda_t \varphi i_t^{\varphi+\mu-1} k_t^{1-\varphi} \psi \left(a_{i,t}\right)^{-\mu} - \lambda_t = 0$

$a_{i,t}^*$: $\lambda_t \varphi i^{*\varphi+\mu-1}\left(k_t^*\right)^{1-\varphi}(1-\psi)\left(a_{i,t}^*\right)^{-\tilde{\mu}} - \lambda_t = 0$

$b_{c,t}$: $\lambda_t(1-\psi)\left(\frac{c_t}{b_{c,t}}\right)^{\mu} - \lambda_t = 0$

$b_{c,t}^*$: $\lambda_t \left(c^*\right)^{\mu}(\psi)\left(b_{c,t}^*\right)^{-\mu} - \lambda_t = 0$

$b_{c,t}^o$: $\lambda_t\left(1-\psi_o\right)\left(\frac{c_t^o}{b_{c,t}^o}\right)^{\mu} - \lambda_t = 0$

$b_{i,t}$: $\lambda_t \varphi i^{\varphi+\mu-1} k_t^{1-\varphi}(1-\psi)\left(b_{i,t}\right)^{-\mu} - \lambda_t = 0$

$b_{i,t}^*$: $\lambda_t \varphi i_t^{*\varphi+\mu-1}\left(k_t^*\right)^{1-\varphi}(\psi)\left(b_{i,t}^*\right)^{-\mu} - \lambda_t = 0$

o_t: $\lambda_t(1-\alpha)y_t\left(\eta k_t^{1-v}+(1-\eta)o_t^{1-v}\right)^{-1}(1-\eta)o_t^{-v} = \lambda_t$

o_t^*: $\lambda_t(1-\alpha)y_t^*\left(\eta k_t^{*1-v}+(1-\eta)o_t^{*1-v}\right)^{-1}(1-\eta)o_t^{*-v} = \lambda_t$

VIII.2 Optimality Conditions

1. *Consumption-labor intratemporal condition.*

2. *Intertemporal optimality conditions.*

3. *International risk sharing.*

   Combining *f.o.cs* with respect to consumption:

$$\theta\left(c_t^{\theta}(1-n_t)^{1-\theta}\right)^{-\gamma}c_t^{\theta-1}(1-n_t)^{1-\theta} \;=\; \theta\left(c_t^{*\theta}(1-n_t^*)^{1-\theta}\right)^{-\gamma}c_t^{*\theta-1}(1-n_t^*)^{1-\theta} \tag{33}$$

$$\theta\left(c_t^{\theta}(1-n_t)^{1-\theta}\right)^{-\gamma}c_t^{\theta-1}(1-n_t)^{1-\theta} \;=\; c_t^{-\gamma} \tag{34}$$

$$\theta\left(c_t^{*\theta}(1-n_t^*)^{1-\theta}\right)^{-\gamma}c_t^{*\theta-1}(1-n_t^*)^{1-\theta} \;=\; c_t^{-\gamma} \tag{35}$$

4. *Leisure-labor choice across countries.*

   Combining *f.o.cs* with respect to labor:

$$\frac{(1-\theta)\left(c_t^*\theta(1-n_t^*)^{1-\theta}\right)^{-\gamma}c_t^{*\theta}(1-n_t^*)^{-\theta}}{(1-\theta)\left(c_t^*\theta(1-n_t^*)^{1-\theta}\right)^{-\gamma}c_t^{*\theta}(1-n_t^*)^{-\theta}} \;=\; \frac{\alpha\frac{y_t}{n_t}}{\alpha\frac{y_t^*}{n_t^*}} \tag{36}$$

5. *Cross-country intertemporal condition.*

   Combining *f.o.cs* with respect to capital:

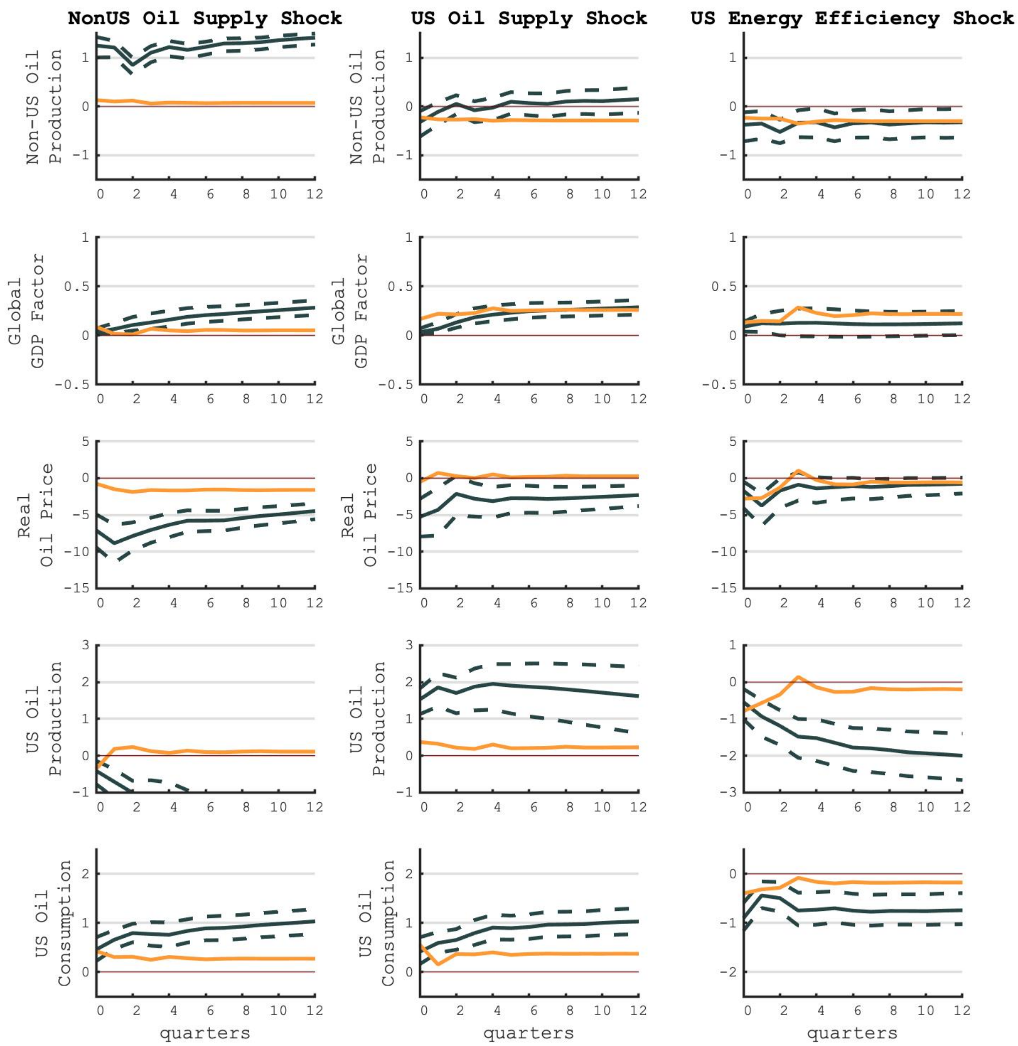
$$1 \;=\; E\left[\frac{\beta E\left[\lambda_{t+1}\frac{(1-\alpha)y_{t+1}\eta k_{t+1}^{-v}}{\eta k_{t+1}^{1-v}+(1-\eta)o_{t+1}^{1-v}}+\lambda_{t+1}\left(1-\delta+(1-\varphi)\left(\frac{i_{t+1}}{k_{t+1}}\right)^{\varphi}\right)\right]}{\beta E\left[\lambda_{t+1}\frac{(1-\alpha)y_{t+1}\eta k_{t+1}^{-v}}{\eta k_{t+1}^{1-v}+(1-\eta)o_{t+1}^{1-v}}+\lambda_{t+1}\left(1-\delta+(1-\varphi)\left(\frac{i_{t+1}}{k_{t+1}}\right)^{\varphi}\right)\right]}\right] \tag{37}$$

6. *Oil demand across countries.*

   Combining *f.o.cs* with respect to oil:

$$1 \;=\; \frac{(1-\alpha)y_t\left(\eta k_t^{1-v}+(1-\eta)o_t^{1-v}\right)^{-1}(1-\eta)o_t^{-v}}{(1-\alpha)y_t^*\left(\eta k_t^{*1-v}+(1-\eta)o_t^{*1-v}\right)^{-1}(1-\eta)o_t^{*-v}} \tag{38}$$

Figure 19: Robustness: Indirect inference with additional moments



Note: Impulse response matching with identification of U.S. energy efficiency, U.S. oil supply, and non-U.S. oil supply shocks. The estimated parameters are $\Omega = \{0.8058, 0.1922, 0.9171, 0.9389\}$ for U.S. energy efficiency shock persistence and correlation, U.S. oil supply shock persistence, and non-U.S. oil supply shock persistence, respectively.

Figure 20: Robustness: Impulse Responses to a Positive U.S. Energy Efficiency Shock

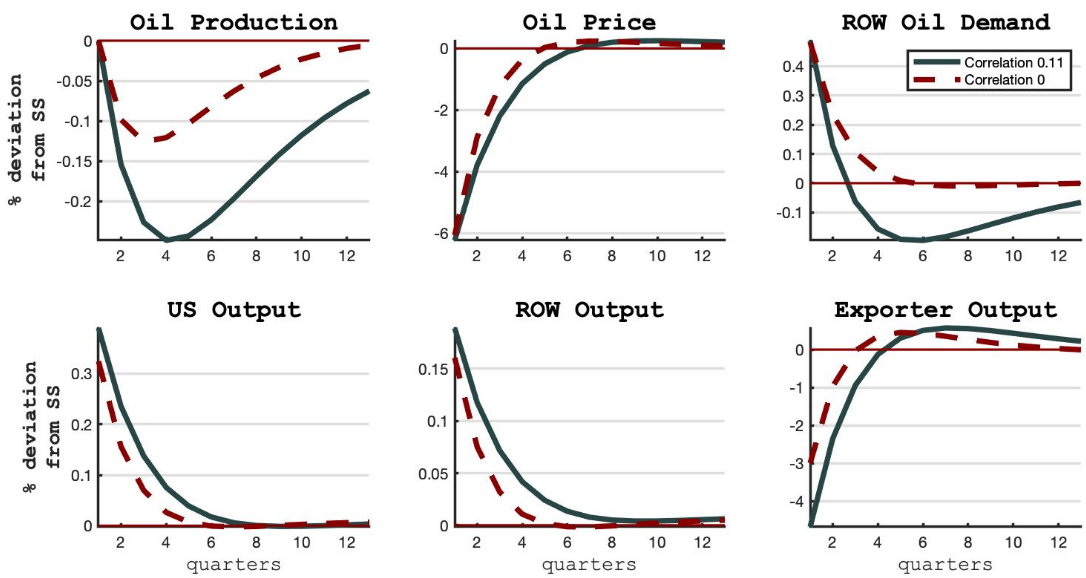
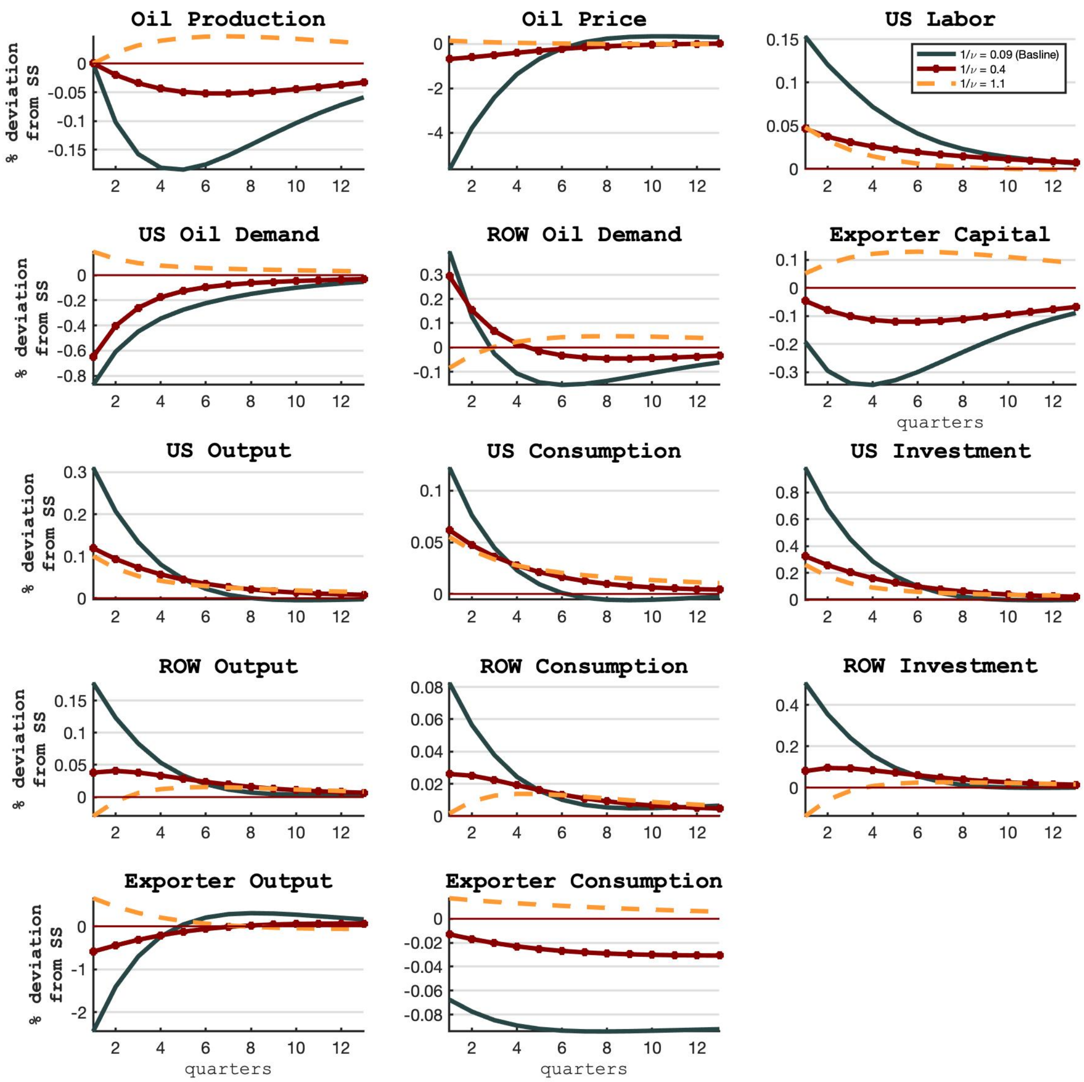


Figure 21: Robustness: Impulse Responses to a Positive U.S. Energy Efficiency Shock



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